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Innovative large-scale energy storage technologies and Power-to-Gas concepts after optimization

D7.5

Report on experience curves and economies of scale

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Responsible	Robert Tichler, EIL
Author(s)	Hans Böhm, Andreas Zauner, Sebastian Goers, Robert Tichler, Pieter Kroon
Reviewer	Steffen Schirrmeister, TKIS
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Abstract

Since the market launch and the development of the power-to-gas (PtG) technology depends, among other things, on the profitability and thus mainly on the investment costs of the plant, potential cost reduction should be examined. The main components of the PtG process are still under development and only a few pilot plants have been built. With a higher number of installed plants, a significant cost reduction is expected for the PtG technology, as experienced also in the case of other technologies. **This deliverable D7.5 focuses on the analysis of investment cost reduction for power-to-gas applications through experience curves and economies of scale.**

In general, the formal concept of experience curves describes the decline of real costs by a constant percentage (learning rate) for every cumulative doubling of its produced volume and therefore represents a relationship between the costs of a product and the experience, expressed in cumulative production of that product. Also the term **economies of scale in this deliverable refers solely to the effect of real cost reductions through an increase of the production volume and not to cost reductions in consequence of an increase in size in form of upscaling (e.g. of nominal power)**.

The **reasons for cost reductions** based on experience curves and economies of scale can be attributed among other things to the following factors:

- fix cost degression (increased utilization of different sectors in the company e.g., administration, R&D, production, logistics, and distribution),
- reduction of production time (efficiency of manpower is increased due to learning effects),
- increase specialization (standardization, focus on core competence and one product family),
- variation in the used resources (e.g., alternative and less expensive (raw-)materials, optimize employment of staff according to their qualifications),
- improvement of existing production technologies,
- and optimization of product design with respect to simplify the production process.

The produced volume of power-to-gas plants and therefore the gained experience and economies of scale depend on the development of the future **global demand for power-to-gas** products which is subject to climate and policy measures (e.g., carbon taxes, the scope of government R&D, subsidies, and market introduction programs) and economic factors (e.g., economic growth).

While literature-based data on learning rates, investment costs, and future global demand for power-to-gas products would principally allow a first estimation of future investment costs for power-to-gas applications, the available data does not fulfill our requirements because of the lack of feasibility in differentiating among different electrolysis or methanation technologies as well as differentiating between system and stack (electrolysis) or reactor (methanation) cost. To get a detailed view of technological learning, a component-based approach was developed with the model **CoLLeCT — Component Level Learning Curve Tool**. This **allows for comparisons of learning effects between different technologies, investigation of cost structure developments, and consideration of spillover effects from concurrent technology sectors.** The potential for cost reductions through technological learning were investigated for electrolysis and methanation systems.

For implementing the theory of learning curves, it would be crucial to estimate the global PtG demand. Depending on the scenario, there would be a need to **install about 6,500 to 14,200 GW electrolysis power capacities and about 3,400 to 7,100 GW SNG-output power capacities (Synthetic Natural Gas) to meet the demand in the year 2050.** These values seem to be very high. However, it is important to remember that, in 2050, in a decarbonized energy system, not only

natural gas but also other fossil energy sources, such as oil and coal, must be substituted by renewable energy carriers. Since not all areas of the energy system can be electrified, green molecules (renewable SNG and hydrogen produced by PtG) would also play an important role in the future energy system. **In order to cover this relative high demand and to produce the required quantities** (for example about 285,000 electrolyzer systems with an installed power of 50 MW would be required), a **mass production would be absolutely necessary.** However, this calls for a standardized and mass production-ready design of the products (e.g., no individual installation planning or piping). The power-to-gas systems must be planned for the construction on the green field (with the interface power supply, gas connection for feed-in and possibly CO_2 supply), to meet the requirements for mass-production.

The costs are thereby stated as **real costs** (reference year 2017, $€_{2017}$). This means that the inflationary effects that are anticipated and will lead to rising nominal costs have not been considered. Additionally, **no significant changes in technology**, such as an implementation of additional functions, control elements and safety devices or efficiency improvements, have been taken into account for calculating the future investment costs; only this approach – the assessment of the product according to the current functional scope and characteristics – allows for the investigation of future costs based on the theoretical concept of experience curves and economies of scale.

The alkaline electrolyzer (AEC) systems show lower potential for cost reductions when compared to proton exchange membrane electrolyzer (PEMEC) and solid oxide electrolyzer (SOEC). With investment costs for **AEC estimated to reach about 440 $€_{2017}/kW_{el}$ in 2050**, the costs are expected to be significantly higher than that stated for **PEMEC systems that are expected to be about 290 $€_{2017}/kW_{el}$.** Besides the lower overall learning rate of AEC, this can be explained by the substantially higher starting value of cumulative productions, which means that significant learning effects have already occurred in the past. Additionally, the learning rate of PEMEC decreases rather fast with increasing production volumes in the beginning, whereas this effect reduces for higher cumulative volumes. Conversely, the experience rate of the AEC is more harmonized over the entire period. **The SOEC shows the highest cost reduction potential of all three investigated electrolysis technologies, with investment costs estimated to reach about 610 $€_{2017}/kW_{el}$ in 2050.** This follows from a rather high learning rate that was defined on the SOEC itself, based on relevant literature. Especially, for this technology, further investigations on cost structure and experience rates are necessary to allow reasonable estimations on future investment costs.

The experience curves for catalytic and biological methanation systems show similar trends for cost reductions. The investment costs for biological methanation reach lower levels in the long term. This is mainly driven by the fact that the relative increase in cumulative produced volume has to be substantially higher when compared to the catalytic application to reach presumed technology production share levels. Additionally, biological methanation does not have the catalyst component unlike the catalytic methanation, which is expected to gain relatively low learning effects when compared to other components in the reactor module. Despite this, **investment costs for both technologies remain on a similar level throughout the investigated period and are expected to reach values of 280 $€_{2017}/kW_{SNG}$ (catalytic) and 220 $€_{2017}/kW_{SNG}$ (biological) in 2050 under the presumed conditions.**

However, it has to be pointed out that the development of the power-to-gas technology is subject to fundamental energy and climate policy decisions.

Executive Summary

An ecologically sustainable energy supply, which is economically viable and socially acceptable, is highly valued in the European policy. The European energy supply must be transformed due to energetic, social, economic, and environmental/climatic factors. The use of green gases on the basis of renewable electrical energy (as hydrogen, synthetic methane, or alternative hydrocarbons from hydrogen) has numerous advantages, which can significantly improve this transition of the energy system. Simultaneously, these gases can solve major problems in the development of renewable energy sources including the long-term storage of fluctuating renewable electricity sources, alternative energy transport via existing gas infrastructure, reduction of greenhouse gas emissions, new renewable energy sources for mobility and industrial processes, and an increase in local production and use. Thus, sector coupling by power-to-gas is a fundamental cornerstone for the transformation process of the European energy systems, and hence also a significant economic parameter.

Therefore, the decarbonization of the European energy system must be considered as an opportunity to get a decisive boost for European leadership in innovative energy technology, energy-related transport technology and services, and the application and implementation of mature and green gas-related technologies.

It must be stated that the direct usage of electricity is often intended. However, there are restrictions and limits, which can be effectively negated by transitioning to gaseous green sources like power-to-gas products, green hydrogen, and green synthetic natural gas (SNG). Although being characterized by a lower technological efficiency, the production of SNG allows for the unrestricted use of the existing natural gas infrastructure and offers a completely mature technology and market availability of all the system-relevant components – right from storage until to the final consumer.

This Deliverable 7.5 “Report on experience curves and economies of scale” of the STORE&GO project focuses on the analysis of investment cost reduction for power-to-gas applications through experience curves, learning effects, and economies of scale. Since the market launch and the development of the power-to-gas technology depends, among other things, on the profitability and thus mainly on the investment costs of the plant, potential cost reduction should be examined. The main components of the power-to-gas process are still under development and only a few pilot plants have been built. With a higher number of installed plants, a significant cost reduction is expected for the power-to-gas technology, as experienced also in the case of other technologies.

Methodological focus of this deliverable and theory of technological learning

In general, the formal concept of **experience curves** describes the decline of real costs by a constant percentage (learning rate) for every cumulative doubling of its produced volume and therefore represents a relationship between the costs of a product and the experience, expressed in cumulative production of that product. Also the term **economies of scale** in this deliverable refers **solely to the effect of real cost reductions through an increase of the production volume** and not to cost reductions in consequence of an increase in size in form of upscaling (e.g. of nominal power).

The different literature on technological learning that is available for a wide range of different technology sectors is not harmonized in terms of the used terminology. Often, varying terms are used without further definition, delimitation, or explanation, which complicates a comparison of different sources. As the theory of technological learning covers a wide range of simultaneously occurring effects, which are often hard to distinguish, a clear definition of mechanisms considered for such an analysis is mandatory.

When comparing different literature on that topic, learning curves and experience curves are rarely distinguished and used synonymously without further definition. Therefore, these two terms are used synonymously within this work as well and both describe the reduction of production costs in relation to the increase of cumulative production volumes of a specific technology. These learning effects are measured by the learning rate and include all kind of cost reduction potentials. While most experience curves in this work are evaluated as specific values related to the rated performance of the product, general improvements in the performance of a technology (efficiency) or significant changes in the technology itself, such as the addition of value-adding functions, are not considered in the calculations; only this approach – the assessment of the product according to the current functional scope and characteristics – allows for the investigation of future costs based on the theoretical concept of experience curves and economies of scale.

The term economies of scale is used in literature for describing two different forms of cost reductions of a product. Economies of scale that directly affect the production process of a certain technology as a step from the unit, over batch, to series production, and therefore reduce unit costs, are considered as part of technological learning. Therefore, the economies of scale are included in the executed investigations on experience curves for power-to-gas applications. On the other hand, reductions for specific investment costs for individual power-to-gas plants as a result of the upscaling of nominal power, according to the reference value used in the experience curve analysis, have not been considered in this deliverable. These effects will be handled separately in the STORE&GO deliverable D7.7 under consideration of inputs from plant manufacturers and other project partners. Briefly summarized, the term economies of scale in this deliverable D7.5 refers solely to the effect of real cost reductions through an increase of the production volume and not to cost reductions in consequence of an increase in size in form of upscaling (e.g. of nominal power).

The concept of learning curves demonstrates the benefit of early investment and policy interventions in emerging technologies. Learning curves are applied to deduce past cost reductions to future cumulative production levels and offer an indication of the "learning investments". These additional investments are necessary for the deployment of the entrant technology while learning effects cover the gap between the costs of the entrant and the incumbent technologies including all the effects that lead to a cost reduction. In addition to technological learning in the narrower sense (improvements in technology), this also includes the learning of employees (faster execution of recurring as well as non-recurring work), economies of scale, and other effects.

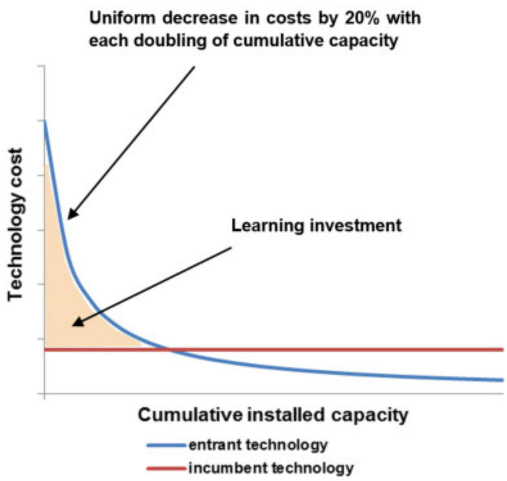

Figure 1-1: Development of entrant and incumbent technologies' costs (Own representation based on [1])

Adapting the concept of learning curves of industrial production activities to innovation and technological development is a substantial step that involves consideration of the nature and factors of innovation[1]. Therefore, it is essential to evaluate the potential and restrictions of learning curves as an analytical tool in energy technology and policy analysis[2].

The formal concept of learning curves describes the empirical finding that the cost of an industrially manufactured product decreases by a constant percentage for every cumulative doubling of its produced volume. This percentage is commonly referred to as the learning rate. Thus, learning curves represent the relationship between the following two quantities: the cost of a product and the experience expressed in the cumulative production of that product.

The **reasons for the cost reductions based on experience curves and economies of scale** can be attributed among other things to the following factors: fix cost degression (increased utilization of different sectors in the company e.g., administration, R&D, production, logistics, and distribution), reduction of production time (efficiency of manpower is increased due to learning effects), increase specialization (standardization, focus on core competence and one product family), variation in the used resources (e.g., alternative and more inexpensive (raw-)materials, optimize employment of staff according to their qualifications), improvement of existing production technologies, and optimization of product design with respect to simplify the production process. The produced volume of power-to-gas plants and therefore the gained experience and economies of scale depend on the development of the future global demand for power-to-gas products which are subject to climate and policy measures (e.g., carbon taxes, the scope of government R&D, subsidies, and market introduction programs) and economic factors (e.g., economic growth).

Literature review on learning rates

The learning rate of the technology or component, which indicates a proportional reduction of the costs for each doubling of the cumulative capacity or production, is a crucial parameter for calculating the future investment costs. Since similar technologies share comparable learning rates, a literature review on learning rates for energy technologies and, especially, methanation and other comparable technologies was performed.

The overall median for learning rates for developing energy technologies (wind, photovoltaic, fuel cells, electrolyzers, and carbon capture) is about 13%, however, with a wide range from 2% to 47%. The literature on methanation has shown no usable data on learning rates for most of the considered processes. There have been a few techno-economic analyses for the processes, but none of them considered experience behavior.

Since no reliable data on learning rates for the power-to-gas technology itself or comparable technologies are available, a disaggregated approach, by using learning rates on a component level, is used for calculating the future investment cost of power-to-gas systems. Therefore, the calculation model CoLLeCT (Component Level Learning Curve Tool) was developed for this purpose.

Current investment costs

A crucial value for the calculation of future technology costs of power-to-gas systems is current costs, which serve as an input parameter and hence the starting point (initial value) for the calculations with the calculation model CoLLeCT. This analysis includes data gathered from relevant literature as well

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[1] Jamasb, T., & Kohler, J. (2007). Learning Curves for Energy Technology: A Critical Assessment. https://doi.org/10.17863/CAM.5144

[2] Köhler, J., Grubb, M., Popp, D., Edenhofer, O. (2006). The Transition to Endogenous Technical Change in Climate-Economy Models: A Technical Overview to the Innovation Modeling Comparison Project. The Energy Journal, Endogenous Technological Change and the Economics of Atmospheric Stabilisation Special Issue.

as cost estimates and experience values based on the erected demo plants collected from STORE&GO project partners.

The different characteristic parameters – specific investment costs, rated power, year of installation – of the analyzed data reveal significant variation. In order to make reliable statements regarding the costs, the individual data points were categorized. Therefore, the different technologies (e.g., PEMEC, AEC, and SOEC) were examined separately. Furthermore, the time of the installation was split into five sections (< 2015, 2015–2017, 2018–2020, 2030, and 2050), whereby the range from 2015 to 2017 was defined as current costs. For these time periods, the range, median, and average value of specific investment costs and rated power were calculated, respectively. Additionally, statistical outliers were identified and no longer included in subsequent analyses. In order to minimize the influence of the plant size on the specific investment costs, the current costs were also calculated for a standardized 5 MW plant size on the basis of the scale factor method, where 0.7 was assumed for the exponent (scale factor). The results of the comprehensive review are summarized in the following table.

According to current information, it can be stated that the current specific investment costs are about 1,200 €/kW and 1,100 €/kW for a 5 MW PEMEC and AEC, respectively. Since SOEC is a rather new technology, which is under development, it is hard to get reliable sources for cost forecasts. Nevertheless, for further calculations, the initial value for SOEC is estimated at 2,500 €/kW for a 5 MW system. The specific investment costs for both catalytic and biological methanation plants with a rated power of 5 MW SNG-output are in the range of 600 €/kW$_{SNG}$. For the carbon dioxide (CO_2) capture technology, the current specific costs per ton of CO_2, and not the specific investment costs were analyzed. Depending on the technology, the median costs vary between 15 and 230 €/t$_{CO2}$.

Table 1-1: Overview of current specific investment cost for electrolyzer and methanation systems as well as specific costs for CO_2

Technology (System)	CURRENT spec. costs range	CURRENT spec. costs Median	initial values (norm.) avg. costs	initial values (norm.) norm. power	# of references
Electrolysis	€/kW$_{el}$	€/kW$_{el}$	€/kW$_{el}$	MW$_{el}$	
PEMEC	960–2,100	1,690	1,200	5	15
AEC	870–2,530	1,480	1,100		
SOEC	700–9,400	-	2,500		13
Methanation	€/kW$_{SNG}$	€/kW$_{SNG}$	€/kW$_{el}$	MW$_{SNG}$	
catalytic	110–2,000	510	600	5	7
biological	100–1,450	720	600		7
CO_2 Capture (biogenic)	€/t$_{CO2}$	€/t$_{CO2}$	€/t$_{CO2}$		
biogas upgrading	0–90	30	-	-	2
bioethanol fermentation	0–25	15			4
direct air capture	80–480	230			7

Power-to-gas demand potential

For calculating the future investment costs of PtG plants, the development of the demand potential of power-to-gas products until 2050 and thus the installed amount (power) of the main components is essential.

Therefore, in the first step, a literature review on the demand potential of PtG on different levels (national, European and global) was performed. The direct comparability of the PtG demand is not possible due to the different framework conditions of the analyzed studies. Nevertheless, in order to make rough statements regarding the development of the PtG demand potential, the studies are divided into groups (sector and region) and the PtG demand potential is defined as the electrical input power of the electrolyzer. Most of the analyzed studies are performed for Germany, and only a few studies focus on PtG-potential at a European or global level. The PtG demand in the power sector on national level (Germany, Spain, and Italy) is estimated to be in the middle of the two-digit GW_{el} range. The literature for Germany, which considers the entire energy system (power, mobility, industry, and heat), estimates the PtG demand potential to be in the lower three-digit GW_{el} range. At the European level, the demand for PtG in the industry as well as in mobility is expected to be in the middle three-digit GW_{el} range. The demand potential for PtG for all sectors is estimated in a high three-digit GW_{el} range. At a global level, which is the most important level for predicting cost reductions by learning curves, only one study and one calculation (SNG replaces the whole gas demand in 2050) are available. It is estimated that the PtG demand potential would rise up to a lower five-digit GW_{el} range.

In the second step, STORE&GO scenarios for the PtG demand potential were developed at the European and global levels.

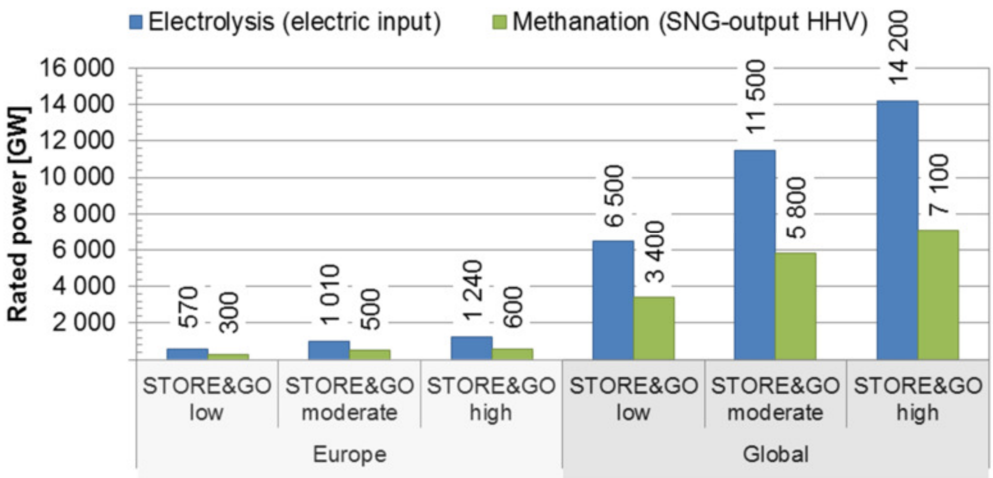

Figure 1-2: STORE&GO Scenarios: Necessary installed power of electrolyzers and methanation units in the year 2050

In general, scenarios serve to identify possible development paths and describe an alternative future. The development of scenarios is influenced by many different variables, which are highly related to fundamental energy and climate policy decisions. Depending on the scenario (low 50%, moderate 75% or high 90% renewable energy sources (RES)), there are about 6,500 to 14,200 GW_{el} installed electrolysis power and about 3,400 to 7,100 GW SNG output power necessary to meet the global PtG demand in the year 2050. These values seem to be very high and regarding the amount of RES, the STORE&GO scenarios are much more ambitious, as for example the EU-Reference Scenarios 2016 or the scenarios defined by the World Energy Council, as these mainly represent an update on the current policy or the trend to 2050. However, with these current circumstances, it will not be possible to reach an ecologically sustainable energy supply and the climate targets. Therefore, it is important to remember that, in 2050, in a decarbonized energy system, not only natural gas but also other fossil energy sources, such as oil and coal, must be substituted by renewable energy carriers. Since all areas of the energy system cannot be electrified, green molecules (renewable SNG and hydrogen produced by PtG) would also play an important role in the future energy system. For this reasons, the STORE&GO scenarios are more ambitious and defined with a comparatively high amount of renewable energy sources. In order to cover this relative high demand and to produce the required quantities (for example about 285,000 electrolyzer systems with an installed power of 50 MW would be required), a mass production would be absolutely necessary. However, this calls for a standardized and mass production-ready design of the products (e.g., no individual installation planning or piping). The power-to-gas systems must be planned for the construction on the green field (with the interface power supply, gas connection for feed-in and possibly CO_2 supply), to meet the requirements for mass-production.

CoLLeCT – A Component Level Learning Curve Tool

The usage of the learning curve theory aims at allowing prospects of the development of future technology costs. However, this is hardly impossible for novel applications on a low technology readiness level (TRL). Since significant effects, which are describable through technological learning, can only be evaluated after a few magnitudes of produced units, the technology under investigation must have reached a certain degree of maturity to assess further the development of production costs.

To get a more detailed view on technological learning, a component-based approach was developed. This allows a comparison of learning effects between different technologies, investigation on cost structure development on the stack/reactor and system level, and consideration of spillover-effects from concurrent technology sectors. Although, at first it seems a lot more extensive owing to an increase in the complexity and the number of learning technologies (components), respectively, it gives us additional and, in some cases, easier methods to evaluate certain cost reduction effects. This means that, on a component basis, factors that influence the production costs can be partly determined and described by simple scaling and innovation processes, like the following:

1. Cost reductions from mass productions:
   By investigating learning rates at a component level, decreases in production costs that occur by upscaling of the manufacturing processes can be easily distinguished.

2. Changing material costs:
   By breaking down an appliance to a number of contained components, the variety of materials used per component is usually more manageable than for the overall appliance. This could allow a more accurate estimation of the development of the future production costs for individual components, by facilitating an investigation of the past as well as future changes in the costs for needed raw materials.

3. Reductions in material usage:
   Minimization of the material's variety through analysis at the component level also allows separating and substantiating expected savings in the material's use of cost-intensive parts. This especially applies to components that require expensive raw materials whose costs cannot be expected to decrease significantly.

4. Improvements in manufacturing time:
   For time-intensive manufacturing processes, distinct cost savings can often be gained by shortening the processing time. Such improvements can be more precisely determined and evaluated at the component level when compared to the whole appliance. This not only considers (automated) machine processing costs but also manual working time costs.

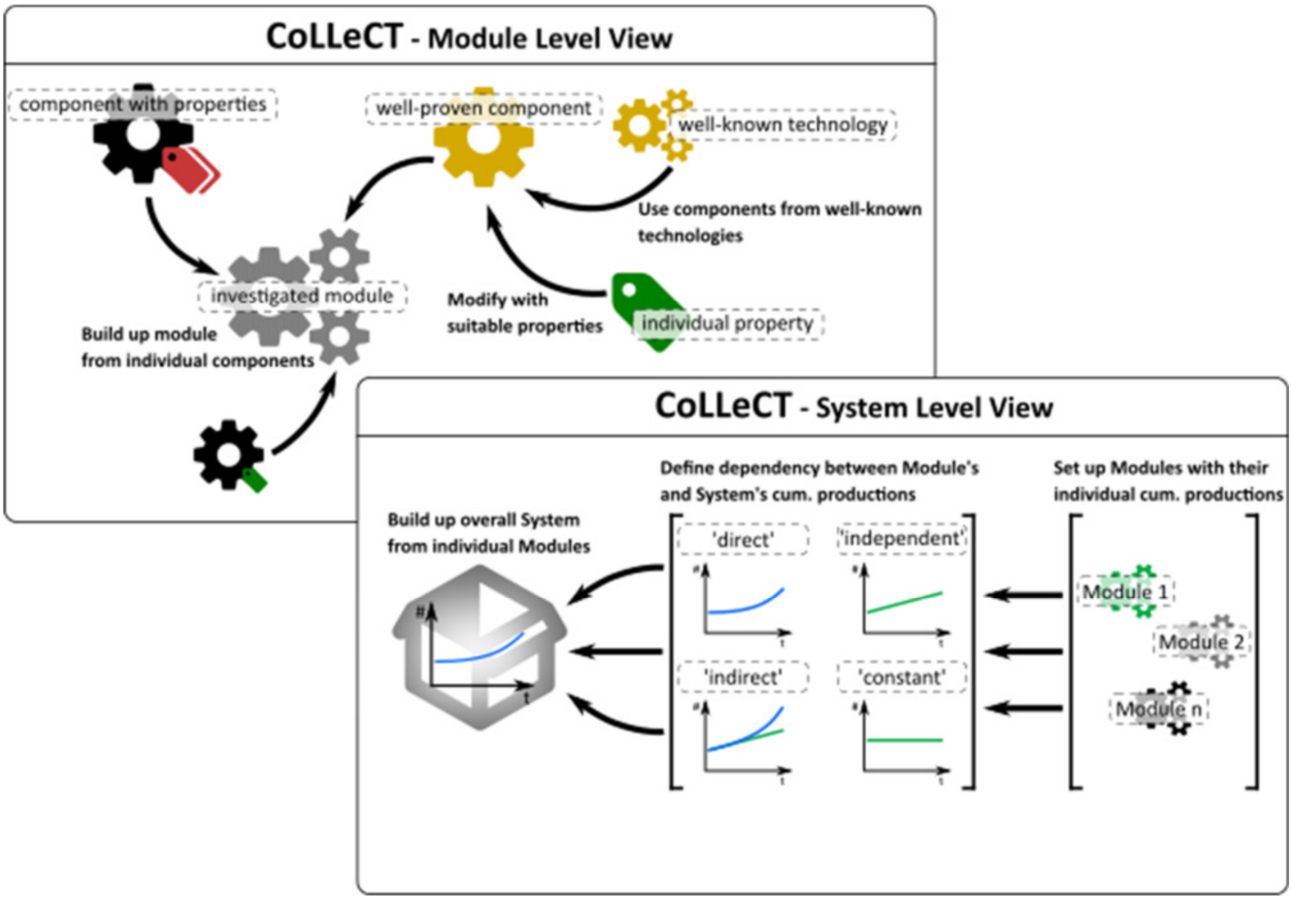

Figure 1-3: Schematic view of the functionality of "CoLLeCT" on "System Level"

Application of the learning curve model to the power-to-gas process

The calculation model CoLLeCT was applied to two main systems of the PtG process (electrolysis and methanation) in their most common configurations. In this context, two different electrolyzer cell stack designs, AEC and PEMEC, are investigated in detail. The details concerning SOEC stack and methanation reactors had to be minimized due to the lack of well-grounded data.

For the determination and evaluation of the model parameters, the data gathered from an intense examination of comparable technologies and component usages in the existing literature was used. In this regard, the detailed analysis of AEC and PEMEC stacks together with the data gained from literature reviews allowed a comparison of the calculation model; additionally, studies using the conventional approach of linear learning were examined to justify the component-based approach (see for example the calculated learning curve for alkaline electrolysis cell stack in Figure 1-4).

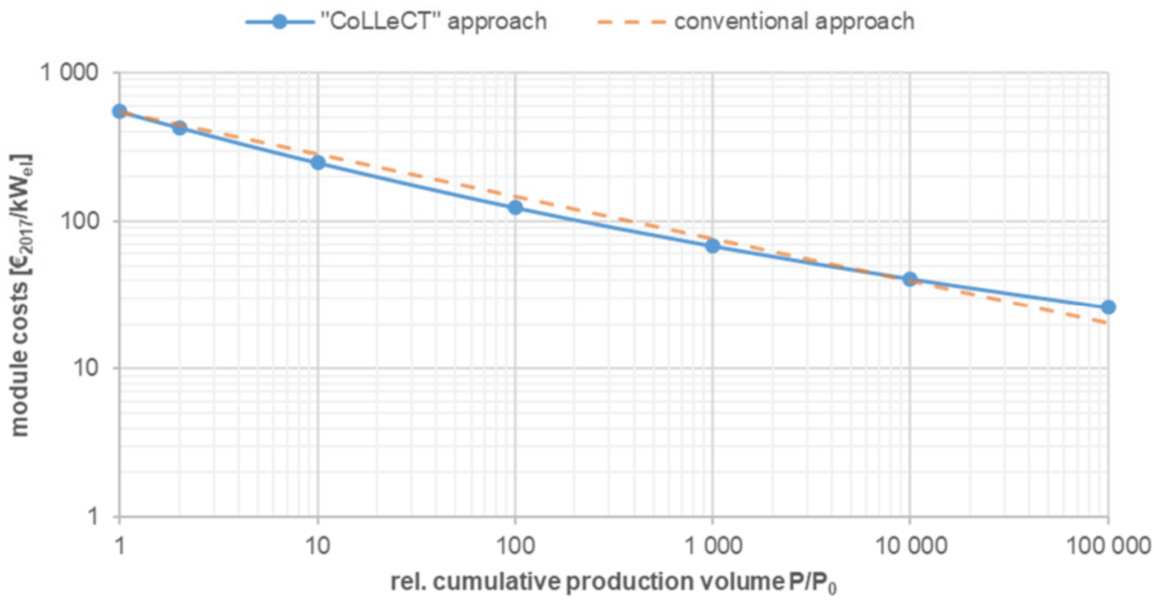

Figure 1-4: Calculated learning curve for alkaline electrolysis cell stack

For analyzing the future investment costs of electrolysis and methanation, both systems were structured in four basic modules as follows:

1. Electrolysis cell stack / methanation reactor
2. Power electronics / electric installation (ICT)
3. Gas conditioning
4. Balance of plant.

Since the first module includes the main technological parts of each system, their component structure is analyzed in detail, and reasonable estimations are conducted in terms of costs shares and learning rates. The other modules are treated as peripheral parts of the process. These are not unique to a single technology but used in different occurrences of the system (e.g., in all investigated electrolyzer modules) or even concurrent technology sectors. Therefore, spillover-effects on technological learning have been taken into account for these parts of the models. This includes conducting an analysis of past and future natural gas and industrial hydrogen treatment to consider learning effects that take place independent of the market development of PtG.

Future investment costs for power-to-gas applications

Unless otherwise mentioned, cost predictions for the PtG technology in this Deliverable are stated as **real costs** (reference year 2017, $€_{2017}$). This means that the inflationary effects that are anticipated and will lead to rising nominal costs have not been considered. Additionally, **no significant changes in technology**, such as an implementation of additional functions, control elements and safety devices or efficiency improvements, have been taken into account for calculating the future investment costs.

Based on the system definitions, future costs for PtG applications have been analyzed according to the evaluated demand potentials for renewable hydrogen and SNG. While common PtG systems, especially those investigated in STORE&GO, usually consist of both electrolysis and methanation systems, the two systems were evaluated separately to allow more elaborate investigations and reduce the number of combinations.

The subsequent Table 1-2 sums up the calculated results for all investigated technologies assuming a “moderate” market penetration for PtG based on the evaluated potentials. These results show significant cost reductions for electrolysis and methanation systems and undermine the decreasing learning rate caused by the applied calculation model.

It must be noted that, unless otherwise mentioned, cost predictions for the PtG technology in this deliverable are stated as real costs (the reference year is 2017, $€_{2017}$). Additionally, no significant change in technology, such as the implementation of additional functions, is taken into account for calculating the future investment costs. This leads to a decline in the future investment costs (real costs) due to learning curve effects. On the other hand, if additional functions are taken into account and/or the nominal costs (including inflation) are considered, then the costs would not necessarily decrease when compared to the reference year 2017, but can remain on the same level or even increase.

Table 1-2: Summary of calculated cost reduction potential for 5 MW_{el} electrolyzer and 5 $MW_{SNG\text{-}output}$ methanation systems for the years 2030 and 2050 as well as the corresponding learning rates

Technology (System)	Calculated costs			Calculated learning rates (avg.)		
	initial (2017)	2030	2050	initial (2017)	2030	2050
Electrolysis		€/kW_{el}			%	
PEMEC	1,200	530	290	16,8	13,8	12,0
AEC	1,100	760	440	13,1	12,3	11,0
SOEC	2,500	1,090	610	15,6	12,4	11,2
Methanation		€/kW_{SNG}			%	
Catalytic	600	440	280	12,1	12,0	11,7
Biological	600	360	220	12,3	12,1	11,7

The following graphs show the calculated learning curves for electrolysis and methanation systems in their individual specifications. To highlight the necessity of a detailed analysis of current investment costs on long-term forecasts, an additional uncertainty of ±15% was added to the initial value for each calculated experience curve range (light-colored areas).

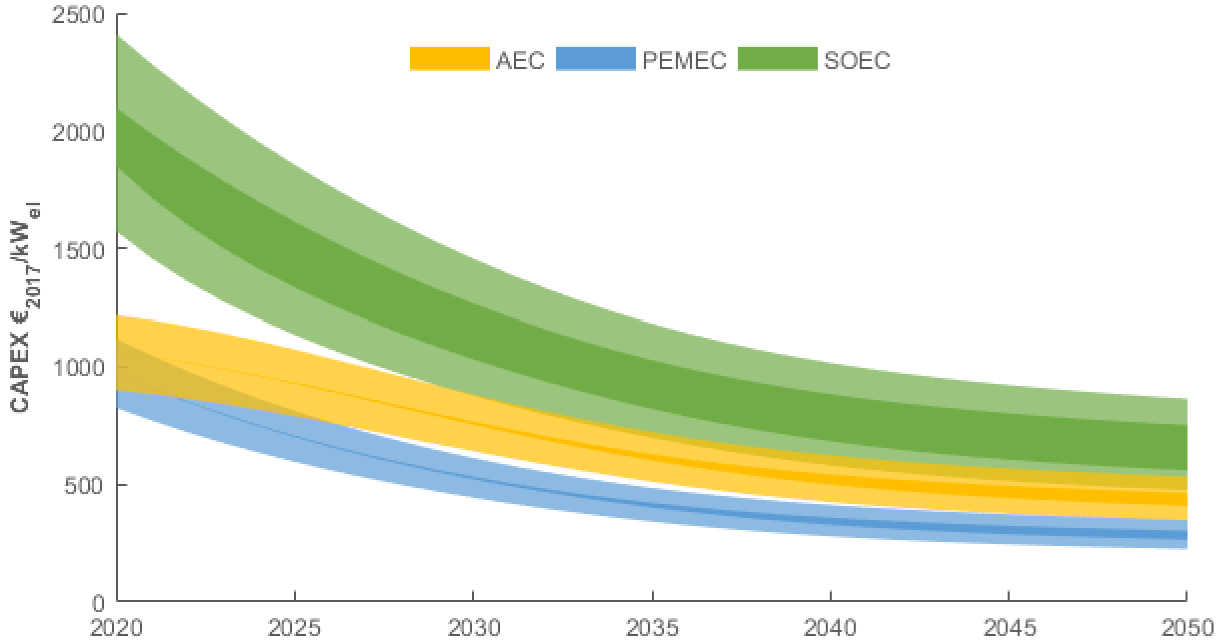

Figure 1-5: Resulting learning curves for electrolysis systems with an uncertainty of ±15 % on initial CAPEX (light-colored areas)

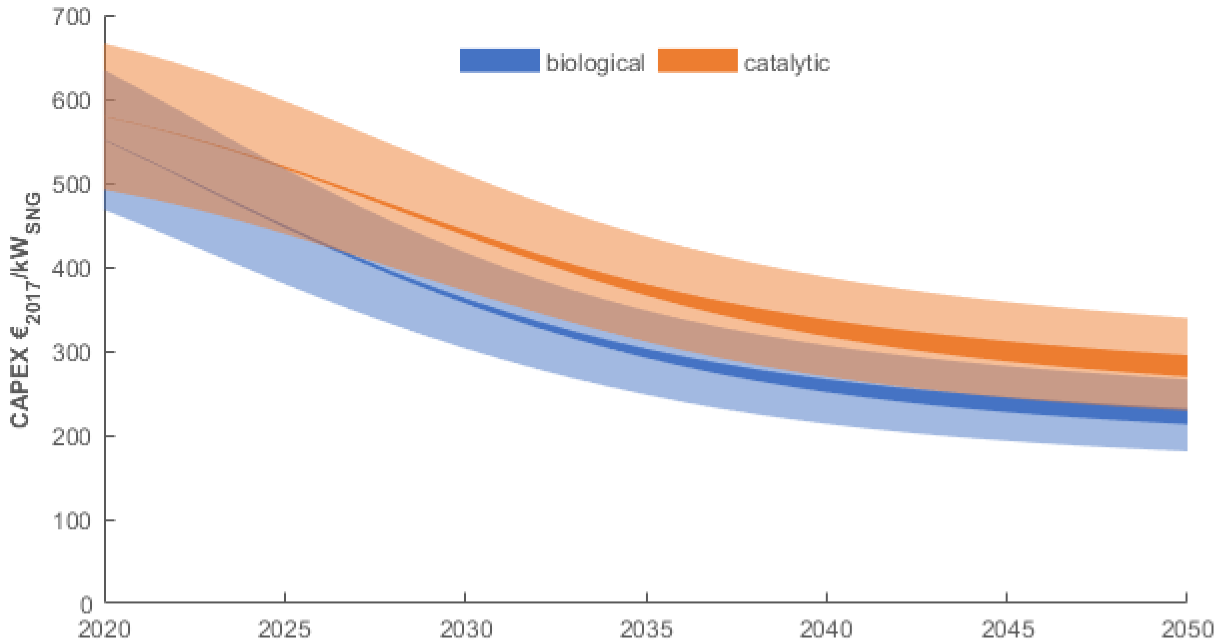

Figure 1-6: Resulting learning curves for methanation systems with an uncertainty of ±15 % on initial CAPEX (light-colored areas)

As all evaluated costs for the whole investigation period representing real costs are referenced to the year 2017, inflationary effects that are highly expectable and will lead to rising nominal costs have not been considered. Additionally, there is no consideration of significant changes in the technologies themselves (e.g. increasing efficiencies) or improvements in the function or quality, which have no direct effect on the related output. Summing up the aforementioned effects, it has to be taken into account that this will potentially reduce the effects gained from technological learning or even result in increasing nominal costs in the long-term.

The evaluation of learning curves for novel and established technologies requires the analysis of an adequate amount of historical cost data. Therefore, the availability of this data is mandatory to allow reasonable predictions on future cost development. While the component-based approach of the CoLLeCT model tries to circumvent this limitation by comparing learning effects on similar sub-components between independent technologies, the collection of base data is still unavoidable, even necessary in a more detailed view, especially in this early stage of model development. Nevertheless, the use of a component-based calculation model allows the incorporation of learning effects on a much lower level, where these can be determined more precisely and narrowed down to certain adaptions to the production process for single parts. This allows the use of experience values for process improvements or raw material costs reduction from unit to mass production, which becomes less obvious when considering a full technology view.

1 Introduction

An ecologically sustainable energy supply, which is economically viable and socially acceptable, is highly valued in the European policy. The European energy supply must be transformed due to energetic, social, economic, and environmental/climatic factors. The use of green gases on the basis of renewable electrical energy, such as hydrogen, synthetic methane, or alternative hydrocarbons from hydrogen and a carbon source like CO_2, has numerous advantages, which significantly improve this transition of the energy system. Simultaneously, these gases can solve the following major problems in the development of renewable energy sources - the long-term storage of fluctuating renewable electricity sources, alternative energy transport via existing gas infrastructure, reduction in greenhouse gas emissions, new renewable energy sources for mobility and industrial processes, and an increase in local production and use. Thus, sector coupling by PtG is a fundamental cornerstone for the transformation process of the European energy systems and thus also a significant economic parameter.

Central contributions of power-to-gas to the energy system

- Storage and transport solution: Through the injection and storage of energy carriers produced from renewable electricity like hydrogen and/or synthetic methane produced from hydrogen into the existing natural gas infrastructure, seasonal fluctuations of renewable electricity generators can be balanced.[3] New power lines or a grid expansion can be substituted by shifting the energy transport from the electric power grid to the natural gas grid. The advantage of an energy transport via the existing natural gas infrastructure is the high energy density in the natural gas grid. A possible expansion of the natural gas network would lead to a much smaller topographical intervention in relation to an expansion of the electricity network, which would increase the population's acceptance and reduce real estate costs. [4]
- Infrastructure solution: In addition to power plants, the Central European gas infrastructure not only includes a high-quality transmission and distribution grid but also enormous capacities for gas storage in caverns and porous reservoirs. Thus, the integration of renewable gases such as hydrogen or SNG into the natural gas infrastructure also avoids enormous stranded investments into the existing energy infrastructure. The possibility of sectoral coupling of the electrical and gas grids via hydrogen production (with optional methanation) also allows the integration of biogas and thus an increased greening of the gas sector. In other words, the long-term use of the existing gas infrastructure will depend on the degree of integration of renewable gases. Thus, the overall climate and energy policies are also supported by the existing gas infrastructure, which can be furthermore used to secure the long-term use of these infrastructures.
- Supply of all segments by renewable energy sources: Green hydrogen and therefrom produced renewable hydrocarbons, such as methane, can be used in all energy segments (e.g., process heat, mobility, space heating, and electrical energy), and thus provide decisive contributions for greening the European energy system. In addition to battery-based electric mobility, the use of green hydrogen or methane from PtG plants will significantly accelerate the transition to a sustainable transport system with low or no emissions. Hydrogen and hydrogen-based synthetic methane can be used in combustion engines and fuel cells, and they have a great potential for reducing primary energy input, emission of air pollutants (e.g. particulates and NO_X), and greenhouse gas emissions. Beside its utilization for energy production, hydrogen as a renewable resource is also important for manufacturing industries in terms of material utilization. In the steel industry, for instance, hydrogen can be used as a reducing agent in pig iron production (hydrogen reduces iron ores by removing the containing oxygen) to aid a low carbon steel production. Instead of reformers using natural gas to produce hydrogen, it would be possible to shift to carbon-neutral hydrogen produced in electrolysis plants under certain conditions (in case there are no natural gas pipelines or only low amounts of hydrogen available at a certain location).

[3] Therefore, refer to R. Tichler, J. Lindorfer, C. Friedl, G. Reiter, H. Steinmüller (2014) FTI-Roadmap Power-to-Gas für Österreich, Energieinstitut an der JKU Linz. Herausgeber: bmvit, Schriftenreihe 50/2014.

[4] Therefore, refer to G. Reiter J. Lindorfer (2013) Möglichkeiten der Integration von Power-to-Gas in das bestehende Energiesystem. In: Steinmüller, Hauer, Schneider (Hrsg.) Jahrbuch Energiewirtschaft 2013. NWV Verlag.

Therefore, endeavors toward the decarbonization of the European energy system must be considered as an opportunity to boost European leadership in innovative energy technology, energy-related transport technology and services, and in the application and implementation of mature, green gas-related technologies. It has to be stated that the direct usage of electricity is often intended; however, there are restrictions and limitations that can be effectively negated by transitioning to gaseous green sources like PtG products (e.g. green hydrogen and green SNG). Although being characterized by a lower technological efficiency, the production of SNG allows for the unrestricted use of the existing natural gas infrastructure and offers a completely mature technology and market availability of all the system-relevant components - right from storage until to the final consumer.

This deliverable D7.5 focuses on the analysis of investment cost reduction for power-to-gas applications through experience curves and economies of scale. Since the market launch and the development of the power-to-gas (PtG) technology depends, among other things, on the profitability and thus mainly on the investment costs of the plant, potential cost reduction should be examined. The main components of the PtG process are still under development and only a few pilot plants have been built. With a higher number of installed plants, a significant cost reduction is expected for the PtG technology, as experienced also in the case of other technologies.

The deliverable's structure comprises a brief introduction that is followed by definition of the methodological focus – learning curves, experience curves, and economies of scale. The next chapter represents the economic theory of the learning curve concept and its application to the evaluation of energy systems. The aim is to provide a theoretical basis for the assessment of learning effects for energy technologies, which subsequently will be used as a basis to deduce learning effects within the application of the PtG technology in the context of the project STORE&GO. In chapter four to six, the most essential parameters – learning rate, current investment costs, and demand potential of PtG products – are analyzed by comprehensive literature reviews. Concerning the demand potential of PtG products, STORE&GO scenarios are developed. The results of chapter four to six serve as input parameters for the calculation model CoLLeCT, which is described in chapter seven. Next, the general approach of CoLLeCT is applied to the components of the PtG technology. Finally, the potential for cost reductions through technological learning is calculated. Additionally, sensitivity analyses and calculations of nominal costs were performed by considering inflation. Finally, some conclusions of the results are derived.

2 Methodological focus: Learning curves, experience curves, and economies of scale

Different literature on technological learning that is available for a wide range of different technology sectors is not harmonized in terms of the used terminology. Often, varying terms are used without further definition, delimitation, or explanation, which complicates a comparison of different sources. As the theory of technological learning covers a wide range of simultaneously occurring effects, which are often hard to distinguish, a clear definition of mechanisms considered in such an analysis is mandatory. Therefore, this section defines the terminology and delimitations used within this deliverable.

In general, the formal concept of **experience curves** describe the decline of real costs by a constant percentage (learning rate) for every cumulative doubling of its produced volume and therefore represents a relationship between the costs of a product and the experience, expressed in cumulative production of that product. Also the term **economies of scale** in this deliverable refers **solely to the effect of real cost reductions through an increase of the production volume** and not to cost reductions in consequence of an increase in size in form of upscaling (e.g. of nominal power).

2.1 Distinction between learning curves and experience curves

There is literature on technological learning that uses different terms for the development of technology costs in relation to cumulative production volumes. In this context, most popular notations are "learning curve" and "experience curve." For these terms, variable definitions can be found in the relevant literature. One such definition is stated below:

"The experience curve is an idea developed by the Boston Consulting Group (BCG) in the mid-1960s. Working with a leading manufacturer of semiconductors, the consultants noticed that the company's unit cost of manufacturing fell by about 25% for each doubling of the volume that it produced. This relationship they called the experience curve: the more experience a firm has in producing a particular product, the lower are its costs. Bruce Henderson, the founder of BCG, put it as follows: 'Costs characteristically decline by 20–30% in real terms each time accumulated experience doubles. This means that when inflation is factored out, costs should always decline. The decline is fast if growth is fast and slow if growth is slow.'" [2]

While a learning curve refers exclusively to the ratio of the cumulative application rate to the production time, an experience curve refers to the ratio of the cumulative application rate to the cost of production.

When comparing different literature on technological learning, learning curves and experience curves are rarely distinguished and used synonymously without further definition. Consequently, these two terms are also used synonymously in this deliverable and both describe the reduction in production costs in relation to the increase in cumulative production volumes of a specific technology.

2.2 Learning effects

Learning effects describe the sum of influencing factors that lead to a decline in production cost, and therefore technology costs, through technological learning. These learning effects are measured by the learning rate and include areas that offer scope for cost reduction. The reasons for the cost reductions based on experience curves and economies of scale can be attributed among other things to the following factors:

- fix cost degression (increased utilization of different sectors in the company e.g., administration, R&D, production, logistics, and distribution),
- reduction of production time (efficiency of manpower is increased due to learning effects),
- increase specialization (standardization, focus on core competence and one product family),
- variation in the used resources (e.g., alternative and more inexpensive (raw-)materials, optimize employment of staff according to their qualifications),
- improvement of existing production technologies,
- and optimization of product design with respect to simplify the production process.

While most experience curves in this work are evaluated as specific values related to the rated performance of the product, general improvements in the performance of a technology (efficiency) by increasing its TRL are not considered in the calculations.

The produced volume of power-to-gas plants and therefore the gained experience and economies of scale depend on the development of the future global demand for power-to-gas products which are subject to climate and policy measures (e.g., carbon taxes, the scope of government R&D, subsidies, and market introduction programs) and economic factors (e.g., economic growth).

2.3 Economies of scale

Economies of scale describe the effect of average cost reductions in production obtained through an increase in the volume, size, or scale of the produced output as the fixed costs are spread out over more output units [3]. According to the mechanisms discussed in this deliverable, two aspects of scaling are distinguished:

1. An enforced deployment of not yet widely established technologies requires a significant increase in individual units produced. Therefore, an upscaling of production is a set of multiple steps necessary to cover the entire product development from prototype over small series to mass production. Since this is at least partially coupled with an increase in cumulative production volumes, it is not really possible to distinguish cost reductions achieved through production scaling by an individual manufacturer from technological learning. Therefore, these effects are considered as part of the technological learning as investigated in this deliverable.

2. Besides production costs of individual units and application components, the specific investment costs for overall plant implementations are also affected by the plant scale (e.g., hydrogen or SNG output) itself. An increase in the nominal plant capacity usually reduces specific investment costs due to various effects. These effects can either be caused by a decline in production costs of larger scale components, a decline in costs of single parts by an increase in the purchased units, or cost reductions through repetitive work.
   These effects are mostly independent of technological learning, and therefore not included in our analysis of future technology costs in the first step. For the detailed assessment of future PtG generation costs for specific plant configuration they are incorporated as individual scaling factors.

The term **economies of scale** is used in literature to describe two different forms of cost reductions of a product. Economies of scale that directly affect the production process of a certain technology as a step from unit, over batch, to series production, and therefore reduce unit costs, are considered as part of technological learning. Therefore, economies of scale are included in the executed investigations on experience curves for PtG applications. Reductions of specific investment costs for individual PtG plants as a result of upscaling nominal power, according to the reference value used in the experience curve analysis, have not been considered in this deliverable. These effects will be handled separately in deliverable D7.7 under consideration of inputs from plant manufacturers and other project partners. Briefly summarized, the term economies of scale in this deliverable D7.5 **refers solely to the effect of real cost reductions through an increase of the production volume and not to cost reductions in consequence of an increase in size in form of upscaling (e.g. of nominal power).**

3 Theory of technical learning

This chapter represents the economic theory of the learning curve concept and its application to the evaluation of energy systems. The aim is to provide a theoretical basis for the assessment of learning effects of energy technologies, which subsequently will be used as a basis to deduce learning effects within the purview of the application of the PtG technology in the context of the project STORE&GO.

The transformation of the energy system to facilitate the intensive use of renewable energies is based on the assumption that the technology costs concerning the generation, applications, and storage of renewable energy will decrease in the future. These cost reductions will eventually develop competitiveness between renewable energy and fossil energy sources. Developing an energy system with lower greenhouse gas emissions and higher resource efficiency requires the consideration of learning curves. In current models of the energy system analysis, technological progress is no longer considered exogenously but needs to be integrated into the model in the form of learning curves and thus endogenized.

The first approach of exogenous technological progress is based on Schumpeter's invention-innovation-diffusion paradigm [4], [5]. Based on this approach, invention implies the generation of new knowledge and ideas. Inventions are further developed and converted into new products, whereas diffusion covers the extensive implementation of new products. Further, Solow [6] qualified the inexplicable element of augmented productivity growth of the economy as technological progress. This technological change was mainly considered in the new macroeconomic endogenous growth literature and in the development of the learning curve concept in microeconomic analyses also including evaluations in the energy sector ([7], [8]). Later, the literature on economics, or energy and climate economics literature, focused on the topic of technical change. Particularly, the Stern Review of the economics of climate change [9] integrated assumptions regarding learning rates of technologies into its long-term cost projections. Learning rates are as important for technology analyses as discount rates are for cost-benefit analyses.

In the following chapters, the general concept of learning curves will be described, and its application for the analysis of energy systems and technologies will be presented.

3.1 The learning curve concept

There are several causes behind the phenomenon of learning and learning curves, whose effects have still not been fully investigated. The essential feature, however, is the acquisition of experience in the entire manufacturing process: the greater this experience, the greater the cumulative production of a good and the lower will be the product costs; this is because the manufacturing process can be optimized, resources can be saved, and economies of scale can be used, among others. The essence of learning curves can be formulated as follows – a competitive environment enables individuals, companies, and industries to enhance their performance. This is an essential aspect of learning curves. The cost reduction is connected to the activity in the market – the actual production of the good as opposed to pure research and development.

In the 1960s, the phenomenon of learning curves was scientifically examined by the Boston Consulting Group [10], and the term experience curve was coined. Contrary to the concept of the learning curve, the experience curve approach does not relate to individual input costs, such as labor costs, but to the total cost of a production process. This means that all costs incurred until the product reaches the end user are included. It also includes research and development, distribution costs, marketing, and overheads. At the same time, potential influencing factors of a cost reduction are defined. These include economies of scale, technical progress, learning curve effects in the narrower sense (learning from executive and managerial posts in operational functions), and rationalization (more economical use of production factors such as a decline in raw material consumption).

The concepts of learning and experience curves cannot be clearly separated because the experience curve concept has its origin in the learning curve. In the literature, these terms are sometimes even used interchangeably. The insights gained from the learning curve are directly incorporated into the experience curve. The learning curve refers to the experience gained in the manufacturing area, with the experience curve more likely to involve the whole company. The insights gained form the learning curve is used not only by manufacturing companies but also by service companies (e.g., banks and insurance companies). The main difference between learning effects and experience curves are the following:

While a learning curve refers exclusively to the ratio of the cumulative application rate to the production time, an experience curve refers to the ratio of the cumulative application rate to the cost of production.

In conclusion, the derivation of the learning curve or experience curve yields a particular learning rate that displays the fractional reduction in the cost for each doubling of the cumulative capacity or production. Although often referred to as the “learning-by-doing” (LBD) rate, this learning rate parameter serves as a proxy for all aspects that contribute to observed changes in the cost [11].

In applying the simple form of the learning curve, the rate of progress remains constant over the entire learning curve. This means that young technologies can learn faster from market experience than old technologies at the same learning rate owing to the significant effect of the same absolute increase in cumulative production at the beginning of a product's lifecycle. For example, if a market expansion from 1 MW to 2 MW cumulative installed capacities of photovoltaic modules causes a cost reduction of 18%, an installed capacity of 100 MW would require the installation of another 100 MW to achieve an additional 18% of cost reduction.

The concept of learning curves demonstrates the benefit of early investment in and policy interventions concerning emerging technologies. Learning curves are applied to deduce past cost reductions to ascertain future cumulative production levels and offer an indication of the “learning investments”. These additional investments are necessary for the deployment of the entrant technology, while learning effects cover the gap between the costs of the entrant and the incumbent technologies.

The key feature of learning curves is that they include all the effects that lead to a cost reduction. In addition to technological learning in the narrower sense (improvements in technology), this also includes the learning of employees (faster execution of recurring as well as non-recurring work), economies of scale, and other effects.

Furthermore, economies of scale should be considered. These indicate advantages of size/amount, which are expressed considering the fact that the cost per unit, that is, the costs incurred by the company for a product, decreases with an increase in production volume (and thus company size). Therefore, the economies of scale denote the cost advantages of mass production and provide a basis for the competitive strategy to attain cost leadership that is, striving to reduce the cost to the lowest level among all competitors. The economies of scale explain why many companies and corporations are striving to increase their size, conquer new markets, or purchase other companies.

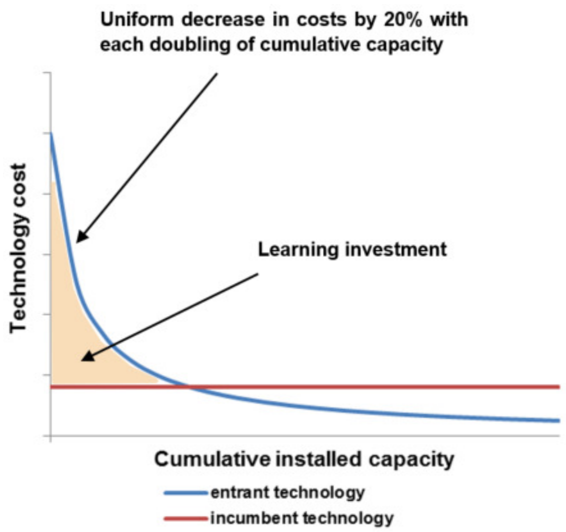

Figure 3-1 : Development of entrant and incumbent technologies' costs (Own representation based on [1])

Learning effects and experience gains can lead to economies of scale effects as a company gains production efficiency and, above all, witnesses an increase in the number of units. Other causes of economies of scale include efficiency gains, which are created by specializing or automating production, which gets profitable at a certain production volume. Additionally, marketing benefits can generate economies of scale effects. It must be noted that the cost of an advertising campaign (e.g., television commercials) are better distributed when the advertiser not only conducts business in some cities but is also represented nationwide (i.e., the cost per store or, as a result, the product sold, is lower). Likewise, large volumes increase the negotiating or purchasing power to the suppliers, and thereby lower the purchase prices. Finally, fixed cost degression must be considered. The fixed or capacity costs (e.g., rent for the production facility, depreciation of machinery, and salaries) are allocated to a higher number of products to achieve a reduction in the fixed costs per unit.

To distinguish pure scale effects from learning curve effects, it is important to clarify the different explanatory variables. Economies of scale refer to cost reductions per input with an increase in output. The costs serve as a function of the output produced at a given time. Conversely, learning curve effects are based on the cumulative output. Therefore, learning curve effects can also occur without an increase in the production capacity [12].

3.2 Formal description of the learning curve concept

As early as 1925, there were first observations of the decrease in assembly time of aircraft through the repetition of production operations at the Patterson Airforce Base in the US. The model of Wright [13] showed that doubling the cumulative production volume leads to a constant decrease in the required aircraft production hours.[5] This laid the basis for the learning curve concept, which describes the relationship between the costs of individual input factors of an industrial process (e.g., the number of working hours and material costs) and the cumulative amount of the produced goods.

The concept of learning curves describes the empirical finding that the cost of an industrially manufactured product decreases by a constant percentage for every cumulative doubling of its produced volume. This percentage is commonly referred to as the learning rate. Thus, the learning curves

[5] Learning curves in production processes were further investigated by Hirsh [176] in mechanical engineering and by Rapping [177] in aircraft construction during the Second World War.

represent the relationship between the following two quantities: the cost of a product and the experience expressed in cumulative production of that product.

Product costs can be represented as the function of the cumulative production:

$$C = C_0 * ACC^{-\varepsilon} \quad \textbf{Eq. 1}$$

where C denotes the costs at a given time, ACC is the cumulative production at that time, C_0 is the cost of one unit of cumulative production, and Ɛ is the (positive) learning parameter.

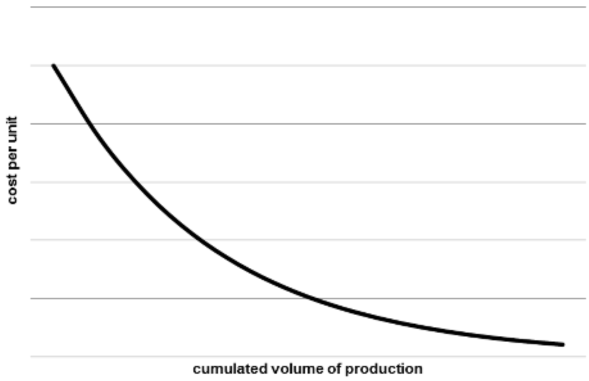

Figure 3-2: Product costs serve the function of cumulative production

A twice-logarithmic plot of the costs related to the cumulative production results in an even function with the gradient -Ɛ. If the cumulative production is doubled, then the costs would decrease to 2−ε of the original costs. This number, the so-called progress ratio (PR), is often used when comparing different learning curves. It is calculated according to

$$PR = 2^{-\varepsilon} \quad \textbf{Eq. 2}$$

In addition, the aforementioned learning rate LR is used, which describes the cost reduction when the cumulative production or capacity is doubled:

$$LR = 1 - PR = 1 - 2^{-\varepsilon} \quad \textbf{Eq. 3}$$

Adapting the concept of learning curves of industrial production activities to innovation and technological development is a substantial step that involves consideration of the nature and factors of innovation [8]. Consequently, it is essential to evaluate the potential and restrictions of learning curves as an analytical tool in energy, technology, and policy analysis [7].

3.2.1 The One Factor Learning Curve (OLFC)

Following Wiesenthal et al. [1], the above explained concept of learning curves can be depicted in the energy policy framework as follows:

$$C_{t,y} = mQ_{t,y}^{-\epsilon} \quad \textbf{Eq. 4}$$

where C represents the unit costs of energy production (€/W), Q is the cumulative production (W), Ɛ is the elasticity of learning (learning index/rate), m is the normalization parameter with respect to initial conditions, t the technology, and y the period (year). This concept of the one factor learning curve (OFLC) benefits from relatively easily accessible data. Investment costs and production (or installation) volumes are often well-documented when compared to other underlying cost drivers [1]. Hence, learning curves that are more consistent can be derived for economic modeling.

As discussed in Wiesenthal et al. [1], for a number of technologies, the learning effect is less apparent or even non-existing, such as gas pipelines [14], [15]. In other cases, the OFLC can be derived, but a low statistical significance may imply high annual fluctuations in costs. Moreover, a rise in the net cost can occur when, for example, the market tightness and commodity price increases counterweigh the cost-reducing technology learning effects [1]. Hence, a proposed development to the OFLC is to divide the accumulated cost into more of its core factors and analyze the parts independently. This would not only put the focus on investment costs but also on the conversion efficiency, maintenance costs, safety features, and reliability of factors of the demand side [1]. This approach can be formally explained by

$$C(x) = \alpha C(x_0)\left(\frac{x}{x_0}\right)^{-L} + (1-\alpha)C(x_0) \qquad \textbf{Eq. 5}$$

where x represents the cumulative output, x0 denotes the cumulative output at t=0, C(x) is the cost at cumulative output, L denotes the learning parameter implying the learning rate LR = 1 - 2-L, and α represents the cost share of the learning component at t=0.

By this multi-component learning analysis, Ferioli et al. [16] and van der Zwaan et al. [15] reveal that some cost components involve learning (e.g., the production process), while others do not (e.g., labor costs and material costs) involve learning. Additionally, the concept of multi-component learning analysis may produce diverse results regarding historical data and technology forecasts or energy scenarios. It must be noted that the overall costs that involve learning represent an accumulation of the costs of the specific components of the technology. Every individual fraction can have a diverse learning index. Hence, it is possible to study the impact of learning on the components independently. Nevertheless, data on particular production processes and costs may be non-existing or challenging to derive [1].

3.2.2 The Two Factor Learning Curve (TFLC)

As explained in 3.2.1, the concept of the OFLC has its strengths in the aggregation of numerous essential factors of cost reduction in one factor; this finding corresponds to observations. On the other hand, individual drivers of cost reductions like research and learning-by-doing cannot be detected, and hence the identification of the impacts of policies addressing R&D investments is particularly limited [1]. In this regard, the division of the OFLC into a Two Factor Learning Curve (TFLC) was realized by Kouvaritakis et al. [17], which is analogous to Wiesenthal et al. [1] and can be depicted formally as

$$C_{t,y} = mQ_{t,y}^{-\alpha} KS_{t,y}^{-\beta} \qquad \textbf{Eq. 6}$$

where C represents the cost of unit production (€/W), Q stands for the cumulative production (W), KS denotes the knowledge stock which is approximated expressed through the sum of R&D investments (€), α is the elasticity of learning-by-doing, β is the elasticity of learning by researching, and m is the normalization parameter with respect to initial conditions.

Rubin et al. [11] summarized empirical evaluations of the concept of TFLC and showed that R&D investments support cost reductions at all the stages of technological progress, and, in several cases, R&D's contribution is more when compared to learning-by-doing (see also [18], [17], [19], [20], [21], [22]). Further analyses indicate the existence of correlations between R&D expenditures and subsequent cost reductions (see [19], [20], [21], [22]). On the other hand, although the investigations of Miketa and Schrattengolzer [23] support the general feasibility of this concept, it is also shown that this does not improve the accuracy of the representation of the cost reductions. Finally, it must be noted that research on the TFLC often limits consideration to public R&D expenditures because data on private R&D spending are usually not accessible or adequately disaggregated [1].

3.3 Qualitative representation of the learning system

In most of the literature on the learning curve for energy technologies, the focus is on the development of a simple model that achieves a balance between public R&D programs and governmental market introduction programs for energy technologies that are still not fully competitive. In order to gain a better understanding of the learning process and learning curves, a model of the phenomenon of learning is sketched. Learning curves provide a connection between the input and output of a learning system. The following sections introduce considerations of the learning system.

3.3.1 The Input-Output-Model of Learning

Wene [24], based on Ashby [25], presented a simple model of the cybernetic theory to a learning system. The learning system could, for instance, be a company producing photovoltaic (PV) modules or wind turbines. In a competing market, the learning system evaluates the impact of the output on its environment and adjusts its internal process flow to improve the performance. These internal improvements are based on the experience of converting an input to output. The learning curve describes the performance as the ratio of the output to input, which is improved over time (more precisely, by increasing the output). The input is normally measured in monetary units (costs comprise materials, personnel, sales, marketing, and general expenses), and the output is mostly measured in physical units (for example, installed power (kW) or produced electricity (kWh)). This provides the cost per physical unit as a quality measure.

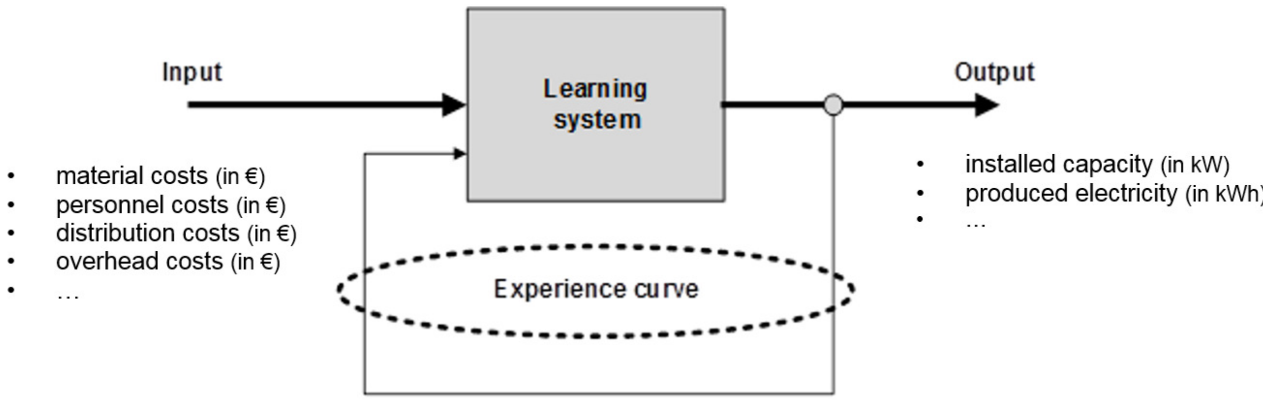

Figure 3-3: An input-output-model of learning from cybernetic theory (Own representation based on [24] and [1])

The model clarifies that learning is the result of activities, which produce output that is subsequently valued by market participants. This means that technologies that do not participate in the market will not experience the learning effects that lead to the downward slope of the learning curve. Hence, it can be stated that new technologies cannot become competitive solely through R&D [24]. However, this does not mean that the importance of R&D should be neglected, but that R&D plays a crucial role in bringing technology to the point where it can be established in the market. Even at this point, R&D plays a significant role as a complementary measure for the development of the technology in the market. However, the cybernetics-oriented input-output model presented here does not provide any information about the processes within the learning system [24] [1].

3.3.2 Areas of learning and their implications for learning curves

To gain a deeper understanding of industrial learning, it would be essential to have theoretical considerations on technology and knowledge and their derived innovation (change in technology) and learning (change in knowledge). When we refer to technological learning and thus what learning curves describe, we refer to both changes in technology and in knowledge [12]. Depending on the perspective, the analysis of technology focused on various individual aspects. As the original meaning of the technology is closer to that of knowledge in the discussed context, classifications of technology have been mostly made as classifications of the knowledge contained in the technology [26].

In order to describe technology with the help of knowledge, this knowledge can be subdivided into the following three basic areas: conceptual knowledge, process knowledge, and expertise [26]. Concept knowledge describes the knowledge of the product's design and its manufacturing process (i.e., plans thereof), process knowledge refers to the knowledge of how a product is produced (implementation of the plans), and expertise is the knowledge acquired through or relevant to the use of a product or the operation of a system.

In today's economy, companies often use the knowledge that they do not own by buying products that already contain a lot of knowledge. To address this problem, Rosenberg [26] coined the terms embedded and non-embedded knowledge. Embedded knowledge refers to knowledge obtained in the early stages of innovation, which is thus contained in the product itself. Non-embedded knowledge refers to the way a product is manufactured, used, or operated.

According to Pieper [12], this implies the following for the theoretical concept of learning curves: based on the three described types of knowledge, a model for describing the sources of learning or experience (acquisition of knowledge) can be derived.

First, knowledge can be acquired during the development and design process of a product, if already existing knowledge is insufficient. This may improve the utilization of information technology or targeted R&D concerning the development of the product.

Second, knowledge can be acquired throughout the process of production (the part of learning described by Wright [13]), for example, through improvements in logistics, distribution, outsourcing, or increasing the production speed. If the product itself does not undergo any change, then it would imply that the knowledge is not embedded. However, experience in production can also lead to suggestions for changes in the design of the product and thus to changes in the concept of knowledge, thereby leading to the embedment of knowledge.

Third, learning can take place through the use or operation of a plant, which would lead, for example, to increased efficiency of plant use; this would imply the non-embedment of knowledge. In the case of feedback on the development aspect, however, knowledge can also lead to a change in the plant design and thus elevate the concept knowledge to embedded knowledge.

Thus, according to Pieper [12], today's concept of learning curves describes technological learning at a higher systematic level. In this context, learning means increasing knowledge in the three areas described above, all of which should be included in the description of the learning curves. As described above, the learning system is very complex. If learning curves include all the three areas of knowledge (concept, production, and usage), then the choice of description of costs should be taken into account. If costs are stated as costs per installed capacity, then learning effects in the area of operation of the plant are not considered. In addition to savings in maintenance and service, this would also include, for example, the increased efficiency of an energy conversion plant that can generate more electricity from the same installed capacity.

3.3.3 Structural technological changes

An important question is how a research breakthrough or structural technological changes in production processes affect learning curves. An example of this could be the development of new high-temperature resistant materials for gas turbines. Importantly, it is a radical change in technology, as opposed to a gliding change.

According to Wene [24], structural changes are seen as a discontinuity in the learning curve in the form of a double knee, as shown in Figure 3-4. A radical change makes it possible to change the entry point of the learning curve and, possibly, the learning rate. It is assumed that the two variants A and B are similar and thus variant B can benefit from the experience gained from variant A.

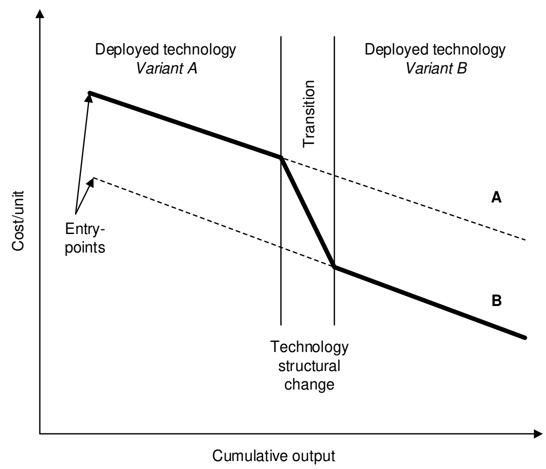

Figure 3-4: Structural technological change (Own representation based on [24])

The predominant view of an entire industry, instead of individual companies or even individual products, produces a significant outcome in that many smaller technological breakthroughs are contained in the entire learning curve in exactly the manner described above, which can be easily missed at the first glance.

3.3.4 Structural changes of the market

Often, detailed data about costs are not available, and the analyst has to deal with the price data. The relationship between cost-based and price-based learning curves was analyzed by the Boston Consulting Group [12]. A complete price-cost cycle of launching a new product consists of four phases. In the development phase, the first-party supplier offers its product below its cost to bring the product to the market. The first-party supplier usually has some market power when his costs fall below prices. In this case, the supplier has the opportunity to keep prices stable, since additional market entrants generally have higher initial costs. During this time, the losses throughout the development phase can be compensated. Gradually, the competitors learn and reduce their costs. This leads to an unstable situation in which the difference between prices and costs increases. In the following phase, prices fall faster than the costs. According to the Boston Consulting Group, the progress rates in this area are around 60%, with predictions of large fluctuations. In the last phase of the price-cost cycle, the situation stabilizes, and prices stay around a fixed price/cost ratio. Thus, in a stable market, the learning rate of the price-based learning curve is identical to the learning rate of a cost-based learning curve. However, it is important to separate the two phenomena: technological change, which can be identified with the cost learning curve, and structural changes in the market, which are reflected in the price learning curve. The latter refers to phenomena that are outside the learning system. Both phenomena can occur simultaneously, which further complicates the analysis. The difficulty in determining costs may mislead the analyst into deducing the price learning curve as an indication of technological change. However, this should be avoided in any case because conclusions cannot be drawn on the cost learning curve due to the kinks of the price learning curve [12].

3.3.5 Influence of governmental R&D and market introduction programs

To understand the impact of government intervention, that is, R&D and market introduction programs, it is necessary to open the black box of the input-output model (see Section 2.2.1). Watanabe et al. [27] have developed a model that demonstrates the interplay between public R&D, industrial R&D, production, and technological knowledge acquired through R&D.

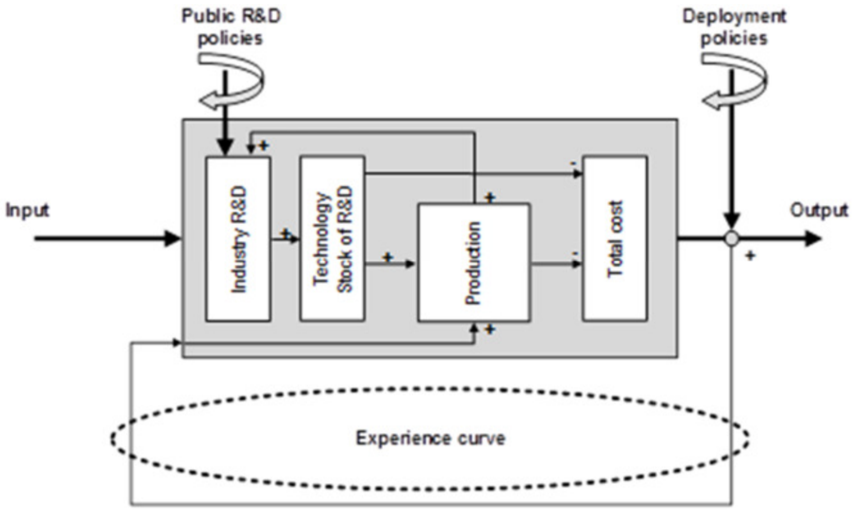

Figure 3-5: Impact of (public) R&D and market launch programs on the learning system (Own representation based on [24] and [1]).

The above representation is based on the simple learning model (input-output model). An increase in output leads to an increase in production, which stimulates industrial R&D. This increases the level of technological knowledge, which further boosts production and reduces costs. Thus, the cycle strengthens itself; it is referred to as the "virtuous cycle" [27]. An important finding is a double boost in production, which emerges from an increase in the output on the one hand and improvements in the technological knowledge through R&D on the other hand. This supports the thesis of the importance of the governmental R&D in stimulating the private R&D and launch programs for learning the processes of a new technology.

It is evident that public R&D can initiate the learning process within the industry, but cannot have a direct impact on overall costs. In order to allow cost reductions, public R&D must be included in the internal (private) R&D process. The special feature of this cycle is that self-reinforcement of the learning process cannot occur without the market component (production of output). Here, again, the significant importance of market participation becomes clear [12].

Therefore, the analysis of Watanabe et al. [27] proposed the following two-stage technology policy. First, public R&D is required to initiate research concerning uncertain technological issues that pose a high investment risk, followed by R&D designed to stimulate industrial R&D. Second, the market launch assistance is needed to ensure the market launch of technologies that are not yet fully competitive. The two-step technology policy proposed by Watanabe et al. [27] only provides a rough direction. The question arises as to whether learning curves can be used to obtain accurate indications of suitable political measures for promoting innovation.[6]

[6] For the commercialization of solar-swimming pool systems in Germany, an ex-post analysis showed the potential use of learning curves to assess public funding [21]. The solar-swimming pool heating was supported by a publicly funded research, development, and demonstration program between 1975 and 1987. The case study also suggested that data obtained should be interpreted with caution. In the transition from a collector to

Policymakers must apply an assessment methodology to decide whether to continue or terminate such a program, owing to stagnation in technology or market readiness. Based on the observed learning curve, the outstanding learning investments can be estimated, and hence can contribute to determining whether to continue or terminate a program. The termination of the support program ultimately depends on the assessment of the willingness of market participants to make the outstanding learning investments. At this stage, wherever appropriate, the state can provide support by facilitating favorable framework conditions such as the endogenization of environmental costs. This shows that learning curves are a systematic way of assessing data and weighing arguments in favor of or against the continuation of a public funding program. Like all methods, it must be used with caution and compared with other information. Learning curves do not replace healthy judgements but help the decision-makers to broaden and sharpen their observations [24].

The EXTOOL program (Experience curve: a tool for energy policy programmes assessment), funded by the European Commission, has been addressing the question of how different policy support programs can be evaluated using learning curves. Wind energy programs in Denmark, Germany, Spain, and Sweden were analyzed and compared. The combination of measures was the same in all countries, which was R&D combined with investment and production subsidies. However, the time horizon and range of the measures varied [28]. The result of the analysis shows that the assessment of the impact of individual measures (e.g., R&D alone) with learning curves is not possible; the result also showed that the cost reduction trend does not differ due to the different measures observed. Rather, learning curves describe the total cost reductions that result from the combination of measures. However, learning curves can be used successfully to assess the success or failure of the entire funding program, and the criteria for this are accelerating the increase in the installed capacity or the electricity produced and the associated cost reduction (i.e., learning rate).

The research also shows that, despite different levels of government subsidies, similar results can be achieved in installed capacity and cost reduction. Hence, it can be concluded that, in some countries, government support was higher than necessary. However, there are limitations of the learning curves as evaluation criteria of individual supporting measures. For this purpose, additional methods complementary to the learning curve need to be developed [28].

In addition to assessing the overall success of policy measures, learning curves can also be used to assess the cost-effectiveness of these measures. In this regard, the total learning investment necessary to achieve the cost-reductions is compared to the level of governmental support. A system-wide approach that uses learning curves based on the total electricity produced from wind energy and total government subsidies proves to be suitable. However, EXTOOL's research shows that, despite a large amount of data available, the development of learning curves based on the total electricity produced from wind energy was not possible [28]. Rather, all the previously developed learning curves for wind energy are presented based on the installed power. Thus, learning curves, at least for the wind energy sector, are not suitable for assessing the cost-effectiveness of political support programs.

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absorber technology between 1982 and approx. 1985 - 1987, a knee curve of the learning curve described in Section 3.3.3 can be observed. When extrapolating a learning curve, based on all data in 1983, it can be seen that the projected learning investment might have been significantly high to have led to the termination of the program. However, the realization that the technology is at the point of a structural change may lead an analyst to consider this in own deductions and discuss the continuation of the program. Since 1990, solar swimming pool heating has been fully commercial, and, today, it is cheaper than fossil alternatives. Paid learning investments can be recovered in this way.

3.3.6 The dynamic of learning

In the learning curve concept, the variable “time” is often not a relevant variable because the basis of technological learning is not the advancement of time but the production of output [12]. However, the right timeframe is a significant factor when assessing the (market) chances of technology and the expected total costs of an energy transition aimed at reducing CO_2 emissions. How can we estimate the proliferation speed of technology and the speed at which the cost reductions can be realized? The development period of carbon-free or low carbon technologies depends crucially on policy measures (carbon taxes, the scope of government R&D, and market introduction programs) and economic factors (such as economic growth). Furthermore, the market assessment of market participants plays a major role in the decision to invest in new technologies.

Another question focuses on the optimal development of renewable energies over a period of time. Wene [24] informs that the development must achieve a fine balance between slow expansion (break-even point is further in the future) and fast expansion (expansion is faster than the technology can learn, which leads to a waste of learning investment). In this case, the government must identify suitable measures to balance these two characteristics, such as degressive feed-in tariffs, as they exist in Germany. For an effective learning process, it is important that the learning takes place on a global level, that is, the experiences in one country should also be transferred to other countries. This has already been noted for wind turbines in Europe [28]. Conversely, the market introduction of technologies must take place at a regional level [24].

4 Literature review on learning rates

The experience or learning curve concept is a method used as part of a techno-economic analysis of future technologies and their costs. They are used to transfer past cost reductions to future cumulative production levels and thus be able to estimate the future costs. The derivation of learning or experience curves leads to a specific learning rate, which indicates a proportional reduction of the costs for each doubling of the cumulative capacity or production. Therefore, for the calculation of future costs, the learning rate of technology or component is a crucial parameter. Therefore, a literature review has been conducted on learning rates to gain information on learning rates for different technologies and components, which serve as an input parameter for the calculation model CoL-LeCT (see chapter 7) for calculating the potential for cost reductions of power-to-gas systems through technological learning.

4.1 Learning rates for energy technologies

In the following section, the results of the literature review undertaken by Rubin et al. [11] regarding power plant learning rates are shown. The results also summarize projected learning rates estimated for the two emerging technologies of interest – carbon capture and storage (CCS) and integrated gasification combined cycle (IGCC) – for which a substantial empirical dataset has not been developed till date for the power plant applications. The literature review of learning rates for electric power generation technologies by Rubin et al. [11] reveals that most of the studies report learning rates (or progress ratios) calculated by one-factor learning curve approaches (see chapter 3.2.1). In a smaller number of studies, two-factor learning curve models (see chapter 3.2.2) that comprise both learning-by-doing and learning-by-researching are applied. Overall, there are technologies that have particularly high learning rates (fast-learners) and technologies that have a much lower learning potential (slow-learner). Fast-learning technologies include, for example, the semiconductor industry and photovoltaics, while wind energy represents slower-learning technologies.

Rubin et al. [11] found that most of the learning rate studies focus on solar PV systems and onshore wind. The range of learning rates of the different technologies differs significantly. In some cases, the range contains negative as well as positive values. This means that costs have increased as well as decayed with increased production (most notably for nuclear power plants). Rubin et al. [11] concluded that "no single estimate of a technology learning rate can be considered "robust." Additionally, the author states that power plant technologies using fossil fuels like coal and natural gas have less likelihood of exhibiting a variance regarding the range of learning rates when compared to renewable energy technologies (wind, solar, and bioenergy). This observation may be explained by different levels of progress, scales of deployment, and timeframes of the analysis.

Based on the literature review, Rubin et al. [11] attests that although prices decrease along with costs over a long period of time generally, they are biased by market structure, subsidies, high market demand, monopolies, oligopolies, and other factors. Consequently, the market price is often considered an unsatisfactory indicator of cost in non-equilibrium markets [29]. Rubin et al. [11] postulates that this can particularly affect the scale and significance of learning rates for renewable energy technologies, which have been the focus of many government regulatory and/or incentive programs in the past years.

Studies on two-factor models that include separate rates for learning-by-doing (LBD) and learning-by-researching (LBR) show that the outcome of R&D spending is larger than that of the LBD effect. However, the difficulty of acquiring complete and reliable data for R&D spending for a particular technology has significantly limited the application and use of this two-factor model for technology forecasting (see chapter 3.2.2).

Table 4-1: Range of reported one-factor and two factor learning rates for power generation technologies elaborated [11]

Technology and energy source	No. of studies with one factor	No. of studies with two factors	One-factor models		Two-factor models				Years covered across all studies
			Range of LR[1]	Mean LR	Range of rates for LBD[2]	Mean LBD rate	Range of rates for LBR[3]	Mean LBR rate	
Coal									
PC	4	0	5.6-12%	8.3%	-	-	-	-	1902-2006
PC+CCS	2	0	1.1-9.9%[d]		-	-	-	-	Projections
IGCC	2	0	2.5-16%[d]		-	-	-	-	Projections
IGCC+CCS	2	0	2.5-20%[d]		-	-	-	-	Projections
Natural gas									
NGCC	5	1	-11 to 34%	14%	0.7-2.2%	1.4%	2.4-17.7%	10%	1980-1998
Gas turbine	11	0	10-22%	15%	-	-	-	-	1958-1990
NGCC+CCS	1	0	2-7%[d]		-	-	-	-	Projections
Nuclear	4	0	<0 to 6%	-	-	-	-	-	1972-1996
Wind									
Onshore	12	6	-11 to 32%	12%	3.1-13.1%	9.6%	10-26.8%	16.5%	1979-2010
Offshore	2	1	5-19%	12%	1%	1%	4.9%	4.9%	1985-2001
Solar PV	13	3	10-47%	23%	14-32%	18%	10-14.3%	12%	1959-2011
Biomass									
Power generation	2	0	0-24%	11%	-	-	-	-	1976-2005
Biomass production	3	0	20-45%	32%					1971-2006
Geothermal	0	0	-	-	-	-	-	-	
Hydroelectric	1	1	1.4%	1.4%	0.5-11.4%	6%	2.6-20.6%	11.6%	1980-2001

[1] … LR (learning rate) = $1-2^{\varepsilon}$ … ε (elasticity of learning) - see equation 4 for a one-factor learning curve

[2] … LBD (learning-by-doing) rate = $1-2^{\alpha}$ … α (elasticity of learning-by-doing) - see equation 6 for a two-factor learning curve

[3] … LBR (learning-by-research) rate = $1-2^{\beta}$ … β (elasticity of learning-by-research) - see equation 6 two a one-factor learning curve

Since Rubin et al. [11] have not considered fuel cells, hydrogen, and carbon capture in their study, further literature research on the following technologies have been conducted:

- Wind energy
- Photovoltaic energy
- Fuel Cells
- Electrolyzer
- Carbon capture

For the well-developed technologies like wind energy and PV, only historical data are used for the learning curve analysis. For the other technologies, due to a lack of data availability, available historical data and forecasts of scientists or expert estimates of the producing companies are integrated. However, some obstacles complicate the comparability of the studies. Different characteristics of the learning curves as well as different system boundaries can be observed. These differences lead to deviations in the learning curve results.

Table 4-2 and Figure 4-1 show the mean learning rate of the gathered information and the standard deviation.

Table 4-2: Overview of the mean learning rates of different energy technologies

Type	Mean learning rate	Standard deviation
Wind [11], [30], [31], [32], [33], [34], [35], [36], [22], [37], [38]	12.8%	8.1%
Photovoltaic [11], [35], [36], [39], [40], [41], [42], [43]	20.9%	8.4%
Fuel Cells [44], [45], [46], [47], [48], [49], [50] [51], [52]	17.3%	6.9%
Electrolyzer [50], [14], [53]	9.6%	5.5%
Carbon Capture [50], [54], [55], [56]	10.4%	5.4%

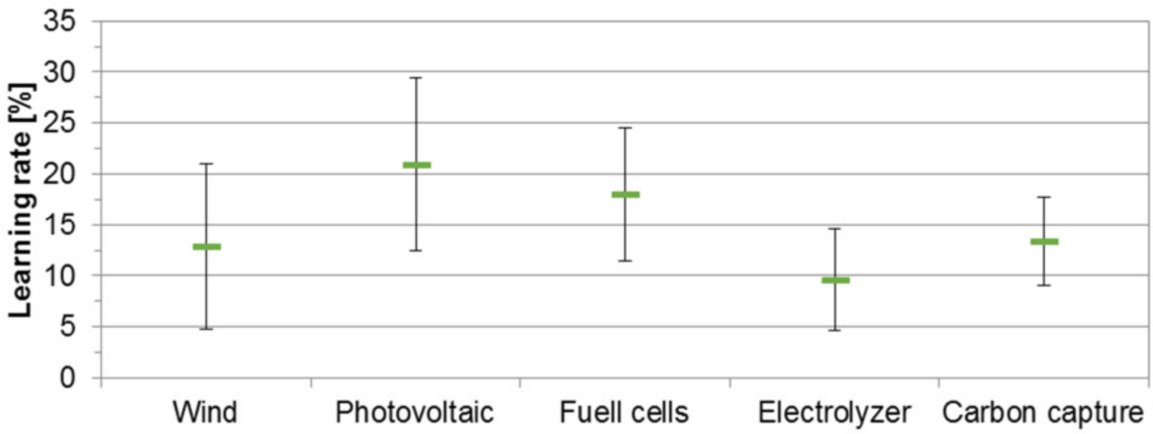


Figure 4-1: Overview of the mean learning rates of the considered technologies

The overall median for learning rates for developing energy technologies (wind, PV, fuel cells, electrolyzers, and carbon capture) is about 13%, however, with a wide range from 2% to 47%.The median learning rate of 13% is also used by Agora [57] and Zapf [58] for estimations concerning the PtG systems.

Although there were several obstacles while performing a comprehensive analysis of learning rates for energy technologies, it can be said that, despite the differences in variables, learning effects can always be observed, and they are within a certain range. Thus, it can be stipulated that, for similar technologies, a similar reduction in costs can be achieved.

While Table 4-2 includes several references for technological learning of carbon capture technologies, it is necessary to mention that those values cover only the exploitation of CO_2 from flue gases in industrial applications. This primarily means carbon capture from industrial combustion and other carbon emitting processes as a method for reducing the greenhouse gas (GHG) emissions. While the suitability of these, mostly fossil, carbon sources as a feedstock for renewable product, like SNG, can be discussed, the far less questionable renewable resources for CO_2, including biogas upgradation, ethanol production, or direct air capture, are not part of these research results. For those sources, a general literature review on observable learning rates was not constructed due to the following reasons:

- Even if some technologies used for separating carbon from flue gases can be reused in a similar way for other diluted or high purity sources, the variety of potential applications (renewable and non-renewable) is huge. Beyond that, the capture efficiencies and therefore the costs are highly dependent on initial CO_2 concentration and impurities in the raw gas. Therefore, while a general prediction about learning rates would not be meaningful, an individual investigation for all potential resources is not feasible.
- Currently, in the early state of CCU, carbon capture from industrial processes is performed as a process step mandatory to meet requirements of the core product of the individual process, irrespective of whether it is the achievement of emission targets (e.g., in power plants) or upgradation of product gases for further usage (e.g., biogas upgrading). Hence, investment costs for carbon capture or separation technologies cannot be separated from actual plant costs as they are a part of the process.
- If CO_2 is treated as a mere operating resource for PtG plants, independent of the original source process, then an investigation of cost reduction potentials based on learning curves would seem principally conceivable. However, in this case, it has to be considered that those cost reductions are not only dependent on technological learning but also on a wide variety of additional parameters particularly emerging from the following regulatory frameworks:
    - Development of costs for emission certificates
    - Profitability for the “producer” of CO_2
    - Utilization of CO_2 in other technologies besides PtG
    - Differentiation of fossil and renewable carbon sources

Consequently, within this deliverable, the learning curve effects for carbon capture technologies were not further investigated. The costs for CO_2 as an operating resource for the PtG process have been included in the calculation, when necessary, as current costs, as stated in chapter 5.3, with a focus on technologies used in the project STORE&GO.

4.2 Learning rates for methanation and other comparable technologies

As described in the previous section, similar technologies share comparable learning rates. Therefore, for the second part of the literature research, other relevant technologies with a focus on methanation have been conducted.

Within the research on learning rates of the catalytic and biological methanation process, no information on learning rates has been found. However, in order to obtain comparative values, a research on learning rates for similar processes in the chemical industry has been performed. Table 4-3 shows the considered catalytic processes [59], [60], [61].

Table 4-3: Considered catalytic processes

Process	Catalyst	Catalytic reaction
Double contact process [62]	Vanadium(V)oxide (V_2O_5)	$2\ SO_2 + O_2 \rightleftharpoons SO_3$
Steam reforming [63]	Nickel-based	$C_nH_mK_k + (n-k)\ H_2O \rightleftharpoons$ $n\ CO + (n+m/2-k)\ H_2$
Fischer-Tropsch process [64], [65]	Iron, nickel, cobalt or ruthenium	$CO + 2\ H_2 \rightleftharpoons CH_2 + H_2O$
Haber-Bosch process [66]	Iron(II,III)oxide (Fe_3O_4)	$N_2 + 3\ H_2 \rightleftharpoons 2\ NH_3$
Ostwald process [67]	Platinum	$4\ NH_3 + 5\ O_2 \rightarrow 4\ NO + 6\ H_2O$

The processes shown in Table 4-3 have been considered because all the reactions are performed with a heterogeneous catalyst. A heterogeneous catalytic reaction occurs when the reactants and the catalyst are present in different phases [68]. In the case of the methanation process, a nickel based catalyst is used.

The catalytic reactions for the methanation process are shown in Eq. 7 and Eq. 8 [69]:

$$CO + 3\ H_2 \rightleftharpoons CH_4 + H_2O \quad -206\ kJ*mol^{-1} \tag{Eq. 7}$$

$$CO_2 + 4\ H_2 \rightleftharpoons CH_4 + 2\ H_2O \quad -164\ kJ*mol^{-1} \tag{Eq. 8}$$

As shown above, the Fischer-Tropsch and steam reforming processes display similarities in the reaction and the catalyst, and hence these two processes are considered for the research. The double contact process, Haber-Bosch process, and Ostwald process have been considered since they are exothermic catalytic reactions, and therefore have a design that is similar to the methanation process.

The literature does not show any usable data on learning rates for most of the considered processes. A few techno-economic analyses have been conducted for the processes. However, none of the studies have considered experience behavior, with the exception of an analysis of steam methane reforming conducted in one study. It shows a learning rate for investment costs of 11 ± 6% for steam methane reforming. The reason for the deviation can be attributed to a lack of data points in the analyzed data [14].

5 Current investment costs of power-to-gas-processes

In order to evaluate the future technology costs of PtG systems, this section examines the current costs of the main components. This analysis includes data gathered from relevant literature as well as cost estimates and experience values from STORE&GO project partners referring to the erected demo plants. These current costs serve as an input parameter and thus as a starting point for the calculations with the model CoLLeCT for calculating the potential for cost reductions through technological learning.

5.1 Current investment costs of electrolyzer

The following section aims to give a brief overview of the estimated investment costs of the different electrolyzer types. The information in chapter 5.1.1 is partly based on the deliverable *D8.3 "Report on the costs involved with PtG technologies and their potential across the EU"*.

5.1.1 Literature review on AEC and PEMEC

In [70], a system analysis of the PtG technology was carried out. One of the chapters dealt with investment costs of the AEC and PEMEC systems. The study revealed the difficulty in indicating existing specific investment costs because the system costs primarily depend on the purpose of the field of application. Therefore, the given costs must be treated as guideline values. The specific system costs for AEC and PEMEC were based on price information from electrolyzer manufacturers in the year 2014. The specific investment costs for an AEC with a hydrogen production rate of about 100 Nm³/h (app. 0.5 MW_{el}) can be estimated with about 1,800 €/kW_{el}. The costs declined to 1,200 €/kW_{el} for an electrolyzer with 500 Nm³/h (app. 2.5 MW_{el}). By way of comparison, PEMEC incurs higher costs for a similar production rate of about 3,500 €/kW_{el} (0.1 MW_{el}) and 1,750 €/kW_{el} (1 MW_{el}). According to various manufacturers and research institutes, the costs of an entire electrolysis system can be approximately divided in 50% stack costs (AEC: 40–50% and PEMEC 50–60%), 10–20% power electronics, and 30–40% remaining costs (BoP).

[71] estimated the total costs of an alkaline and a PEM electrolysis system with a rated power of 5 MW and 100 MW. The costs were related to a 5 MW system at the development level in the short-term future (2017) and to a 100 MW system in the long-term future (2030). The calculations were based on a stack cost model as well as on price offers by an engineering company and a manufacturer. The remaining costs (planning, steel construction, and fittings, among others) were estimated. The specific investment costs for the 5 MW AEC system were about 1,070 €/kW_{el} and were significantly lower for the 100 MW system of about 520 €/kW. In comparison, the 5 MW PEMEC system has specific investment costs of about 960 €/kW. For a 100 MW PEMEC plant, specific investment costs were estimated at 300 €/kW.

[72] calculated the specific investment costs for the alkaline pressure-less and pressurized electrolyzers on the basis of offers and price requests from the year 2002 to 2009 and summarized them in a graph. Depending on the hydrogen production rate (up to 500 Nm³/h), the specific investment costs range from around 750 €/kW_{el} to 6,000 €/kW_{el}. Additionally, the costs for PEMEC were determined; in this case, there was no information on the prices of electrolyzers possessing a production rate greater than 10 Nm³/h (equals to approximately 50 kW_{el}). The investment costs in the range of 0.5 to 6 Nm³/h (2.5–3 kW_{el}) were obtained from a manufacturer through telephonic conversation, and the costs were in the range from 50 to 200 Nm³/h (250–1,000 kW_{el}) as per theoretical calculations. Depending on the hydrogen production rate of the PEMEC, the specific investment costs approximately range from 900 €/kW_{el} (for 200 Nm³/h) to 10,000 €/kW_{el} (for 0.4 Nm³/h). For the calculation of the hydrogen production costs, which is carried out in this study, existing specific investment costs of about 2,500 €/kW for a PEMEC (30 Nm³/h) and 1,000 €/kW for an AEC (500 Nm³/h) have

been used. For a future scenario, specific investment costs of a 1,200 €/kW PEMEC (250 Nm^3/h) and AEC 800 €/kW (1,500 Nm^3/h) have been used.

[73] provided an overview of the current status and a forecast for the development of alkaline and PEM electrolysis technology. The key figures for the electrolyzers were taken from various literature (2010–2013), presentations, reports from the US Department of Energy, and data sheets from manufacturers. For an alkaline electrolyzer, the specific investment costs ranged from approximately 1,100 to 580 €/kW, depending on the year of installation from 2012 to 2030. In comparison, the costs of a PEM electrolyzer are higher, ranging from approximately 2,090 to 760 €/kW. The stated costs were not directly linked to an electrolyzer of a certain size and referred to systems with a rated power that was lower than 5 MW and as high as 10 MW.

[74] published key data on energy generation technologies, and thus also on electrolysis technologies at regular intervals. The data were taken from well-founded public sources as well as from expert information. The specific investment costs for alkaline electrolyzers with a nominal power of less than 3.4 MW were specified with 1,400 €/kW in the year 2015. The costs were projected drop to 1,000 €/kW in the year 2020. The costs for a PEMEC are comparatively high and amount to 6,000 €/kW, however, with a very low rated power of 45 kW, and these costs are expected to drop to 1,000 €/kW in the year 2020.

The data given in [75] were based on assessments by scientific actors and operators of existing pilot plants. Manufacturers already had the capacity to offer large AEC for less than 1,000 €/kW in the year 2016. The cost reduction to around 700 €/kW beyond the year 2030 is considered realistic. The PEM technology is currently still significantly more expensive, with costs of around 2,000 €/kW. As per the study, a reduction to 700 €/kW is projected for the period following 2030.

[76] addressed the economic potential of the Power-to-X applications. The costs of the electrolysis technologies were derived from current literature sources. The current specific investment costs for AEC were stated as 2,000 €/kW (rated power 500 kW), 1,500 €/kW (rated power 1 MW), and 1,000 €/kW (rated power 10 MW). In addition to the rated power, the investment costs for PEMEC were also distinguished in terms of the year of installation. As per the study, in the subsequent years, the CAPEX is projected to reach 1,000 €/kW (rated power 10 MW). The costs are projected to decrease in the year 2030 to 700 €/kW (10 MW electrolyzer) and 1,000 €/kW (1 MW electrolyzer). The study also shows that the CAPEX would witness a further decline in the year 2050 and reach 500 – 550 €/kW (1 MW electrolyzer) and 350–400 €/kW (10 MW electrolyzer).

The specific investment costs stated in [77] were based on different literature sources. The study revealed that the costs for alkaline electrolyzers (1,000 €/kW to 5,000 €/kW) had a very wide range due to scale effects. The specific costs of 1,000 €/kW were for a MW-scale plant. For a PEM electrolyzer, the specific investment costs in the year 2014 were quite higher at about 2,000 €/kW.

In the article [78], a price level of approximately 1,800 €/kW was given for an alkaline electrolysis plant in the lower MW range. The price was based on the offers. The information that the investment costs for PEMEC are a factor of 1.5 to 2 higher than that of the AEC is taken from [72].

[79] analyzed 16 offers of commercially available electrolyzers in a power range of 0.35 to 3.35 MW. The investment costs included costs for electrolyzer, transportation, installation, and commissioning. The investment costs of AEC ranged from 2,100 $\$/kW_{H2\text{-}LHV}$ (output 54 kg_{H2}/h) to 5,700 $\$/kW_{H2\text{-}LHV}$ (output 5.9kg_{H2}/h) and the AECs had an efficiency between 52% and 62%. The PEMECs had higher costs between 3,100 $\$/kW_{H2\text{-}LHV}$ (output 47 kg_{H2}/h) and 6,600 $\$/kW_{H2\text{-}LHV}$ (output 9 kg_{H2}/h). However, their efficiency was higher, between 57% and 64%. This resulted in specific investment costs of approximately from 875 €/kW_{el} (3.35 MW) to 2,370 €/kW_{el} (0.35 MW) for AEC and 1,370 €/kW_{el} (3 MW) to 2,915 €/kW_{el} (0.6 MW) for PEMEC.

The investment costs for a PEM electrolyzer in [80] were derived from data provided by industrial partners. These costs were assumed to be at about 1.5 $/W for a 5 MW and about 1.25 $/W for a 30 MW electrolyzer. This resulted in specific investment costs of about 1,130 €/kW (rated power 5 MW) and 940 €/kW (rated power 30 MW), respectively.

[81] discussed Siemens announcement of the second product generation of PEM electrolyzer with a nominal power of 1.25 MW and costs below 2,000 €/kW. The study also revealed that further improvisation would reduce the costs significantly to reach below 900 €/kW by 2018. Additionally, the third generation electrolyzers were projected to have a rated power of about 100 MW.

In the PtG Roadmap for Flanders [82], most of the assumptions for the specific investment costs of alkaline and PEM electrolyzers for the years 2015, 2030, and 2050 were taken from the manufacturer Hydrogenics and from literature. It is also mentioned that the assumptions are in line with [73]. The specific investment costs for an alkaline electrolyzer system are stated to range from approximately 660–2,000 €/kW, depending on the rated power and year of installation. Comparatively, the costs for PEM electrolyzers are in a range of 550–1,500 €/kW and therefore slightly lower.

Since only a few reliable data on investment costs for electrolyzers are available and the future development of these costs is also uncertain, an expert elicitation was conducted in [83]. The costs are based on a 10 MW electrolyzer system, which is powered by intermittent renewable energy sources. The hydrogen is generated at a pressure of 20–30 bar and fed into the natural gas grid. In the year 2016, the reference values were 1,100 €/kW for AEC and 2,100 €/kW for PEMEC. As per the experts' estimates for the year 2020, the specific investment costs for AEC systems would be in the range of 700–1,400 €/kW and approximately 800–2,200 €/kW for PEMEC. Given the current R&D status and lack of scalability in production, the projected costs in the year 2030 would be slightly lower when compared to 2020. The costs for AEC and PEMEC range from 700–1,000 €/kW and 700–1,980 €/kW, respectively. Furthermore, it is reported by the experts that the costs of electrolyzers can be reduced by up to 24% if the R&D funding is increased. Additionally, the scaling-up of production can lead to a further reduction of 17–30%.

According to the information in [84], obtained from different projects based on requests, in the year 2017, the investment costs for alkaline electrolyzers were approximately in the range of 900–2,500 €/kW at a power of about 0.5–2.5 MW. For PEM electrolyzers, the costs are about 1,600–2,000 €/kW for a rated power of 0.5–2 MW.

Assessment of literature data

An overview of the data points from the literature regarding the investment costs of electrolyzers (AEC and PEMEC) is shown in Figure 5-1. The different characteristic parameters of the data points show a wide variation as follows: specific investment costs from 300–8,000 €/kW, the year of installation from 2009–2050, and the rated power of the electrolyzer from 0.05–100 MW.

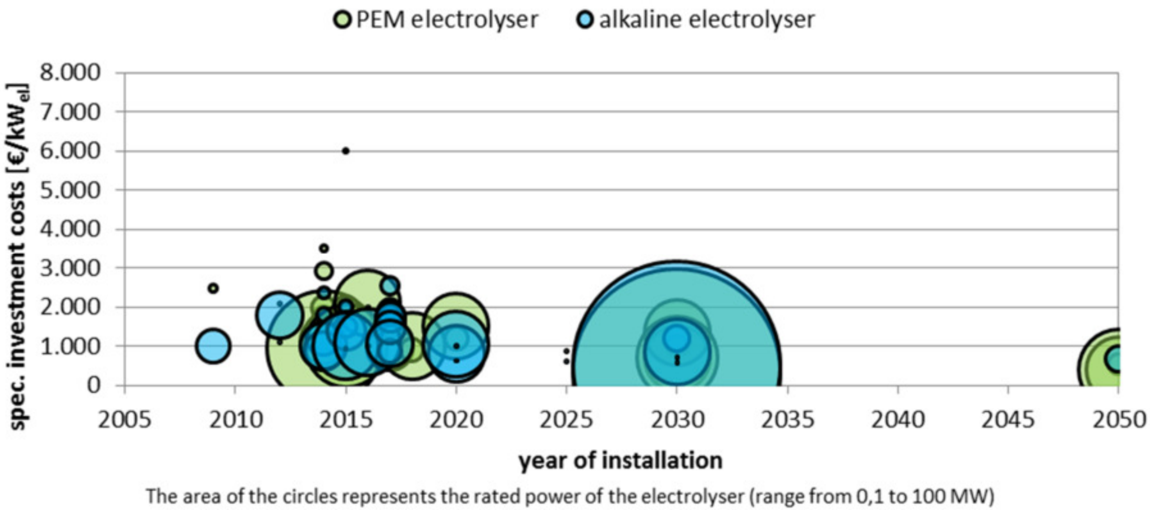


Figure 5-1: Overview of the specific investment costs for different electrolyzer technologies related to the year of installation and rated power (Sources: [83], [73], [71], [74], [75], [80], [77], [72], [81], [76], [79], [70], [82], [84], [78]**)**

In order to make reliable statements regarding the costs of an electrolyzer system, the individual data points must be categorized. Therefore, different electrolyzer technologies were examined separately. Furthermore, the time of the installation was divided into five sections (< 2015, 2015–2017, 2018–2020, and 2030 and 2050). For these time periods, the range and the average value of the specific investment costs and rated power were calculated, respectively. Additionally, the statistical outlier (6,000 €/kW for a 45 kW PEM electrolyzer) was identified and no longer included in further analyses. Further, in order to minimize the influence of the plant size on the specific investment costs, the current costs were also calculated for a standardized 5 MW plant size on the basis of the scale factor method, where 0.7 was assumed for the exponent (scale factor). The results of the comprehensive review are summarized in the following table.

Concerning alkaline electrolyzers, the current (the year 2015–2017) specific investment costs according to data in existing literature are in the range of about 900–2,500 €/kW and have an average value of about 1,500 €/kW, see Figure 5-2. The average rated power in this time section is about 3 MW. It can be assumed that the costs will halve in the future (about 750 €/kW in 2030). If the current costs are standardized for an alkaline electrolyzer with a rated power of 5 MW, then they will decrease to about 1,100 €/kW.

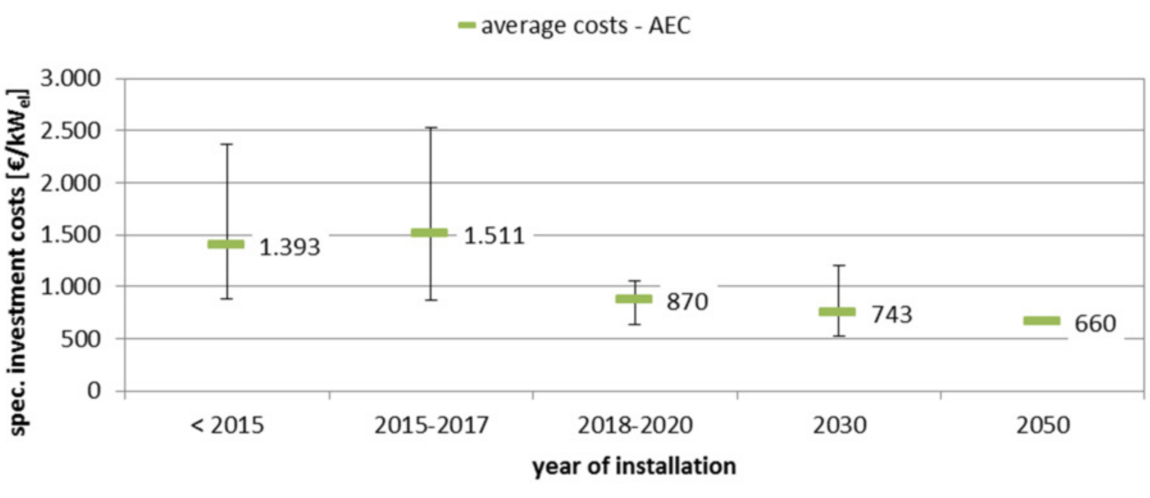


Figure 5-2: Range and average value of the specific investment costs for alkaline electrolyzers (AEC) related to the year of installation (Sources: [83] ,[73], [71], [74], [75], [77], [72], [76], [79], [70], [82], [84], [78]**)**

Compared to an alkaline electrolyzer, the current (2015–2017) specific investment costs of a PEM electrolyzer are slightly higher, with an average value of about 1,650 €/kW (average rated power of about 4 MW) and a range of 950–2,100 €/kW (see Figure 5-3). Additionally, in the case of the PEM electrolyzer, the costs are projected to decline by half in the year 2030. The current average costs are expected to drop to approximately 1,200 €/kW if the data from the literature with their different rated power are standardized to a 5 MW PEM electrolyzer.

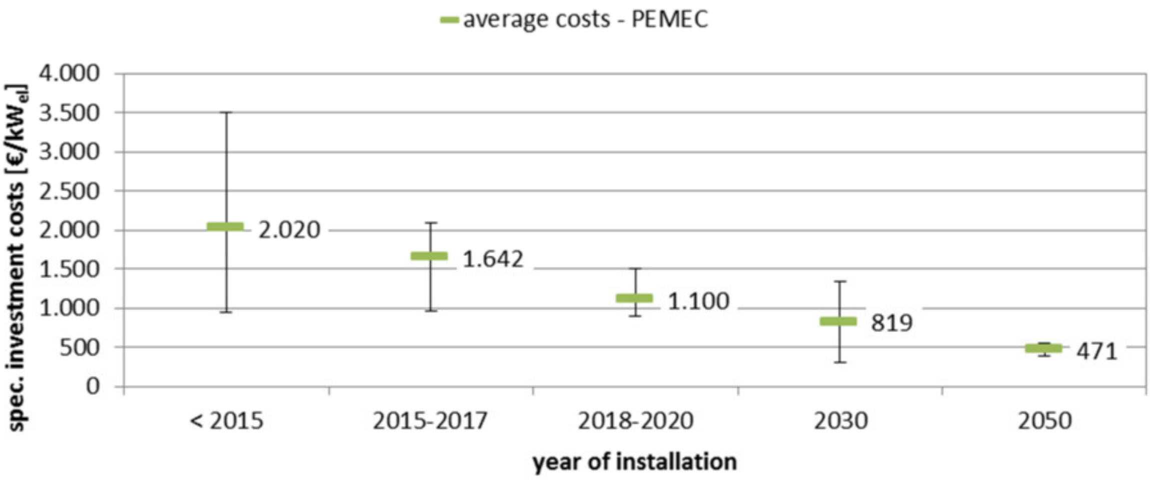


Figure 5-3: Range and average value of the specific investment costs for PEM electrolyzers (PEMEC) related to the year of installation (Sources: [83], [71], [73], [74], [75], [76], [77], [80], [81], [78], [79], [70], [82], [84]**)**

In conclusion, according to current information, it can be stated, that the current specific investment costs for both AEC and PEMEC are quite similar. Nevertheless, the current costs for PEM electrolyzers are slightly higher than that for alkaline electrolyzers, on an average, with about 1,650 €/kW for a rated power of about 4 MW and 1,500 €/kW for a rated power of about 3 MW, respectively. Even though the costs are standardized to a 5 MW electrolyzer, this difference would remain, and the costs of a PEM electrolyzer are, on an average, about 1,200 €/kW, which is more than the alkaline one with 1,100 €/kW.

5.1.2 Literature review on SOEC

Since SOEC was not a part of the research on the deliverable D8.3 but was seen as a promising technology, a literature analysis of investment costs was performed for this deliverable. The information was classified into information about the specific stack costs and the total specific costs for an SOEC system.

The two main influences on the investment costs according to literature are the year of installation and the rated power. Therefore, for an 8–10 MW SOEC, Mathiesen et al. forecasted a CAPEX of 860 €/kW, 280 €/kW, and 210 €/kW for the years 2020, 2030, and 2050, respectively. A lifetime is assumed to be about 10–20 years. Since a connection to the electric grid leads to extra costs, the grid bound SOEC CAPEX are expected to be 930 €/kW, 350 €/kW, and 280 €/kW for 2020, 2030, 2050, respectively. The maintenance costs are expected to be 3% of the CAPEX. All costs are based on a large-scale plant. As an example, concerning the difference between large-scale and small-scale plants, the following values have been stated by Mathiesen et al.: 710 €/kW for small-scale and 280 €/kW for large-scale plants [85].

Scataglini et al. [86] showed the same effect. They showed how to achieve the target stack cost of 238 $/kW of the US Energy Department. It is mentioned that the target stack price can only be attained if the annual SOEC installation reaches 100–250 MW. It also calculated different scenarios with production rates of 10, 1,000, 10,000, and 50,000 systems per year with capacities of 1, 10, 50, 100 and 250 kW. For the scenarios, the costs differ from 166 $/kW (143 €/kW)* to 5,387 $/kW

(4,629 €/kW). It is stated that low costs can be primarily attained through thinner cells and stack components as well as through improved production automation [86].

Butter et al. [87] considered specific investment costs of 1,500 €/m² (375 €/kW with 4 kW/m²) as the reference value for large-scale industrial manufacturing. The lifetime of the SOEC stacks is stated to be 3 years. As process parameters, Butter et al. set the temperature at 850°C, which is a standard condition for SOEC systems. The year of installation has not been mentioned.

Besides literature that compares costs of plants with different capacities, there exists literature that predicts comparatively low CAPEX, less than 500 €/kW, even for SOEC in an early stage of development. A few examples of such studies are Manage et al. [88], Jensen et al [89], Giglio et al. [90], Milobar et al. [91], and the US Energy Department [92]. Manage et al. mentioned that the investment costs are 235 $/kW (202 €/kW)* for the year 2020 [88]. Jensen et al. stated that the US Energy Department used specific costs of 350–550 $/kWh (303-476 €/kWh)* based on a 5 kW SOEC. It is operated with 5% energy that is lost in the heat exchange. The cells are operated at 950°C, and they have a lifetime of 5 years [93]. The study by Giglio et al. calculated target stack costs of 540 $/m² for future SOEC stacks, housing costs accounting for 1,000 $/m², 82 $/kW for the AC/DC rectifier, 48 $/m² for the transportation, and 148 $/m² as foundation costs. The energy density was assumed to be 4 kW/m². Hence, the overall specific costs would be 516 $/kW (444 €/kW)*. The stated stack modules have a power of 1 MW. All assumptions are based on the information from the US Department of Energy. The year of installation has not been mentioned [90]. Milobar et al. calculated the specific costs of SOEC with 500 $/kW (430 €/kW)* for a 25 kW SOEC capacity. The year of installation has not been mentioned [91]. The US Energy Department reported an amount of 287 $/kW (246 €/kW)* as stack investment costs and a BOP with 533 $/kW (453 €/kW)*. The department also reported future stack investment costs with 99 $/kW (85 €/kW)* and the BOP with 331 $/kW (282 €/kW)*. The plant capacity was given at 50,000 kg/d [92].

However, since SOEC is a new technology and hence not available on an industrial scale, it is hard to predict the CAPEX. In this regard, there are studies that predict a much higher CAPEX for SOEC. The following three studies serve as examples. Nevertheless, especially, the first and third studies show a high deviation in their results, which supports the thesis that it is hard to predict future costs for a new technology like SOEC. Schmidt et al. discussed capital costs for SOEC system with 3,000–5,000 €/kW. The capital costs projected for the year 2030 are 1,040–4,250 €/kW [83]. Seits et al. discussed the CAPEX of SOEC with 1,500 €/kW. This forecast considered the next 5–10 years [94]. Concerning the SOEC system, Rivera-Tinoco et al. reported a CAPEX between 4,000 and 11,000 $/kW (3,429–9,430 €/kW). However, Rivera-Tinoco et al. also mentioned that the costs would reduce in the future due to the economies of scale [95].

Besides literature that analyses only the total CAPEX, there are studies where only stack prices are given. However, since the stack costs are mainly responsible for the CAPEX in SOEC systems, the two studies found that only state stack costs are shown. For a renewable solid oxide cell with 100 kW stacks, specific costs of 874 $/m² are estimated. The lifetime of the stacks and the other components are estimated to be 5 years and 20 years, respectively [96]. With an energy density of 5 kW/m², the specific costs amount to 175 $/kW (150 €/kW).* Brynolf et al. mentioned stack costs that vary from 100 to 300 $/kW (86–257 €/kW)* and 500 to 1.200 $/kW (429–1,029 €/kW) [97].

*All US$ values are converted to € with 1 $ = 0.86 €.

Assessment of literature data

Since SOEC is a very new technology that is under development, it is hard to get reliable sources on investment cost. Table 5-1 shows a brief summary of the analyzed sources and the stated values. The different characteristic parameters of the data points exhibit a wide variance as follows: specific investment costs from 140–9,400 €/kW, year of installation from 2016–2050, and the rated power of the electrolyzer from 8 MW to large scale. Additionally, the given information in the studies is often incomplete. A constant assertion through all sources is that SOEC has an important and future orientated role in the field of PtG. Therefore, it is expected that investment costs of SOEC will reduce and the technology will become more efficient and robust in the future. Although the data on current investment costs are very poor, for further calculations, the investment costs (initial value) for a 5 MW SOEC system is fixed at 2,500 €/kW.

Table 5-1: Summary of the analyzed sources and the stated costs and setups of SOEC based plants (1 $ ≙ 0.86 €)

Specific system costs	Stack costs	Year	Power	Source
€/kW	***€/kW***		***MW***	
860	-	2020	8-15	[85]
280	-	2030	8-15	[85]
210	-	2050	8-15	[85]
143		-	Large Scale	[86]
4,629		-	Small Scale	[86]
-	375	-	-	[87]
202	-	2020	-	[88]
303-476	-	-	-	[93]
373	116	-	1	[90]
430	-	-	-	[91]
703	246	2016	-	[92]
369	85	Future	-	[92]
3,000-5,000	-	2017	-	[83]
1,040-4,250	-	2030	-	[83]
1,500	-	2025	-	[94]
3,429-9,430	-	2016	-	[95]
-	150	-	0.1	[96]
-	86-257	-	Large Scale	[97]
-	429-1,029	-	Small Scale	[97]

5.2 Current investment costs of methanation units

A key factor in the project STORE&GO is the methanation process, which contributes toward maintaining SNG in the existing European infrastructure as a clean energy source, but with an already advantageous and continuously improving environmental footprint.

First, the gas input in STORE&GO is not syngas[7], the normal source for methanation, but a mixture of H_2, CO_2, and, depending on the source, CO. Therefore, the focus will be on information about this input. Second, in the project, three processes will be used – see work package 2 (WP2), WP3, and WP4. The WP2 and WP4 both demonstrate the cooled-reactor methanation. The biological methanation will be demonstrated in WP3.These three processes would be the focus of the data collection and can be compared with a “commercial standard” of the fixed bed methanation.

In this chapter, the most common methanation processes are described based on the available data on the current situation. This includes technological parameters and costs. Since scale effects and cost reduction developments (learning effects) differ for different parts of the installations, costs are split up to the maximum extent possible.

The methanation technology is still in the development phase, and information on its costs is limited. In other words, there are several uncertainties regarding the acquisition of the information on investment costs for methanation plants (currently, there are no commercial facilities in the context of PtG). Since manufacturers maintain the confidentiality of the existing specific costs for methanation plants, it is difficult to determine real costs. Therefore, the reviewed literature sources provide a rough estimate of the costs of a methanation reactor for both chemical and biological methanation systems.

The determination of investment costs is further complicated by a variety of different processes, reactor types, and operating modes. Also the quality of the SNG is an issue, if it is injected in the gas net. For instance to reach a high methane content and a low hydrogen content in catalytic methanation the last reactor should work under relative high pressure and low temperature. Furthermore, in most of the analyzed studies, the system boundaries of the indicated investment costs are not well-defined, thereby further limiting the comparability. Moreover, costs for methanation plants strongly depend on the carbon dioxide source used and therefore the quality and purity of the CO_2 stream. Usually, the specific investment costs are expressed in €/kW_{CH4} (rated CH_4 output power). If the costs are related to the rated power of the electrolyzer of the PtG plant, then the unit would be €/kW_{el}.

The screened studies on the investment costs of catalytic and biological methanation systems are briefly described below, and the subsequent sections summarize and analyze the data.

5.2.1 Literature review on chemical methanation

In a techno-economic study of PtG concepts, [98] estimated the total investment costs (apparatus, steel construction, foundations, electrics, instrumentation, and engineering) of catalytic methanation plants of three different sizes (5 MW_{SNG}, 30 MW_{SNG}, and 110 MW_{SNG}). Depending on the size, the total investment costs for the plants were estimated at € 1.5 m, € 4.9 m, or € 12.1 m, which led to specific investment costs of around 300 €/kW_{SNG}, 160 €/kW_{SNG}, or 110 €/kW_{SNG}.

[99] investigated the impact of process pressure for thermochemical production of SNG from lignocellulosic biomass. The study reveals that specific costs of about 190 €/kW_{SNG} are expected to facilitate methanation at 15 bar when compared to approximately 550 €/kW_{SNG} at 1 bar.

[100] estimated specific investment costs of about 580 €/kW_{SNG} for the methanation part in a 10 MW_{th} bio-SNG plant (production of SNG from biomass) run at atmospheric pressure. For a larger plant with a power of 100 MW_{th}, which is run at a pressure of 7 bar, the costs drop to about 107 €/kW_{SNG}.

[7] Syngas, or synthesis gas, is a fuel gas mixture consisting primarily of hydrogen, carbon monoxide, and some amount of carbon dioxide.

In a PtG analysis [70], the investment costs for methanation in a PtG plant with an electrical input of 48 MW_{el} (equals to about 27 MW_{SNG} output) was stated to be about 140 kW_{el} (equal to about 250 €/kW_{SNG}).

[101] provided a graph, based on several sources, for investment costs of chemical methanation plants against the rated power. The study revealed that costs decrease with an increase in capacity, and they were estimated at approximately 1,500 €/kW_{CH4}, 1,000 €/kW_{CH4}, and 750 €/kW_{CH4} for sizes of 1 MW_{CH4}, 3 MW_{CH4}, and 6 MW_{CH4}, respectively. This resulted in costs related to the input power of the electrolyzer that was estimated at about 840 €/kW_{el}, 560 €/kW_{el}, and 420 €/kW_{el} (by assuming a combined efficiency of 56%). However, the study mentioned that since currently small methanation (< 20 MW_{CH4}) plants are not offered as a standard or mass-produced product on the market, the investment costs seem to be relatively high. The costs are expected to drop to 300–500 €/kW_{CH4} (170–280 €/kW_{el}) if the market for small scale methanation develops.

For an assessment of different PtG process chains, [102] assumed the investment costs of a chemical methanation plant (there are no details regarding the CH_4 production rate of the plant mentioned in the study) to be 720 €/kW_{CH4}, which is equal to approximately 400 €/kW_{el} by assuming a combined efficiency of 56%.

[103] carried out a literature review on renewable PtG. The specific investment costs reported in the study had a wide range from 130–1,500 €/kW_{SNG} and were not highly reliable. The study stated that the estimation, which was conducted by the Outotec GmbH (see also [98]) based on size-specific calculation, of 400 €/kW_{SNG} and 130 €/kW_{SNG} for a 5 MW and a 110 MW plant, respectively, might be the most realistic cost estimates. This implies that the other estimates are too high.

[104] analyzed the costs of producing renewable gases. For this purpose, specific investment costs for a 3.7 MW_{CH4} methanation plant were estimated at approximately 3,300 €/kW_{CH4} (2013), 2,000 €/kW_{CH4} (2016), 660 €/kW_{CH4} (2020), and 600 €/kW_{CH4} (2030). It must be noted, however, that the study's assumptions were conservative and would be rated lower by other market participants. Additionally, further cost reductions were conceivable, but they could not be assessed reliably on the basis of the current data situation.

For the STORE&GO project, the project partner ECN calculated the costs for a first of a kind 3 MW SNG methanation plant. The investment costs are around 1,000 €/kW_{CH4}, but might be higher if gas streams have to be compressed.

5.2.2 Literature review on biological methanation

In [105]'s assessment of various PtG concepts including biological methanation, the specific investment costs (engineering, construction, machinery, and peripherals, excluding the provision of H_2) were indicated by two plant manufacturers with approximately 340–1.200 €/kW_{SNG}, depending on the size of the plant (1 MW to 110 MW).

[106] reported significantly low costs of 1.150 €/kW_{SNG} for a rather small methanation plant with 130 kW_{CH4} output and approximately 100 €/kW_{SNG} for a plant with 10 MW_{SNG} output.

In [107], the investment costs of biological methanation were estimated at 400 €/kW_{el} for a 2 MW_{el} PtG plant in the year 2017. At the beginning of the year 2016, the costs were twice as high. Due to upscaling in size, these cost reductions seams to be possible in 2017.

In a fact sheet for biological methanation plants, [108] estimated the specific investment costs to range from 700 to 1,500 €/kW_{CH4} (bioreactor, engineering, approval, and installation). The costs were projected to drop to a range from 300 to 700 €/kW_{CH4} in the future (year 2030).

[101] also provided a graph for investment costs of biological methanation against the capacity (the study mentioned that the graph is based on the data in [106]; however, they differ from each another). The specific investment costs decrease with an increasing methane output of the plant and were estimated at approximately 320 €/kW$_{CH4}$, 120 €/kW$_{CH4}$, and 90 €/kW$_{CH4}$ for an output power of 200 kW, 1,000 kW, and 2,000 kW, respectively.

[109] quantified specific investment costs for a biological methanation demo/pilot plant (combined with an electrolyzer with a rated power of 1 MW) in the year 2016; the costs were estimated at 1,200 €/kW$_{el}$ (about 1,800 €/kW$_{CH4}$). The study projected the cost to decrease in the near future (2025) to approximately 700 €/kW$_{el}$ (about 1,050 €/kW$_{CH4}$).

Based on an analysis done by Electrochaea for a 1 MW biological methanation plant for a wastewater treatment plant, and owing to the lack of information in existing literature, [110] assumed investment costs of 145 CHF/kW$_{el}$ for the methanation reactor and another 337 CHF/kW$_{el}$ for the BOP of the methanation reactor; these costs totaled to about 480 CHF/kW$_{el}$. This resulted in the total specific investment costs for the methanation plant at about 715 €/kW$_{CH4}$ (overall efficiency 0.56; 1 EUR$_{2014}$ = 1.2 CHF$_{2014}$).

In the project "Power-to-Gas via Biological Catalysis (P2G-Biocat)" [111], there was done an estimation on investment costs for biological methanation plants with different plant sizes, based on current information. The CAPEX range from 10.9–63.54 Mio.DKK for 1 to 50 MW power. This resulted in the total specific investment costs for about 1,440 €/kW, 370 €/kW, 240 €/kW, and 170 €/kW for a power of 1 MW, 10 MW, 20 MW, and 50 MW, respectively (1 DKK$_{2017}$ = 0,132 €$_{2017}$).

5.2.3 Assessment of literature data

An overview of the specific investment costs for chemical and biological methanation plants from the screened literature sources is presented in Figure 5-4. The range of the costs is very large (chemical methanation 55–3,300 €/kW$_{SNG}$ and biological methanation 90–1,800 €/kW$_{SNG}$). Additionally, a significant variation is observed for the nominal SNG output power of the plants (chemical methanation 1–1,000 MW and biological methanation 0.1–110 MW). Furthermore, some studies do not state whether these are current costs or future costs. It must be noted that in the case of a lack of information, in the following analyses, the study would have considered the year of dissemination as the year of installation.

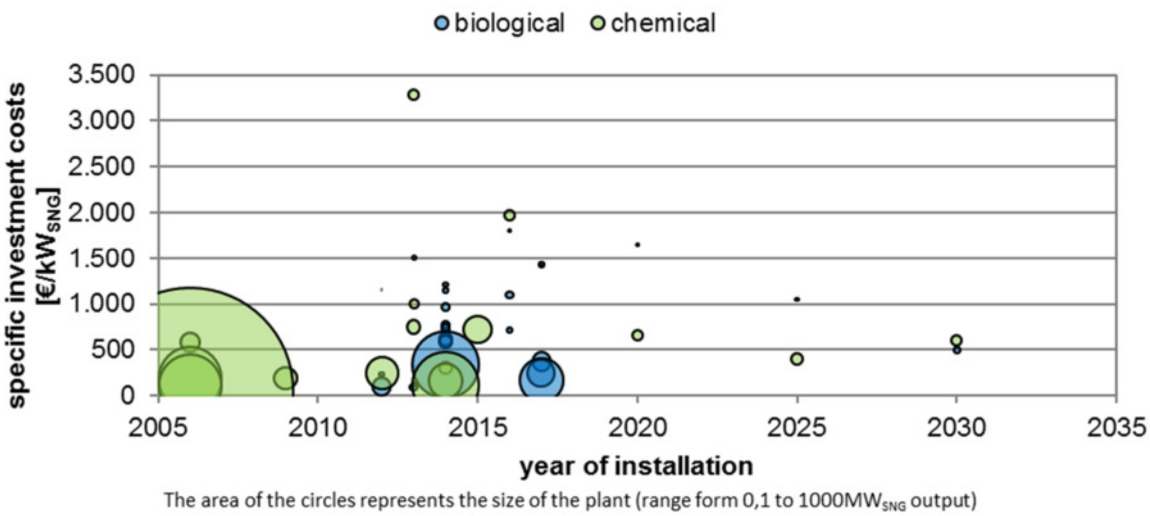


Figure 5-4: Overview of the specific investment costs for chemical and biological methanation plants related to the year of installation and the nominal output power of the plant (Sources: [98], [99], [100], [70], [101], [102], [104], [105], [106], [107], [108], [101], [109], [111]**)**

In order to be able to make better statements on the specific costs of methanation plants, both technologies were examined separately. Furthermore, statistical outliers were identified and no longer included in subsequent analyses. Both, the data point with the smallest and the largest cost value as well as the data point with the smallest and largest rated output power of the plant were deleted. Further, in order to minimize the influence of the plant size on the specific investment costs, the current costs were also calculated for a standardized 5 MW plant size on the basis of the scale factor method, where 0.7 was assumed for the exponent (scale factor). The results of the comprehensive review are summarized in the following table.

In Figure 5-5, the specific investment costs of the analyzed chemical methanation plants with the related rated output power and the specific investment costs for a standardized 5 MW plant are shown. The costs vary between 100 and 2,000 €/kW$_{SNG}$ and the rated power between 3 and 110 MW. On average (from 2006 to 2030), this results in costs of about 530 €/kW$_{SNG}$ with approximately 30 MW SNG-output. If the current investment costs (2012–2017) are standardized on a 5 MW plant, then they would total to about 600 €/kW$_{SNG}$.

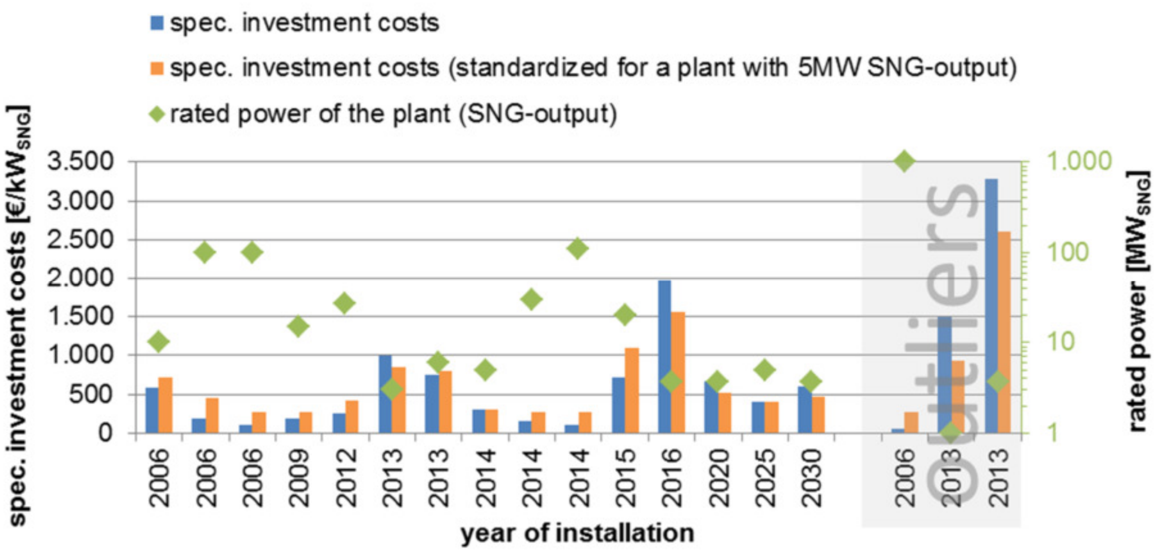


Figure 5-5: Specific investment costs (and standardized for 5 MW) and rated output power of chemical methanation plants related to the year of installation (Sources: [98], [99], [100], [70], [101], [102], [104]**)**

The characteristics of the biological methanation in terms of specific investment costs are shown in Figure 5-6. The costs range from 100 to 1,650 €/kW$_{SNG}$, and the rated power of the examined plants varies between 0.2 and 50 MW. Compared to the chemical methanation, the average (2012–2030) costs of the biological methanation are about 780 €/kW$_{SNG}$ and therefore about 250 €/kW$_{SNG}$ higher. However, this is probably due to the fact that the average rated power of the plants is significantly lower, with approximately 6 MW when compared to 30 MW. If the current investment costs (2012–2017) are standardized on a 5 MW plant, then they would incur approximately 600 €/kW$_{SNG}$ and would thus be similar to costs for a chemical methanation plant.

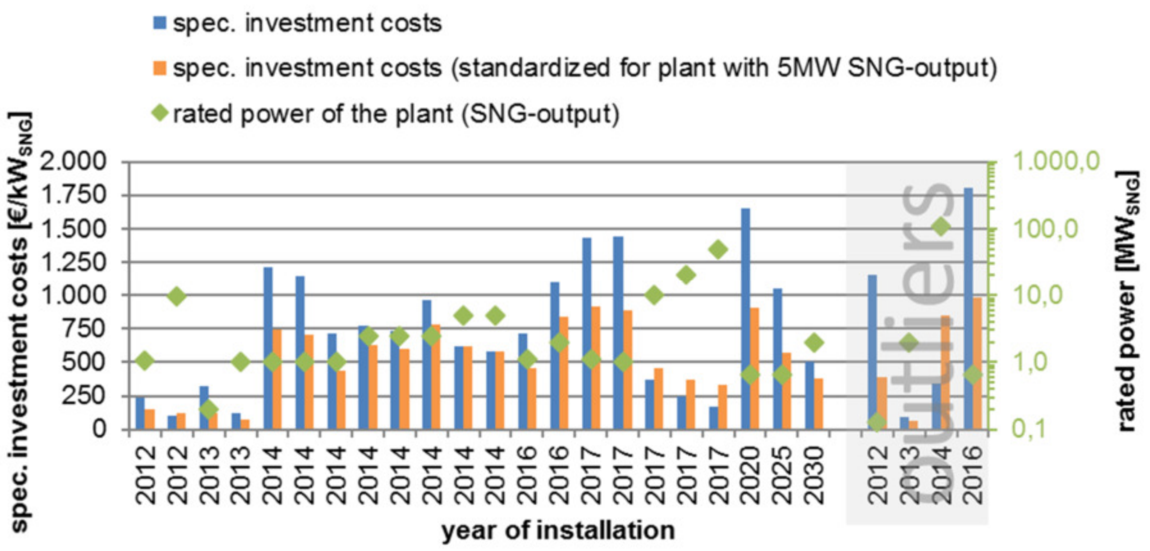


Figure 5-6: Specific investment costs (and standardized for 5 MW) and rated output power of biological methanation plants related to the year of installation (Sources: [105], [106], [107], [108], [101], [109], [110], [111]**)**

In conclusion, it can be stated that, according to current information, the current specific investment costs for both chemical and biological methanation plants with a rated power of 5 MW SNG-output are in the range of 600 €/kW$_{SNG}$. However, it should be pointed out again that this is only a rough estimate because there are no or very few reliable data.

5.3 Current costs for CO_2-capture

Generally, investment costs for CO_2 sequestration are not easy to define. It is reasonable to set a reference for specific costs according to the used CO_2 source. Affordable sequestration rates strongly depend on the concentration of carbon dioxide in the, usually gaseous, source stream and the underlying emitting process. As the CO_2 sources and the reference values for assessing investment costs exhibit significant variance, it seems more practical – at least for the usage of carbon dioxide in the methanation process – to value the needed CO_2 as an operating supply and therefore represent its costs as per ton CO_2, depending on its source and sequestration technology, respectively.

5.3.1 CO_2 from biogas or bioethanol plant

Biogas plants with feed-in to the natural gas net lend itself to a source of otherwise unused carbon dioxide. Specific costs for CO_2 sequestration in such biogas plants are at approximately 12 € cents per standard cubic meter of methane. Assuming a CO_2 fraction of 40% in the raw gas flow, this would lead to costs of about 90 € per ton CO_2 (for 2012). However, the sequestration, as well as the removal of impurities (like sulphur), is normally done for the retrieval of biomethane that can be fed in to the gas net, and hence costs are assigned to the methane production. In this aspect, the sequestration of CO_2 is neutral in terms of costs [111, 112].

When using biogas as a source of carbon dioxide, it should be noted that the CH_4/CO_2 mixture can be used for further methanation without any additional treatment. Hence, if it is not mandatory to separate the feed-in of the biogas from the methanation process, additional costs for CO_2 sequestration can be totally avoided [111].

The costs of carbon dioxide from a bioethanol plant, as a source, would behave in a similar manner. In the fermentation process, a high-quality stream of CO_2 is accumulated as a by-product. If only this method is considered as a potential source, then the sequestration costs would be limited to the costs necessary for the compression of the gas, which can be assumed at about 12–25 €/t CO_2 [113, 112, 114, 115]. If the bioethanol plant uses cogeneration for energy provision, and the CO_2 capture from the cogeneration process is also considered, then the costs would be between 42 €[116] and 111 €[113] per ton CO_2 (capturing and compression).

5.3.2 CO_2 from wastewater treatment plant

Wastewater treatment plants that produce sewage gas, as a source for CO_2, have almost the same preconditions as biogas plants. As the incoming sewage gas also comprises a high-quality mixture of methane and carbon dioxide, it can also be directly used in the following methanation process without further treatment and therefore without any additional costs for sequestration of CO_2. If, out of any reason, the separation of CH_4 and CO_2 is really needed, same costs as mentioned for biogas treatment (90 €/t CO_2) can be assumed.

5.3.3 Direct air capture

The direct capture of CO_2 from the atmosphere is a new technology. The major problem of this technology is the low concentration of CO_2, currently approximately 410 ppm, in the atmosphere. Due to the early development stage only cost estimates are available. Those estimates partially exhibit significant variation and are between 150 € and 475 € per ton of CO_2 for the current technology [111, 117, 118, 119, 120, 121]. Expected future costs with improved technologies are found in literature at about 30 $[117] to 300 $[122] per ton of CO_2.

These costs all refer to sequestration by the sorption processes. Though condensation in cryogenic distillation processes or separation from the air with membranes would also be possible, those procedures are presumed to be intense in energy usage [111].

5.3.4 Assessment of literature data

In Table 5-2 the gathered carbon capture costs for CO_2 supply of the PtG process are summarized. Compared to the previous sections, the data was extended with CO_2 from fossil sources, though their acceptability for the generation of renewable hydrogen or SNG has to be discussed (e.g. CO_2 can come from waste gases from industrial processes, that cannot be shifted to use renewable energy, and therefore fossil CO_2 cannot be avoided).

Table 5-2: Average capture costs for CO_2 related to industrial sectors

	CO_2 Source	Capture costs *€/t$_{CO2}$*	Year	Exchange rate *USD/EUR*	Ref.
Energy industry; power & heat from fossil fuels	Coal	34 – 42	2017	0.83	[114]
		19 – 47	2015	-	[112]
		20 – 63	2015	0.72	[123]
	Natural gas	63 – 83	2017	0,83	[114]
		54 – 101	2015	-	[112]
		35 – 75	2015	0.72	[123]
	Biomass	54 – 101	2015	-	[112]
Chemical industry	Refinery	29 – 83	2017	0.83	[114]
		44 – 94	2015	-	[112]
		48 1)	2012	-	[124]
		97	2014	0.82	[115]

CO_2 Source		Capture costs €/t_{CO2}	Year	Exchange rate USD/EUR	Ref.
	Ammonia production	12	2017	0.83	[114]
	Ammonia production	23 – 54	2015	-	[112]
	Ammonia production	22	2014	0.82	[115]
	Other chemicals	12 – 52	2017	0.83	[114]
	Other chemicals	21	2014	0.82	[115]
Iron & steel production		19 – 33	2017	0.83	[114]
Iron & steel production		16 – 41	2015	-	[112, 124]
Iron & steel production		81 – 83	2014	0.82	[115]
Cement, clinker & lime production		22 – 35	2017	0.83	[114]
Cement, clinker & lime production		33 – 69	2015	-	[112, 124]
Cement, clinker & lime production		17 – 37 1)	2012	-	[124]
Cement, clinker & lime production		82	2014	0.82	[115]
Pulp, paper & board production		18 – 27	2003	0.79	[116]
Pulp, paper & board production		57 – 87	2017	-	[125, 126]
Biogenic CO_2 sources	Biogas upgrading	0 – 90	2012	-	[111]
Biogenic CO_2 sources	Biogas upgrading	5 – 9	2015	-	[112]
Biogenic CO_2 sources	Bioethanol fermentation	12	2017	0.83	[114]
Biogenic CO_2 sources	Bioethanol fermentation	0 – 18	2011	-	[113]
Biogenic CO_2 sources	Bioethanol fermentation	25	2014	0.82	[115]
Biogenic CO_2 sources	Bioethanol fermentation	5 – 9	2015	-	[112]
Biogenic CO_2 sources	Bioethanol fermentation (incl. cogeneration)	83 – 111	2011	-	[113]
Biogenic CO_2 sources	Bioethanol fermentation (incl. cogeneration)	42	2003	0.79	[116]
Direct air capture		150 – 320	2012	-	[111]
Direct air capture		22 1)	2012	-	[111]
Direct air capture		150	2010	0.75	[117]
Direct air capture		331 – 423	2011	0.77	[118]
Direct air capture		268 – 309	2013	0.72	[119]
Direct air capture		341 – 475	2014	0.82	[120]
Direct air capture		81 – 201	2018	0.86	[121]

1) long term prediction

As it can be seen, capture costs for CO_2 are highly dependent on the source used. While capturing from diluted industrial flue gases (combustion of natural gas or biomass, refinery) ranges from 50-100 €/t, efforts for sources with high concentrations (ammonia production, bioethanol fermentation) are substantially lower, reaching values clearly below 50 €/t. Due to the low concentration of CO_2, direct air capture shows the highest costs that is additionally covered with high uncertainties according to the low maturity of the technology.

6 Demand potential of power-to-gas products

According to the theory of technical learning, see chapter 3, the cost of an industrially manufactured good decreases by a constant percentage for every cumulative doubling of its produced volume. Therefore, for calculating the future investment costs of the PtG-technology, the development of the demand for PtG plants is essential. For the calculation of future costs, the demand potential of PtG products (hydrogen and SNG) was used, as this will be at least as large as the demand for electricity storage by PtG (which emerges from the supply potential of RES). Therefore, the development of the demand potential of PtG products until 2050 and thus the installed amount (power) of the main components are determined in this chapter.

In the first step, a literature review of PtG's demand potential at different levels (national, European, and global) is performed. In this literature review, different definitions and distinctive features of the PtG demand potential are discussed. Finally, possible scenarios for the development of the demand potential of PtG products are defined. These future PtG demands serve as the basis for the calculation of the cost reduction potential of PtG systems through technological learning (see chapter 9).

In general, the development of the future demand potential for PtG products (green hydrogen and SNG) is subject to fundamental energy and climate policy decisions; for example, the steel industry will not adopt renewable energy for production purposes if it is not politically required. As a result, the definition of scenarios for the demand potential of PtG products is connected with high uncertainty.

6.1 Literature review power-to-gas potential

This section summarizes the results of a literature review of PtG-potential at different levels. Since the potential for energy technologies differs in many parameters, the review is divided into three parts. First, the PtG-potential was analyzed at a national level, followed by the European and global levels. If no additional information is given, the unit GW corresponds to the electrical input power GW_{el}.

6.1.1 Power-to-gas demand potential at a national level

Different studies have been found to analyze the PtG-potential at a national level. Most of the studies have been performed for Germany, but literature for France and Austria has also been investigated.

Germany

In the "*Energiesystem Deutschland* 2050," the Fraunhofer Institute [127] stated that the optimum electrolysis power for an energy system in 2050 would be 33 GW (electrical energy input of 103 TWh and a hydrogen output of 82 TWh). The aim of the optimization is to achieve a total energy system that would include full coverage of maintenance and operation at minimum full costs on an annual basis. A CO_2 reduction of 80% through the installation of 147 GW photovoltaic plants, 120 GW onshore wind plants, and 32 GW offshore wind plants has been assumed as external conditions.

Agora Energiewende [128] calculated the necessary electrical power for PtG plants for 2050 with 26 GW (if 27 GW battery energy storage capacity is installed) and 36 GW installed capacities without short-term energy storage. The study assumed a share of 95% renewable energy in its estimations.

The study "*Minimaler Bedarf an langfristiger Flexibilität im Stromsystem bis 2050*" [129] assumed that short-term flexibility options must be maximized to ensure their usage in cases of a surplus of electrical energy. If the short-term storage fails to fulfil the necessary capacities, then it would be essential to use long-term storage (i.e., PtG). Concerning the year 2050, this would mean an installed electric power of 89 GW PtG-plants, if enough short-term storage is available. Without considering short-term storages, a PtG power of 134 GW must be installed in 2050.

In a study performed by Jentsch [130] for an 85%-renewable energy-scenario, the use-cost-optimum power for PtG energy storage was found to be between 6 and 16 GW.

Fürstenwerth et al. [57] analyzed the usage of PtG-plants for mobility and chemistry (Power-to-X). For 2050, a maximum PtG power of 130 GW was identified, with 6 to 16 GW of electricity storage, 75 GW for fuel production, and about 59 GW for raw materials of the chemical industry. Since development depends on a variety of different factors, from today's point of view, it is hard to forecast the usability of PtG. This is also the reason for the fact that the possible installed power is subject to a large bandwidth.

In the study "Power-to-gas (PtG) in transport - Status quo and perspectives for development," which was conducted for the Federal Ministry of Transport and Digital Infrastructure in Germany, three different scenarios were analyzed. The main goal was to determine the amount of PtG in 2050 that is required to reduce the GHG emissions by about 80% in transportation. Additionally, the necessary electricity demand for PtG was calculated. In one scenario, about 614 TWh/a of electricity was required for the production of hydrogen and methane. [131] This led to an installed electrolyzer power of approximately 150 GW (if 4,000 full-load hours are assumed).

"*Deutsche Energie-Agentur GmbH*" stated, in their lead study, a requirement of 94 TWh of Power-to-X (PtX) in 2050 for German mobility, in one of the scenarios aimed at reducing the GHG emissions by 80% [132]. This would lead to an installed power of about 16 GW (if 6,000 full load hours are assumed).

Schneider et al. revealed the factors limiting P2G's potential in Germany; these factors included the availability of adequate CO_2, lack of internal restricted area, gas grid connection, proximity to RE, and scaling losses. On the basis of the theoretical PtG potential of 44.6 GW_{el} in Germany in 2013 and by applying these limiting factors, Schneider et al. found the usable PtG potential to be about 15.4 GW_{el}. Due to these restrictions, the usable potential was only 35% of the theoretical PtG potential [133].

Breyer et al. analyzed different scenarios for an electricity supply of 100% renewable energy from an economic point of view. It is stated that, depending on the scenario, in 2040, an installed electrolyzer power of 43 to 45 GW will be necessary [134].

As per the investigations conducted by the FNB Gas on the "*Strom und Gasspeicher*" scenario, there would be a need for an installed electric PtG power of 134 GW or 244 TWh of green gas production. The "*Strom und grünes Gas*" scenario necessitates an installed capacity of 254 GW or 646 TWh green gas production. This model based analysis has investigated all the sectors (power, mobility, industry, and heat) [135].

A study by the ewi Energy Research & Scenarios GmbH analyzed two scenarios for Germany, namely, the revolution (greenhouse gas reduction through electrification of all sectors and an increase in electricity production from renewable energy) and evolution (CO_2 reduction through optimization of existing infrastructure and increase in renewable energy production) scenarios. The revolution scenario showed a demand for 267 TWh of power-to-methane, 129 TWh of power-to-fuel, and 52 TWh of power-to-hydrogen capacity for 2050. Concerning the evolution scenario, the capacity increase was higher with 445 TWh of power-to-methane, 136 TWh of power-to-fuel, and 52 TWh of power-to-hydrogen [136]. This would result in an electrolyzer power of 137 to 194 GW; this deduction is based on the following assumption: 65% electrolyzer efficiency, 55% of power-to-methane, 50% efficiency of power-to-liquid, and 6,000 h of full load hours of the electrolyzer.

The Enervis energy advisors GmbH stated that the demand for PtG technologies for Germany in 2050 would be 280 TWh for feedstock, 140 TWh for mobility, and 400 TWh for the heating market. The investigated scenario is similar to that of the evolution scenario presented by the ewi Energy Research & Scenarios GmbH [137]. This will result in an electrolyzer power of about 248 GW, based on the following assumption: 65% of electrolyzer efficiency, 55% of power-to-methane, and 6,000 h of full load hours of the electrolyzer.

France

According to Scamman et al., France would require about 3.25 TWh of electrical energy in the year 2030 for producing hydrogen to fuel approximately 773,000 fuel cell electric vehicles (FCEVs). The required amount of electrical energy might rise in the year 2050 to 33 TWh, approximately, if 7.3 million FCEVs are fueled by hydrogen. This would lead to an installed electrolyzer power of about 5.5 GW [138].

Spain

Bailera et al. analyzed two scenarios for Spain. In both scenarios, an increase in the global mean temperature would be 2°C in 2100 when compared to 1990. In the first scenario, the demand for electricity would increase moderately (1.36% per year), while, in the second scenario, the growth would be higher (1.73% per year). The research predicts a potential installed PtG capacity between 10.5 GW (scenario 1) and 15 GW (scenario 2) in 2040 and 13 to 19.5 GW in 2050 [139].

Italy

Guandalini et al. stated that an increase in the installed electrolyzer capacity over 30 GW would reduce the attractiveness of hydrogen production because it would be oversized and would not be able to run on full load [140].

Austria

As part of the project "Greening the gas," the *Energieinstitut an der JKU Linz* performed a study about the PtG potential in Austria for space heating. It is stated that, in 2030, the annual production of SNG would increase up to 100 million Nm^3 and up to 500 million Nm^3 in 2050. This would result in about 5 TWh SNG per year in 2050. According to the conditions, as described below, the demand for the installed electrolyzer power in Austria will increase up to 0.3 GW in 2030 or 1.5 GW in 2050, respectively [141]. This deduction is based on the following assumption: 65% of electrolyzer efficiency, 85% of methanation efficiency, 55% of total efficiency, 6,000 h of full load hours, LHV CH_4 = 10 kWh/m^3, and 1 Mtoe = 11.63 TWh.

6.1.2 Power-to-gas demand potential at the European level

The *Energieinstitut an der JKU Linz* calculated the potential for substituting natural gas in the industrial sector in the European Union (EU) (=SNG potential) to be approximately 3,107 PJ (863 TWh SNG). This would result in about 260 GW installed electrolyzer power, based on the following assumption: 6,000 full-load hours and a total efficiency of 55%. Due to the substitution of all oil derivatives in the industrial sector, there would be an additional potential for about 1,398 PJ (388 TWh H_2) of green hydrogen, which would result in about 100 GW of installed electrolyzer power; this deduction is based on the following assumption: 6,000 full-load hours and 65% of electrolysis efficiency. In the course of process adaption, there would be further potential for green hydrogen in the industrial sector of about 906 PJ (252 TWh H_2), if all the coal products from the iron and steel industry are substituted. This would result in approximately 65 GW of installed electrolyzer power, based on the assumption of 6,000 full-load hours and 65% efficiency electrolysis. The total potential for installed electrolyzer power in the industry sector in Europe in the year 2050 would be about 425 GW. This implies that, in the year 2050, about 51% of the total energy demand in the industrial sector can be covered by green gases (H_2 and SNG).

However, besides the industrial sector, the mobility sector is a major emitter of CO_2. The "e-fuels-study" by DENA and LBST analyzed different scenarios for CO_2 reduction in the mobility sector. In the gaseous-fuel-dominated scenario, the study investigated an increasing use of hydrogen in electric power trains, a reduction of 95% of GHGs, and a moderate increase in the mobility. The scenario would result in a PtG-potential of 378 GW (1,250 TWh) electrolyzer capacity [142].

The key conclusion of the study "Business cases for H_2 in energy storage and more broadly power to H_2 applications" by FCH-JU is that 2.8 GW electrolyzer power may be installed in 2025. This value of 2.8 GW is based on sound economics in the power sector [143].

As part of the STORE&GO deliverable "D6.3 Impact Analysis and Scenarios design" by Blanco et al., different scenarios for the potential of power-to-methane (PtM) for 2050 have been analyzed. In about half of the investigated scenarios, the Power-to-Methane capacity is in the range of 40 to 200 GW. In the "realistic" scenario (95% CO_2 reduction, no CO_2 underground storage, low CAPEX for methanation), there is a need to install about 40 GW (approximately 8% of the total gas demand) of PtM in the EU28+ states (EU, Switzerland, Norway, and Iceland). By considering liquefied methane gas as the energy carrier in marine transport, the PtM capacity would increase to 122 GW (19% of total gas demand). If all the conditions that favor PtM will occur, then the PtM capacity would reach about 546 GW, thereby meeting 75% of the gas demand. The PtM capacity will lead to an installed electrolyzer power in the range of about 73 to 993 GW; this deduction is based on the assumption of a total efficiency of 55%.

For comparison, the necessary installed electrolyzer power that would be required to cover the total European natural gas demand in 2050 through renewable SNG is estimated. According to the business-as-usual scenarios, the "EU Reference Scenario 2016 – Energy, transport and GHG emissions – Trends to 2050" [144], which acts as a benchmark of current policy and market trends, the final gas consumption in the year 2050 is estimated to reach about 237 Mtoe (2,750 TWh). This result in a SNG potential of approximately 460 GW SNG and a potential of approximately 835 GW_{el} of installed electrolyzer power, based on the following assumptions: 65% of electrolyzer efficiency, 85% of methanation efficiency, 55% of total efficiency, 6,000 h of full load hours, and 1 Mtoe = 11.63 TWh.

6.1.3 Power-to-gas demand potential at a global level

Pleßmann et al. calculated the requirements for the power plant and storage capacities at a global level by the dynamical simulation of a global, decentralized 100% renewable electricity supply scenario (PV, wind, and concentrating solar power (CSP)). This included batteries, high-temperature thermal energy storage coupled with a steam turbine, and the renewable power methane (RPM) (generated via the PtG process), which is reconverted to electricity in gas turbines. This would result in required global storage capacity of 2,360 GW of electrical input power for the production of RPM [145].

For comparison, the required PtG potential was also estimated, considering the possibility of the global natural gas demand in 2050 being replaced by SNG. A study conducted by DNV GL stated that the global demand for natural gas would reach 135 EJ/a (37.5 PWh) in 2050 [146]. With the conditions stated below, this would lead to 11.4 TW of installed electrolyzer power at a global level. This deduction is based on the following assumptions: 65% of electrolyzer efficiency, 85% of methanation efficiency, 55% of total efficiency, 6,000 h of full load hours of the EC, LHV CH_4 = 10 kWh/m^3, and 1 Mtoe = 11.63 TWh).

6.1.4 Assessment of literature data

Concerning the PtG potential, the literature review shows the usage of several definitions and distinctive features, which complicates the direct comparability of studies. The most important differences in the definitions are addressed below. The determination of the PtG-potential can be based on the supply side (e.g., how much surplus electricity is available) or the demand side (there is a need for a certain amount of renewable gas). Another differentiation lies in the form of energy (see Figure 6-1). The PtG-potential can be exploited in the form of the electrical input power [GW_{el}] potential of the electrolyzer, the hydrogen output power potential [GW_{H2}], or the SNG output power potential [GW_{SNG}]. Alternatively, the PtG-potential can also be utilized as an amount of energy (electrical, hydrogen, or SNG).

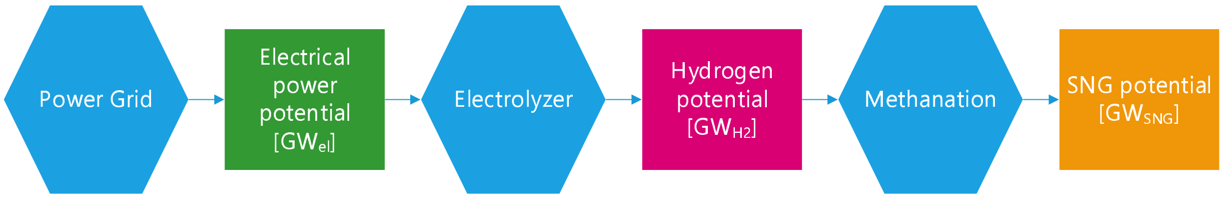


Figure 6-1: PtG-demand potential regarded to different energy forms

Additionally, the indicated potential differs depending on the sector (comprising the power, mobility, industry, heat, or multiple sectors). A big impact on the PtG-potential also comprises the discussed regions in terms of the geographical extent (national, European, or global) and the composition of the energy system (e.g., mainly based on wind power, PV, or hydrogen, and on the amount of RES). In some cases, the calculated PtG-potential is subjected to several limitations, including the use of only CO_2 sources from biogas, use of only surplus electricity, and the location of the plant near wind parks or at the site of a biogas plant. Furthermore, in general, due to the fact that the development of the energy sector depends on different parameters, it is hard to predict its development. Therefore, the analyzed literature has a high deviation regarding the estimated PtG potentials.

As mentioned earlier, it is difficult to conduct a direct comparison due to the different framework conditions of the analyzed studies and papers. Nevertheless, to make rough statements regarding the development of the PtG potential, the studies have been divided into groups (sector and region) and the PtG potential is defined as the electrical input power of the electrolyzer (see Figure 6-2). Most of the analyzed studies are for Germany, and only a few studies deal with the PtG potential at a European level or a global level. The PtG potential in the power sector at a national level (Germany, Spain, and Italy) is in the middle of the two-digit GW_{el} range. The literature for Germany that considers the whole energy system (power, mobility, industry, and heat) estimates a PtG potential in the lower three-digit GW_{el} range. At a European level, the demand for PtG in the industrial and mobility sectors is expected to be in a middle three-digit GW_{el} range. The potential for PtG for all sectors is estimated in a high three-digit GW_{el} range. At a global level, which is the most important one for predicting cost reductions by learning rates, only one study and one calculation (SNG replaces the whole gas demand in 2050) are available. It is estimated, that the PtG potential is up to a lower five-digit GW_{el} range. Nevertheless, even with the high deviations, all the analyzed literature grants PtG a leading role in the future decarbonized energy system.

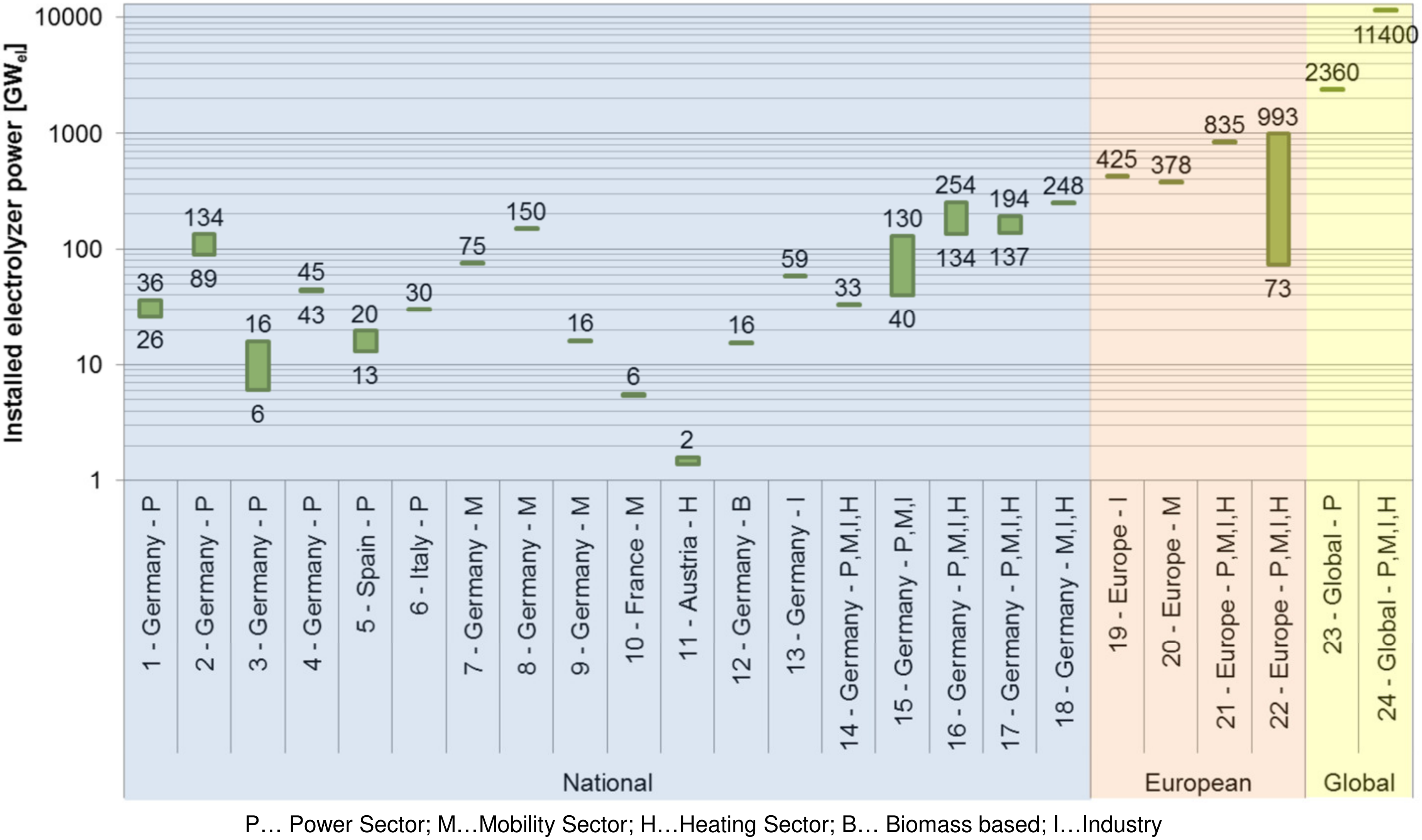


Figure 6-2: Overview of the literature review: PtG demand potential (electrical input power electrolyzer) for different regions and sectors in 2050

6.2 Derivation of future PtG demand

To apply the learning curve theory, it is essential to examine the cumulative produced volume of the component (electrolyzer and methanation unit). The cumulative produced volume is in turn directly related to the global PtG demand. In order to determine the global PtG demand for the year 2050, on the one hand, a literature study was carried out (see chapter 6.1) and, on the other hand, own STORE&GO-scenarios were developed. Due to poor data at the European and, especially, the global level (only one study and one calculation (SNG replaces the whole gas demand in 2050) are available), the literature review gives only a rough idea of the development of the demand potential of PtG until 2050. Therefore, additionally, the STORE&GO project scenarios for estimating the global PtG demand potential were developed to gain detailed information on the possible installed power of electrolyzers and methanation units.

In general, scenarios serve to identify possible development paths and describe an alternative future. The development of scenarios is influenced by many different variables, which are related to the past, present, and future and are highly related to fundamental energy and climate policy decisions. These variables (e.g., the development of the amount of renewable energy sources (RES), natural gas price, and CO_2 prices) affect each other very strongly and are, in turn, often difficult to interpret and predict. According to the World Energy Scenarios 2016 of the World Energy Council [147], there are additional uncertainties—the pace of innovation and productivity, evolution of international governance and geopolitical change, prioritization of sustainability and climate change, and the balance between the use of markets and state directive policy—which are critical for describing the future energy system. This circumstance and the underlying framework conditions (e.g., energy system with a high amount of RES, maximum CO_2 reduction, or lowest costs) often results in a wide range of possible scenarios. Most of the studies dealing with energy scenarios use simulation tools, based on many different variables, for predicting a possible development path and describing an alternative future. For example, the EU Reference Scenario 2016 [144] acts as a benchmark of current policy and market trends and provides a model-derived simulation (e.g., PRIMES) trend projection in certain conditions (e.g., legally binding GHG and RES targets). Additionally, in the STORE&GO deliverable D6.3 “Impact Analysis and Scenarios design” by Blanco et al., different scenarios for the European potential of power-to-methane (PtM) for 2050 have been analyzed by implementing several variables in the modelling software TIMES. The World Energy Council [147] uses its tool (the global multi-regional MARKAL model (GMM)) for quantifying the scenarios, by accounting for the technical and economic parameters, and is driven by input assumptions and optimization algorithms to give forecasts. These three methods can be summarized as a bottom-up approach.

When compared to the aforementioned studies and numerous other studies dealing with energy scenarios, the development of STORE&GO scenarios for the global PtG demand in 2050 is based on a different, very simple approach—a top-down approach. In order to achieve the transition to an energy system with predominantly renewable energy sources, thereby significantly reducing CO_2 emissions and achieving the climate goals, it would be essential to have a high amount of RES and renewable energy carriers in the energy sector (power, mobility, industry, and heat). Therefore, for each sector, three STORE&GO scenarios with a different amount of renewable energy sources (50% = low, 75% = moderate, and 90% = high) are defined. To achieve the amount of RES in each sector, the share of energy carriers (especially, hydrogen and SNG are important for STORE&GO) is estimated for an energy system in the year 2050. For different amounts of RES, the following figures show the estimated share of various energy sources/carriers of the final energy demand or generation for each sector in the year 2050.

Regarding the amount of RES, the STORE&GO scenarios are much more ambitious, such as the EU-Reference Scenarios 2016 [144] or the scenarios defined by the World Energy Council [147], as these mainly represent an update on or a trend of the current policy to 2050. However, with these current circumstances, it would be difficult to achieve an ecologically sustainable energy supply and climate targets. Therefore, the STORE&GO scenarios are more ambitious and defined with a comparatively high amount of renewable energy sources.

The different STORE&GO scenarios for the mobility sector are shown in Figure 6-3. The estimated share of SNG/LNG of the final energy demand in the year 2050 is up to 20% and the share of hydrogen is up to 25%. Additionally, renewable electricity and biofuels dominate the energy demand scenario. The rest is covered by fossil fuels. In comparison to the EU-Reference Scenario were only 7% RES are forecasted, these values seem very high. However, in a decarbonized mobility sector, most of the fuels must be covered by green electrons, green molecules (SNG/LNG and hydrogen), and biofuels (not available in abundance).

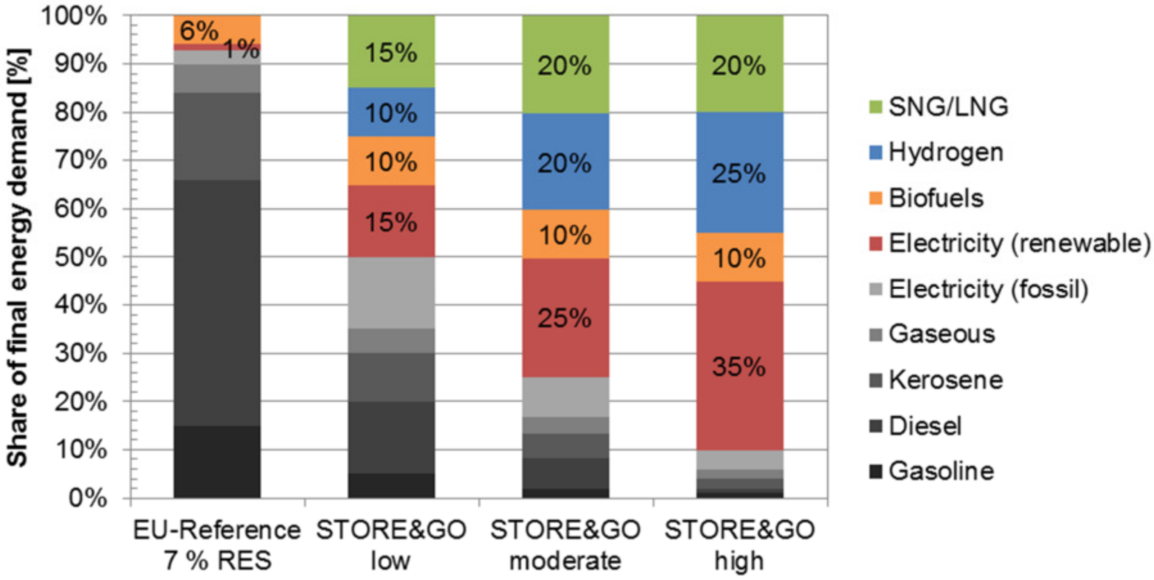


Figure 6-3: Mobility sector: Share of energy sources/carriers in the EU-Reference and STORE&GO Scenarios in the year 2050

The situation is similar in the industrial sector, where increased electrification of processes is foreseen. Conversely, where an increased electrification is not possible, alternative energy sources, such as hydrogen and SNG, are used. In the year 2050, depending on the scenario, up to 11% SNG and 11% hydrogen can be used in the industry. Additionally, up to 18% of the final energy demand that is needed for steam production is covered by renewable SNG.

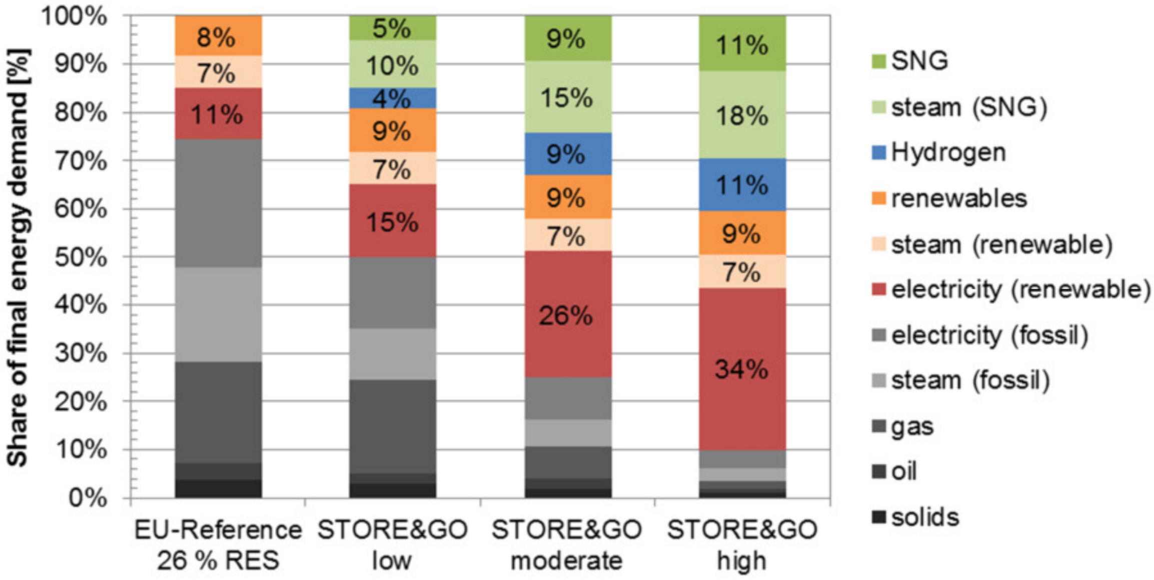


Figure 6-4: Industry sector: Share of energy sources/carriers in the EU-Reference and STORE&GO Scenarios in the year 2050

It is estimated that a large part of the energy demand in the residential sector in 2050, mainly for heating, is covered by renewable electricity, SNG (up to 20% for gas heating and 8 % for districted heating) and other renewables (like wood). Additionally, a small part can be provided by renewable hydrogen.

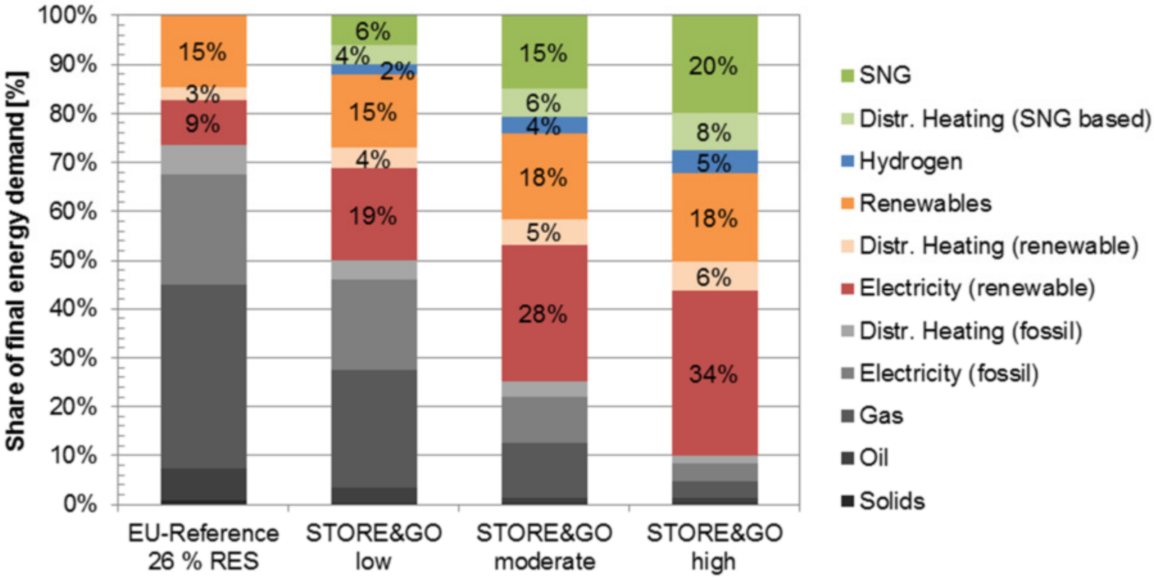


Figure 6-5: Residential/Heat sector: Share of energy sources/carriers in the EU-Reference and STORE&GO Scenarios in the year 2050

The future power sector in 2050 would be predominately based on renewable energy sources. To deal with the fluctuating energy sources, like PV and wind, there would be a need to install production capacities if there is no production from these sources. These necessary capacities should also be based on renewables, like SNG or hydrogen generation from PtG. It is estimated that up to 8% SNG and 2% hydrogen would be needed for producing the additional electric power.

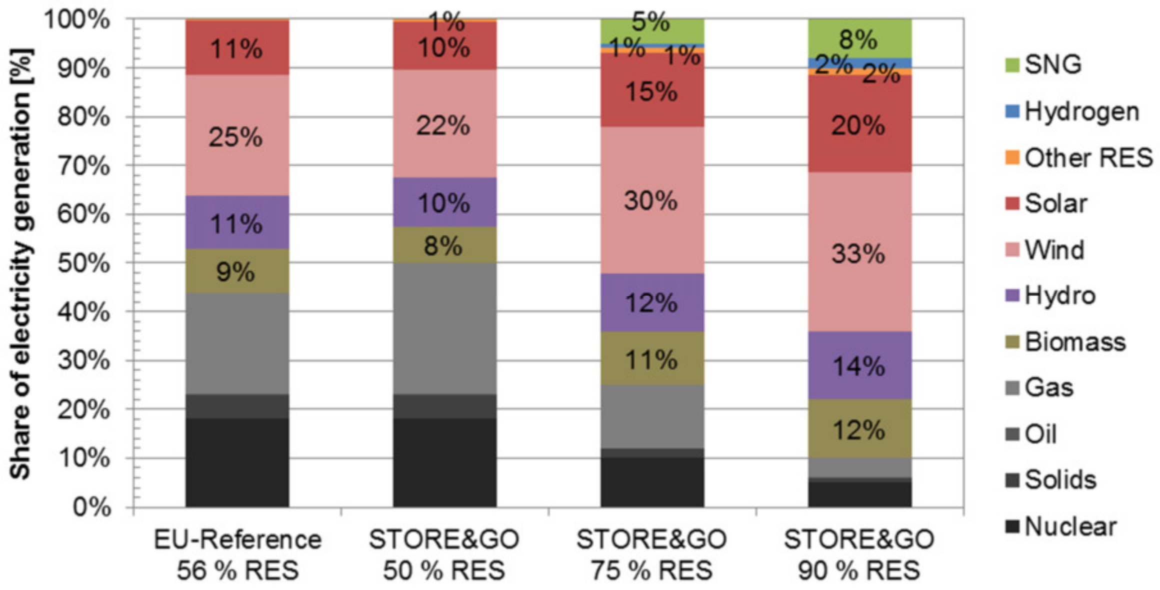


Figure 6-6: Power sector – Share of energy sources/carriers in the EU-Reference and STORE&GO Scenarios in the year 2050

Based on the estimated share of SNG and hydrogen and the final energy demand in each sector, in the next step, the European and global PtG potential in the sense of installed electrolyzer and SNG output power is calculated. Table 6-1 presents the European and global final energy demand in 2050 for the mobility, industrial, residential, and power sectors.

Table 6-1: European and global final energy demand in 2050 for the mobility, industrial, residential, and power sectors

Sector	European[1] [TWh]	Global[2] [TWh]
Mobility	4.166	37.169
Industry	3.059	40.914
Residential	3.390	42.066
Power	3.920	39.843

[1] … According to EU-Reference Scenarios 2016 [144]
[2] … According to World Energy Scenarios 2016 of the World Energy Council [147]

Additionally, for the calculation of the required installed rated power of electrolyzers and methanation units for different scenarios in 2050, following assumptions have been made:

- Average efficiency electrolysis: 75%
- Average efficiency methanation: 85%
- Average full-load hours of the PtG-plant: 6,000 h/a
- Battery Electric Vehicle (BEV) is 70% more efficient as an internal combustion engine (ICE) vehicle
- Fuel cell electric vehicle (FCEV) is 30% more efficient as an ICE-vehicle

Based on the assumptions made above, the estimated shares of SNG and hydrogen in 2050, the final energy consumption in 2050, and the required installed power of electrolyzers and methanation units are calculated. These estimates are shown in Figure 6-7 for Europe and global STORE&GO scenarios for different amounts of RES.

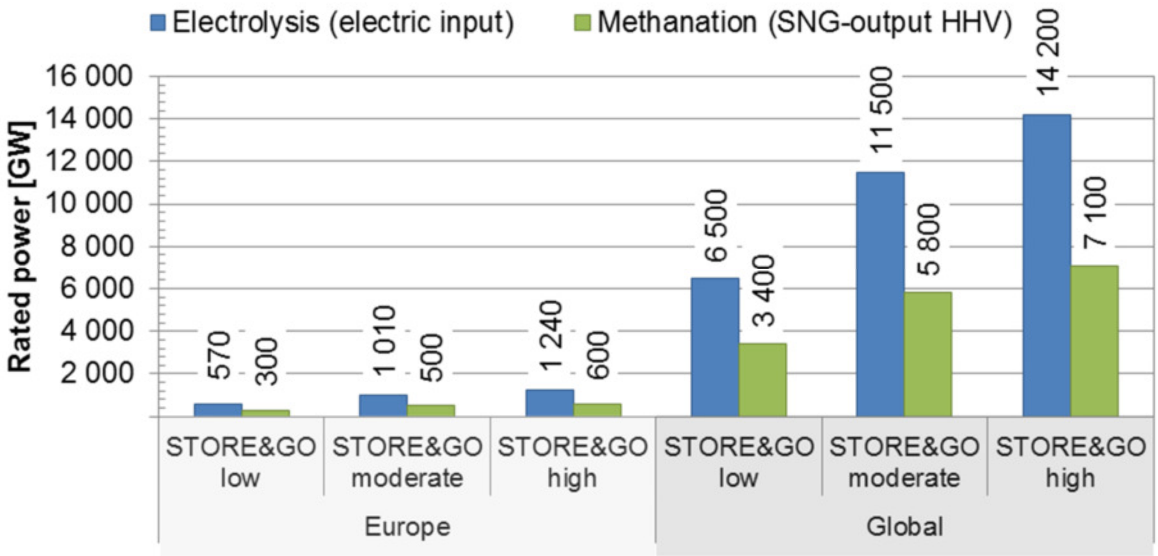


Figure 6-7: STORE&GO Scenarios: Necessary installed power of electrolyzers and methanation units in the year 2050

At a European level, there is a need for up to 1,240 GW of installed electrolyzer power and 600 GW methanation units (SNG output power).This is, depending on the STORE&GO scenario, quite similar or slightly higher than the results presented in the literature (see chapter 6.1), wherein the PtG potential (rated electrolyzer power) is estimated in a high three-digit GW range. Additionally, the calculations in the STORE&GO deliverable D6.3 “Impact Analysis and Scenarios design” by Blanco et al. provide similar results in the scenario that favors power-to-methane (about 550 GW), thereby predicting the need for generating an installed electrolyzer power in the range of about 1,000 GW. This demand for PtG products has been calculated by implementing several variables through the modelling software TIMES. Since the results from the STORE&GO scenarios, which are based on the relatively simple top-down approach, are comparable to the results from other calculations in the literature (which are largely based on the bottom-up approach and simulation models), it can be assumed that the STORE&GO scenarios also provide useful values for the global demand for PtG products.

As already mentioned before, for implementing the theory of learning curves, it would be crucial to estimate the global PtG demand. Depending on the scenario (low = 50%, moderate = 75%, or high = 90% RES), there would be a need to install about 6,500 to 14,200 GW electrolysis power capacities and about 3,400 to 7,100 GW SNG-output power capacities to meet the demand in the year 2050. These values seem to be very high. However, it is important to remember that, in 2050, in a decarbonized energy system, not only natural gas but also other fossil energy sources, such as oil and coal, must be substituted by renewable energy carriers. Since all areas of the energy system cannot be electrified, green molecules (renewable SNG and hydrogen produced by PtG) would also play an important role in the future energy system. In order to cover this relative high demand and to produce the required quantities of PtG components (for example about 285,000 electrolyzer systems with an installed power of 50 MW would be required), a mass production would be absolutely necessary. However, this call for a standardized and mass production-ready design of the products (e.g., no individual installation planning or piping). The power-to-gas systems must be planned for the construction on the green field (with the interface power supply, gas connection for feed-in and possibly CO_2 supply), to meet the requirements for mass-production.

7 CoLLeCT - Component Level Learning Curve Tool

While the results found in the previous sections for learning rates, based on literature (section 4) and future demand for PtG products (section 6), would principally allow a first estimation on future investment costs for PtG applications, the gathered data from literature does not fulfill our requirements. With the available data, a distinguishing between different electrolysis or methanation technologies as well as between system and stack (electrolysis) or reactor (methanation) cost is hardly feasible.

To get a more detailed view of technological learning, a component-based approach was developed. This allows a comparison of learning effects between different technologies, investigation of the cost structure development at the stack/reactor and system levels, and the consideration of spillover effects from concurrent technology sectors.

7.1 The idea of component-based technological learning

Though the aim of using the learning curve theory is to allow prospects of future technology costs, this is hardly possible for novel applications at a low technology readiness level (TRL). As significant effects, which are describable through technological learning, can only be evaluated after a few magnitudes of produced units, the technology under investigation must reach a certain degree of maturity to allow an assessment on the further development of production costs. Nevertheless, it is often mandatory to consider technological learning, along with an analysis of future potentials of the product, when doing techno-economic assessments for such technologies before they enter the market. These assessments allow an early investigation of market potentials of a certain product and thus allow initial decisions on investments. However, among the aforementioned reasons, alternative approaches for an early estimate of the used experience rate must be used.

An obvious approach would be to use the same experience rates as already found for applications with comparable functionality or usage; for example, using the same value for offshore wind power plants as found for on-shore wind plants. Though this looks quite promising in theory, it is not as easy as expected. This is because minor changes in technology can have a significant influence on its observable technological learning process. For example, a comparison between the PEM fuel cell (PEMFC) and electrolysis cell (PEMEC) installations would yield significantly different learning rates (cf. [46] &[83]). Such differences can have multiple reasons. On the one hand, this could be explained by the available price basis, which often only considers installation or rather investment costs instead of pure production costs. Due to the fact that the knowledge of the margin between those cost levels (production vs. purchase) is often confined to the manufacturers, it is hardly not possible to consider influences like price umbrellas or shakeout effects. On the other hand, those differences could be a result of learning spillover effects (cf. [148]). In this context, it can be expected that technological experiences made on one technology are also reflected in the experience curve of the related technology; for example, technological improvements on PEMFC are also seen as decreasing costs in the learning curves of PEMEC, which cannot be explained by increased cumulative productions of PEMEC only.

Another approach to get a rough and reasonable estimate on experience rates for low maturity technologies would be to divide the appliance into its subcomponents. Subsequently, the theory of technological learning can be applied to every single component and subsequently summed up to an overall experience curve for the appliance. Therefore, it is mandatory to know the initial underlying component and corresponding cost structure in detail. While the acquisition of this data should be feasible in many cases, additional learning rates for every single used component should be known or estimated. Though this seems a lot more extensive at first as the complexity and the number of learning technologies (components) to investigate increases respectively, it gives us additional and, in some cases, easier methods to evaluate certain cost reduction effects. This means that, on a component basis, factors that influence the production costs can be partly determined and described by simple scaling and innovation processes like the following:

1. Cost reductions from mass productions:
   By investigating learning rates on a component level, a decline in production costs that occur by upscaling of the manufacturing processes can be distinguished easily.
2. Changing material costs:
   By breaking down an appliance to several contained components, the variety of materials used per component becomes more manageable than those for the overall appliance. This could allow a more accurate estimation of future production costs development for individual components, by investigating past and future changes in costs of the needed raw materials.
3. Reductions in material usage:
   A minimization of the material variety through analysis at a component level also allows for separating and substantiating expected savings in the material usage of cost-intensive parts. This especially applies to components using expensive raw materials where raw material costs cannot be expected to decrease significantly.
4. Improvements in manufacturing time:
   For time-intensive manufacturing processes, a distinct lowering of costs can often be gained by shortening the processing time. Such improvements can be more precisely determined and evaluated at the component level than for the whole appliance. This does not only take (automated) machine processing costs but also manual working time costs.

Among the mentioned reasons, though it seems practicable to evaluate the learning or progress rates' applications in the early stages of maturity at a more detailed and component level, this is not doable without the corresponding experience made through a few orders of produced units.
However, many individual components are not reinvented for every single purpose, but they are often reused inside many different applications. As a conclusion, it would be reasonable to combine both the mentioned approaches to assess learning effects for novel technologies—evaluate cost reduction potentials at a component level and use existing experiences, as base data, from comparable component usage inside well-established applications.

7.2 Implementation in CoLLeCT

The considerations about the disaggregated analysis and representation of learning curve effects explained above and hence needed computer operations, have been combined within the calculation model CoLLeCT (Component Level Learning Curve Tool) which was developed especially for this purpose. The corresponding basic principles are illuminated in the following sub-sections.

7.2.1 Module Level

7.2.1.1 Using the bottom-up approach

The idea of splitting up energy technologies into its components along with their individual experience rates to determine their overall learning curves is also stated by Ferioli et al. [16], as mentioned in section 3.2.1. As they described, a certain product, process, or technology can be considered as an aggregate of several components or costs factors, wherein the costs for each component decrease over time according to the learning curve theory. The resulting cost curves can be subsequently summed up to present the total costs of the investigated application.

$$C(X_t) = \sum_{i=1}^{n} C_{0i}\left(\frac{X_{ti}}{X_{0i}}\right)^{-r_i} = C_{01}\left(\frac{X_{t1}}{X_{01}}\right)^{-r_1} + C_{02}\left(\frac{X_{t2}}{X_{02}}\right)^{-r_2} + \cdots + C_{0n}\left(\frac{X_{tn}}{X_{0n}}\right)^{-r_n} \qquad \textbf{Eq. 9}$$

where the variables are defined as follows:

X_{0i} … cumulative number of component i produced at time $t = 0$
X_{ti} … cumulative number of component i produced at time t
C_{0i} … costs of component i at time $t = 0$
$C(X_t)$ … total costs at time t
r_i … learning parameter for component i (where $lr = 1 - 2^{-r}$)

While, in Ferioli et al. [16], the approach is simplified by only using the learning and non-learning parts (cf. section 3.2.1), this can be used to break down the investigated technology to an appropriate level of detail.

The equation above assumes that the learning effect for every single component relies on its individual number of produced units. While this fully comprehensible, we want to consider the observed learning on the produced units of the whole appliance only (Eq. 10). Though this excludes some factors like spillover effects, it is still adequate and more practical for early learning rate estimations at a component level.

$$C(X_t) = \sum_{i=1}^{n} C_{0i} \left(\frac{X_t}{X_0}\right)^{-r_i} = C_{01} \left(\frac{X_t}{X_0}\right)^{-r_1} + C_{02} \left(\frac{X_t}{X_0}\right)^{-r_2} + \dots + C_{0n} \left(\frac{X_t}{X_0}\right)^{-r_n} \qquad \textbf{Eq. 10}$$

A similar approached was used by Tsuchiya et al. [52] for the evaluation of mass production cost for PEM fuel cells.

As a result of the determination of learning rates at a component level, components with known learning effects can be defined faster and, especially, independent from the other parts. Thus, the necessity of estimating single learning rates, and the potential for errors, is reduced to a minimum number of individual components. This also allows for specifying relevant scenarios more precisely.

7.2.1.2 Investigating comparable component usages

Experience curves for single components, or rather cost elements, can be estimated by means of the aforementioned factors from individual forecasts, such as the variation in material costs. For other components, where no such data is available, comparable use cases in other applications have to be consulted to evaluate certain learning curve effects. On the one hand, this can be done through the existing literature; in this context, a screening of the relevant complementary technologies, as shown in the meta-analysis carried out in Section 4, can provide a fundamental basis. On the other hand, it can be suitable to consider values of experiences from manufacturers, which can especially allow an estimation regarding the reduction in processing times and material usage.

The main difficulty in the implementation of the given concepts arises as a result of generating an appropriate amount of experience as well as estimating the comparability within and between different fields of application. Thus, the involvement of particular (part) manufacturers and their expertise can represent an essential advantage in the evaluation.

7.2.1.3 Combining both disciplines at a Module Level

The calculation model CoLLeCT offers an opportunity to combine the mentioned approaches. Based on the deliberations of Ferioli et al. [16] and Tsuchiya et al. [52], the “Learning Module” to be investigated is divided into its underlying components. Therefore, the necessary level of detail must be chosen adequately and carefully. A classification that is structured perfectly comprises a corresponding high effort for the determination of the learning rates per every single component; however, it does not generate any relevant additional benefit in the calculated results. Additionally, the associated initial cost structure, that is, the distribution of the modules’ costs to the individual components, must be known at the forefront of the work or must be investigated collaterally. Furthermore, the appropriate learning or experience rates, respectively, for the individual components and their initial costs, or their particular share on the modules' total costs, must be defined.

In the course of elaborating and implementing the approach described above, it turned out to be necessary to introduce an additional parameter that considers different indirect influences on the learning rates of comparable components. This idea is amplified in the following section.

Necessity of Learning Properties

According to the considerations described before, although similar or identical components or cost factors, respectively, with comparable learning rates, are consulted for the calculations, it would be necessary to consider additional criteria that have at least an indirect influence on the learning rate, especially, if the learning rates are applied to the particular applications in different extents. Practically, this means that if a component is used in a similar or even identical manner within two considered applications, individual properties of the single applications can nevertheless result in different experience rates for that component.

For example, when considering the proton exchange membrane (PEM) of PEM fuel cells (PEMFC) and PEM electrolysis cells (PEMEC), comparable experience rates that are related to the material usage, can be expected due to the material and component usage. However, concurrently, it is to be assumed that, relating to the cell power, there will be a variance in the development of the current densities (the cell power per square meter) of these two technologies along with the material usage of the membrane. This circumstance can be considered directly within the appropriate learning rate per application; however, in relation to the cell power, there would be no easy comparison and interchangeability between the learning rates of the two technologies.

In the presented model, therefore, an alternative approach is chosen. The individual properties, which indirectly influence the learning rate of one or more components or cost factors, respectively, are stored for every affected component as a so-called "Learning Property." In this context, each of these "Learning Properties" is defined by an initial value and its own learning rate and, likewise, follows the basic equations of the learning curve theory as a function of the cumulative production of the overall module.

$$P_t = P_0 \left(\frac{X_t}{X_0}\right)^{-r_p} \quad \textbf{Eq. 11}$$

with:

- X_0 … cumulative number of productions at time $t = 0$
- X_t … cumulative number of productions at time t
- P_0 … initial value of property P at time $t = 0$
- P_t … value of property P at time t
- r_p … learning parameter for property P (where $lr = 1 - 2^{-r}$)

When applying such a "Learning Property" to an appropriate component i, its value relates to its initial value:

$$C_i(X_t) = C_{0i} \left(\frac{P_0}{P_t}\right)^{ex} \left(\frac{X_t}{X_0}\right)^{-r_i} = C_{0i} \left(\frac{X_t}{X_0}\right)^{(-r_i + ex * r_p)} \quad \textbf{Eq. 12}$$

where the exponent ex represents an "influence exponent" that defines the mathematical dependency between the property and the component. Hence, an "influence exponent" of $ex = 1$ connotes linear dependency, as it is the case with the power density mentioned in the earlier example. A quadratic dependency ($ex = 2$) would, for example, be necessary, if the variation of the component is related to a single dimension (e. g., its length), whereas a two-dimensional relationship (e.g., area-based) is used for the considered component to which it is applied.

Therefore, the model supports the application of several such "Learning Properties" to a single component as well as the application of a single property to several individual components. Hence, the mathematical determination of the total learning curve for the overall module is defined as follows:

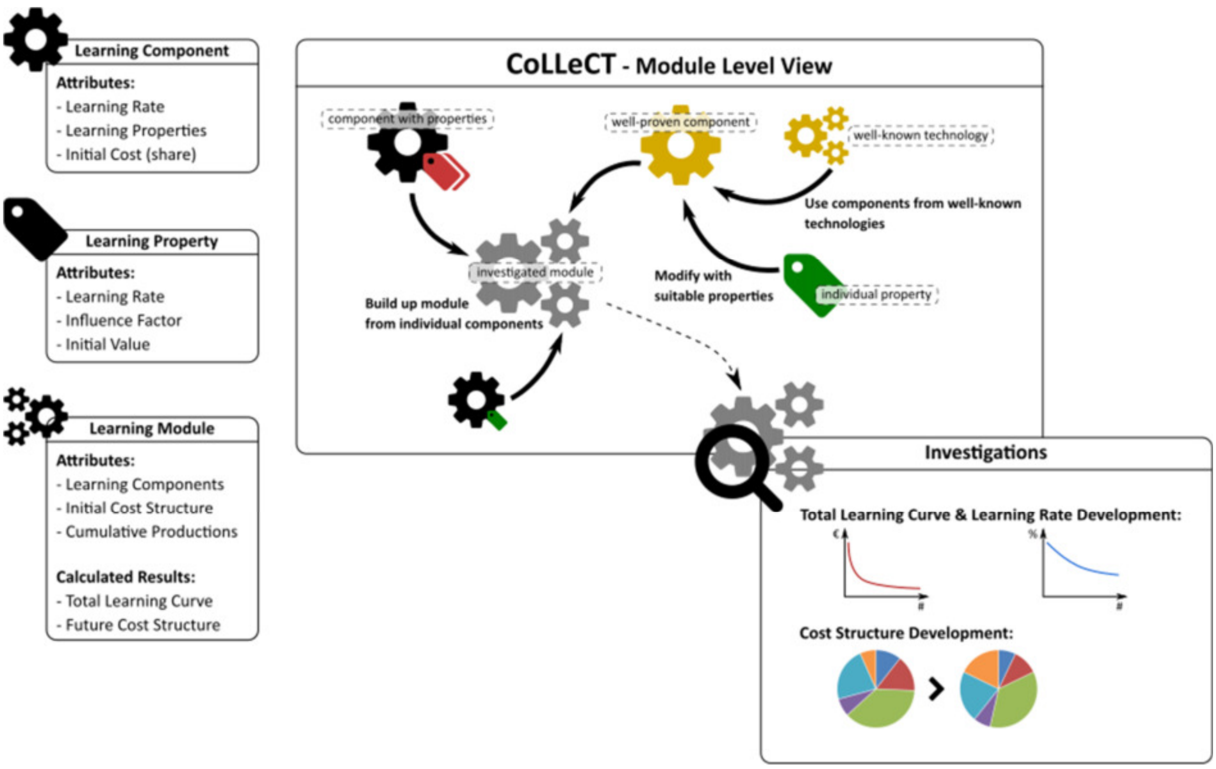
$$C(X_t) = \sum_{i=1}^{m} \left\{ C_{0i} \cdot \prod_{j_i=1}^{n_i} \left[\left(\frac{P_0}{P_t} \right)^{ex} \right] \left(\frac{X_t}{X_0} \right)^{-r_i} \right\} \qquad \textbf{Eq. 13}$$

Additionally, "Learning Properties" offer an opportunity to prepare individual, clearly distinguishable learning effects like cost reduction by material savings and those by savings in working or processing time, respectively, without the need of additional cost factors within the component structure.

A similar application of this concept for the power density of PEMFC can also be found in Tsuchiya et al. [52].

Realization inside CoLLeCT

Figure 7-1 schematically shows the scope of operation done within our calculation tool CoLLeCT. As already described, we try to reuse proven "Learning Components" from well-known technologies that are suitable for the investigated application (module). These properties can be modified with individual suitable "Learning Properties" to further consider experience effects. Subsequently, the investigated "Learning Module" can be constructed from its individual (modified) components and can be further examined.



Source: Energieinstitut an der JKU

Figure 7-1: Schematic view of the functionality of "CoLLeCT" at a "Module Level"

The functions implemented in CoLLeCT allow not only a calculation of the modules' overall learning curve. Through the composition from a certain number of individual components, all with their own learning rates, the resulting overall learning rate does not remain constant, as it would be when using the conventional approach for one-factor learning curves (OFLC), but depends on the underlying time-related cost structure.

This time-related cost structure is another point that can be observed by the usage of the tool. As costs for components decrease faster with a higher learning rate (as we assume same units of production for all components), the division of the module costs over all used components will vary depending on the production values. Therefore, cost shares for components with higher experience rates will decrease, whereas those components with low rates will become higher rated. This will allow a detailed analysis of the development of the module cost structure—as long as the initial costs and learning rates are chosen reliably—including an insight which components are cost determining at which level of technological learning.

7.2.2 System Level

In the next step, the calculation tool was extended by an additional application level with a lower level of detail to allow an assessment of experience curves for overall systems or constructions as a whole; this assessment would consist of a compound of different entities of the introduced "Learning Modules."

7.2.2.1 Need for a full system view

The examination of learning curve's effects on full system level is accompanied by several additional challenges. Basically, when studying relevant literature, it can be observed that the usage of the learning curve theory is mainly done for the most novel technology. This means that plant components (=modules) with the lowest technology readiness level (TRL) and therefore highest expected potential for cost reduction are analyzed primarily (e. g., cell stacks within an electrolysis plant).

With respect to that, the easiest method would be to split the system into two parts: a "learning" one, defined by the novel technologies provided with certain learning curve effects, and a "non-learning" part, which describes the miscellaneous conventional plant components. Therefore, the simplest case with constant learning rate, without using the "Learning Modules" and their contained "Learning Components" as described before, would match the following mathematical form, as already described by Ferioli et al. [16].

$$C_s(X_t) = \alpha \cdot C_0 \left(\frac{X_t}{X_0}\right)^{-r} + (1-\alpha) \cdot C_0 \qquad \textbf{Eq. 14}$$

with:

X_0	… cumulative number of productions at time $t = 0$
X_t	… cumulative number of productions at time t
C_0	… initial costs at time $t = 0$
$C_s(X_t)$	… total system costs at time t
r	… learning parameter for the learning part (where, $lr = 1 - 2^{-r}$)
α	… share of the total costs that can initially be attributed to the learning part

To additionally consider the learning curve effects from the other plant modules, basically the same approach as it was applied on module level seems reasonable, the experience curves for the single modules are calculated and analyzed individually, and further summed up to present the total learning curve for the overall system.

Although this could have been realized with the methods described for the “Module Level,” an additional observation level called “System Level” is introduced. On the one hand, this has the advantage that the analysis of learning curves and cost structures for modules (and components) can be executed independently from the overall system, and hence a differentiation and grouping of the individual parts can be done easily. On the other hand, this approach allows a consideration of the spillover and indirect learning effects, as described in the following section.

An observation on system level can be used to assess several “Learning Modules” within the complete system and to conduct a simple estimation of the influence of learning curve effects of well-established plant components, which are not the main drivers in cost reduction by technological learning on a novel technology.

7.2.2.2 Consideration of spillover and indirect learning effects

When analyzing the overall systems of novel technologies, wherein peripheral plant components (=modules) that indicate the novelty and therefore the potential for technological learning barely or only partially are considered, some supplemental aspects must be respected for the evaluation of the overall learning effects. Cost reductions that are observable for certain plant modules, which are not only used within the investigated system but also inside other technology in an identical or comparable manner (e. g., gas conditioning/compression), cannot thoroughly be assigned to the cumulative production of the observed system.

As described earlier, while this was neglected at a component level, among other things compensated by the usage of “Learning Properties” or rather reduced to the production volumes of the “Learning Modules,” such simplifications were avoided at a system level. This can be particularly attributed to the fact that, in comparison to the “Module Level,” the individual plant parts primarily comprise technologies that are independent of each other. In addition, independent of the chosen system boundaries, the major part of technological learning can often be confined to just a few different modules.

To qualify learning curve effects, which are not directly assignable to the production volumes of the complete system, but rather justified by secondary usages within other systems, certain dependencies between the time series of production amounts of the total system and those of the single modules were defined inside the calculation module. It means that while individual time series for the production volumes of every single module and complete system is de-fined, in the next step, the relationship between the time series of those two observation levels is determined for every single module inside the CoLLeCT.

Currently, the module includes four different dependencies, as described below:

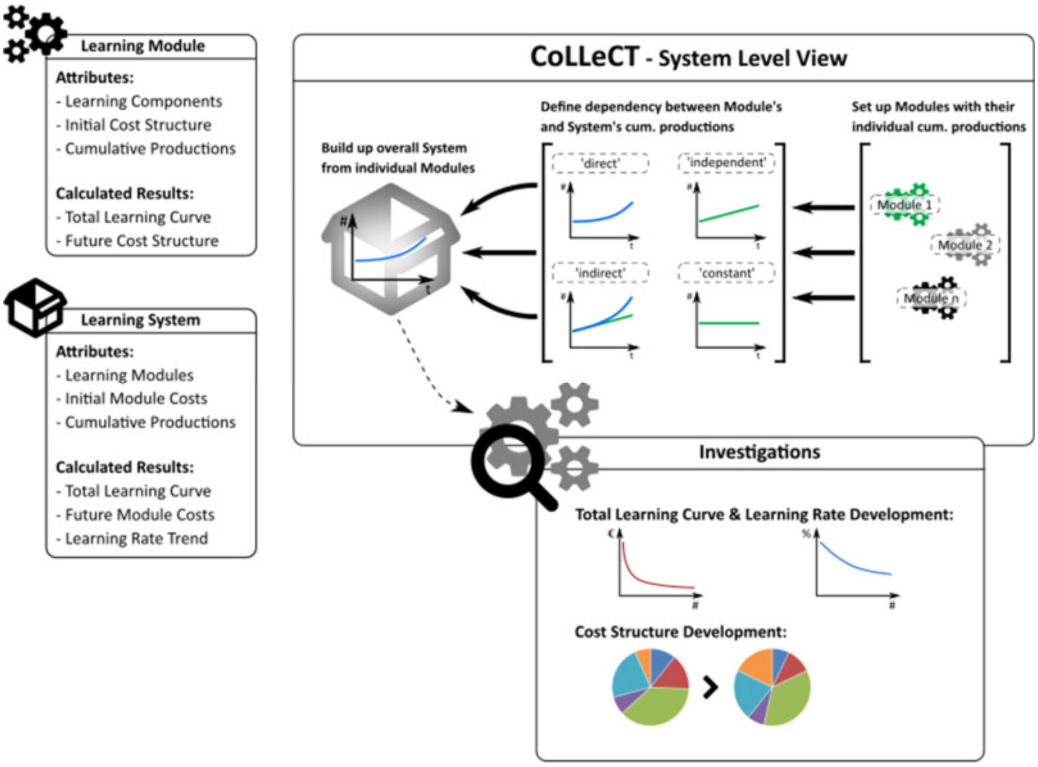
- Direct: In this case, the time series, which was defined for the overall system, is used for the calculation of the modules’ learning curve. This means that the learning effects for certain modules are also directly coupled to the production amounts of the complete system.
- Independent: In this connection, only the time series of the module is considered for the calculation of its learning curve. As a result, an increase in the production of units of the system does not have a direct influence on the cost reductions of the module.
- Indirect: When choosing this dependency, the time series of a module and a system are added. In this manner, the direct learning effects from the production of new units of the overall system as well as the indirect ones from other usages (in different applications) of the particular module are considered.
- Constant: In this case, the cumulative production of the particular module is supposed to be constant; it means that additional units are not produced theoretically. Furthermore, it means

that learning effects cannot occur, and hence this dependency can be equated with setting the learning rate of lr = 0 for the particular module.

7.2.2.3 Realization inside CoLLeCT

The Figure 7-2 again shows how functions at a “System Level” mentioned earlier are realized inside our calculation tool CoLLeCT. On the one hand, we take our individual “Learning Modules” defined at a “Module Level,” each with their specific time-series of cumulative productions. On the other hand, we define our “Learning System” with its own cumulative production over time, comprising a certain number of “Learning Modules.” Now, to connect these different time-series between the two levels of observation, one of the dependencies mentioned in the previous section is chosen for each of the modules contained in the system.

The calculated results allow the same analysis to be done at a “System Level,” as already stated for “Module Level.” Therefore, besides an obvious examination of the overall learning curve for the complete system, the development of the overall learning rate for each data point can be analyzed. Furthermore, changes in the cost structure for the system based on technological learning can be observed, as described at the “Module Level.”



Source: Energieinstitut an der JKU

Figure 7-2: Schematic view of the functionality of "CoLLeCT" on "System Level"

8 Application of the CoLLeCT approach to power-to-gas

The following subsections show how the principles of the calculation tool CoLLeCT have been applied to the water electrolysis and methanation technologies, relating to their use in PtG applications. In this context, two different cell stack designs, AEC and PEMEC, have been investigated in detail. The elaboration on SOEC stack and methanation reactors had to be minimized due to the lack of well-grounded data.

In the first step, experience curves and possible cost reductions are described in relation to theoretical amounts of produced or rather installed units and systems. Subsequently, an interrelationship between annual production and stack/system costs in a specific period is established and discussed in section 9.

8.1 Electrolysis Stack Module

The analysis of experience curves for electrolysis cell stacks (PEM and alkaline electrolysis cells) are described in the following section. Technological data, such as data on current densities or cell voltage, are based on literature by Carmo, et al. [149], Bertuccioli, et al. [150], and Smolinka, et al. [72], considering that this data is not mentioned in other literature.

8.1.1 Analysis of the experience curve for PEM electrolysis cells

To evaluate experience curves for PEM electrolysis cells by using the presented component-based approach, a definition of the cell composition is mandatory. In this regard, the classification given in the report about water electrolysis in the EU published by E4tech Sàrl and Element Energy Ltd [150], since it also provides the initial cost structure, which is also needed in the further steps, was used. This component structure used is, on the whole, comparable to data and descriptions available in other literature about PEM cell stack technology, be it PEM electrolysis ([149], [70], and [151]) or PEM fuel cell ([52], [152], and [153]). It consists of 11 individual components and is shown in Figure 8-1 together with their particular share on total cell stack costs.

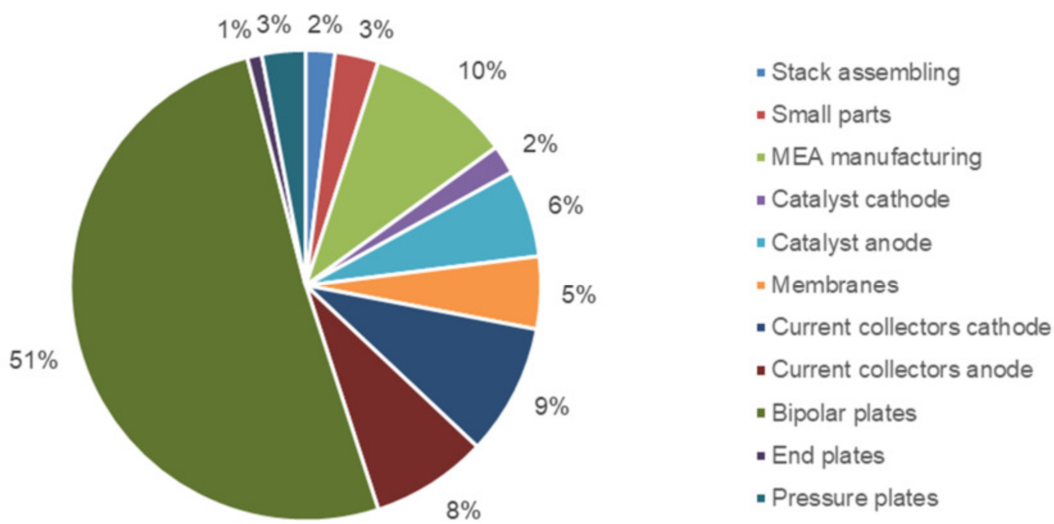


Figure 8-1: Break down in the case of PEM electrolysis cell stack, including the initial (2014) cost share of the individual components (source: Bertuccioli, et al. [150])

In the next step, the appropriate experience rates for each of these components are defined. Following the approach of interchangeability of component characteristics between different use cases, as one of the fundamental ideas behind CoLLeCT, the values used are based on the learning effects identified and described by Tsuchiya et al. [52] for PEM fuel cell applications. The individual values are shown in Table 8-1.

Table 8-1: Cost shares and learning rates chosen for PEM electrolysis cell analysis

Component	Initial cost share	lr*	pr**
Stack assembling	2 %	8 %	0.920
Small parts	3 %	5 %	0.950
MEA manufacturing	10 %	8 %	0.920
Catalyst cathode	2 %	8 %	0.920
Catalyst anode	6 %	8 %	0.920
Membranes	5 %	12..**22**..25 %	0.780
Current collectors cathode	9 %	12..**22**..25 %	0.780
Current collectors anode	8 %	12..**22**..25 %	0.780
Bipolar plates	51 %	12..**22**..25 %	0.780
End plates	1 %	8 %	0.920
Pressure plates	3 %	8 %	0.920

* lr = learning rates used in calculations; bold values were effectively used if not stated differently

** pr = „progress ratio“ =(1 – lr)

Sources: initial cost shares based on Bertuccioli, et al. **[150]**; learning rates based on Tsuchiya, et al. [49]

In general, it can be said that, for technology-independent standard parts, a rather low learning rate of $lr = 0.05$ is chosen, while peripheral parts that are specific to the technology are defined with $lr = 0.08$. Learning rates for technology-decisive parts like parts of the membrane electrolyte assembly (MEA) of PEM cells were determined iteratively to match experience curves observed from past cost development for electrolysis cells.

As already mentioned, despite all comparability between the PEM fuel cell components used by Tsuchiya et al. [52] and the ones used in this calculation for electrolysis cells, there will be technological differences that are not covered by the learning effects given in Table 8-1. Particularly, the power density of the cells, given by the current density and cell voltage, significantly differs between the two technologies both in value and evolution. At the same time, when comparing experience rates between these two cell designs, for single components that will only be feasible in an area-related manner. Therefore, the power density acts as the transformation factor between area and power related views. As the specific production or installation costs should be analyzed in relation to their rated power (e. g. €/kW_{el}), the power density will have a relevant impact on the evaluated learning curves. Thus, the power density was implemented as a “Learning Property” (cf. section 7.2.1.3), influencing relevant (area-related) components to overcome those circumstances. The characteristics of this property and the components influenced by it are shown in Table 8-2.

Table 8-2: Characteristics of the used "Learning Properties" for PEMEC

Learning Property	Initial value	lr*	Influence exponent	Influenced Components
Power density	38 kW_{el}/m^2	-2,5 %	-1	Small parts MEA manufacturing Catalyst cathode Catalyst anode Membranes Current collectors cathode Current collectors anode Bipolar plates End plates Pressure plates

** lr = learning rate*

It can be seen that the chosen learning rate possesses a negative value. This means that the property's value will increase with an increase in the amounts of produced units. It seems feasible as the power density is expected to rather increase than decrease in future implementations of the PEM cells. Furthermore, the component "Stack assembling" is not influenced by the "Power density" property as it is expected to be rather independent of the power gainable per cell area.

The supposed value for the learning rate is based on a literature review combined with some iterative calculations. The NOW study by Smolinka et al. [72] provides mid-term and long-term forecasts of electrolysis cell characteristics, which are shown in Table 8-3 below.

Table 8-3: Present and future characteristics of alkaline and PEM electrolysis technology

Technology		Present (2011)	Mid-term (~2015-2020)	Long-term (~2020-2030)
AEC	Power density	<1,0 W/cm^2	<1,3 W/cm^2	<1,8 W/cm^2
	Efficiency	62-82 %	67-82 %	67-87 %
PEMEC	Power density	<4,4 W/cm^2	<5,0 W/cm^2	<5,4 W/cm^2
	Efficiency	67-82 %	74-87 %	82-93 %

Source: Smolinka, et al. (2011): "NOW-Studie: Stand und Entwicklungspotential der Wasserelektrolyse zur Herstellung von Wasserstoff aus regenerativen Energien" **[72]**

The initial value for the power density is an average value based on literature (mainly [150] and [72]) on current densities and cell voltages.

As an initial value for the experience curve, the overall costs for the cell stack at starting time $t = 0$ must be set (alternatively, fixed costs can be defined for the individual components). In pertinent literature, current system costs (including power supply, system control, and gas drying) for PEM electrolysis cells range from 960 €/kW_{el} to 2,100 €/kW_{el} (cf. section 5.1). To further divide these system costs to the "Module Level," detaching the costs for the PEM cell stack, the appropriate system cost breakdown, according to Bertuccioli, et al. [150], is used. Comparable classifications found in other literature like Carmo et al. [149], differ slightly in the subdivisions used, but show similar shares for the stack part. The cost breakdown used for the component structure is shown in Figure 8-2.

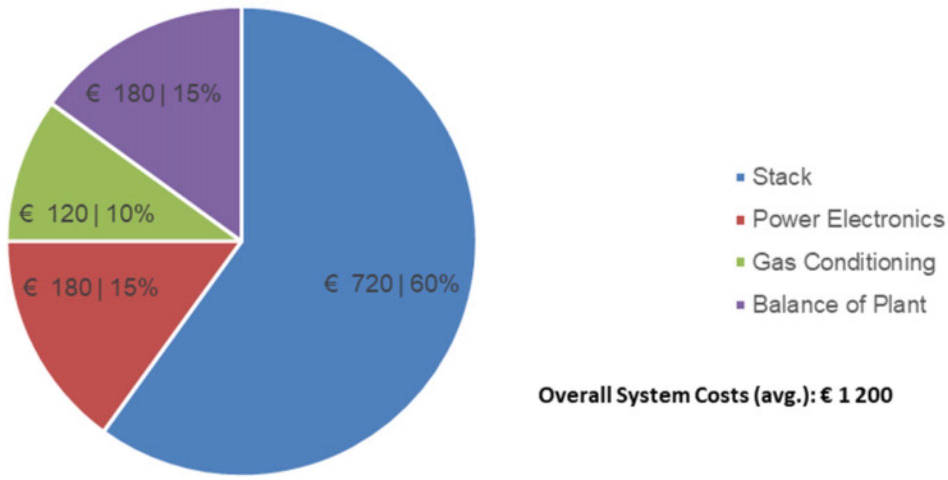


Figure 8-2: Cost breakdown for PEM electrolysis system (2014) including cost share for overall cell stack costs (source: Bertuccioli, et al. [150])

The data on these costs can also be assimilated with the data found in a review study carried out by Saba et al. [154], thereby comparing cost studies from the past 30 years for the observed timeframe.

With all this data, the learning curve for PEMEC is evaluated based on an assumptive amount of produced units. The calculated curve is shown in Figure 8-3.

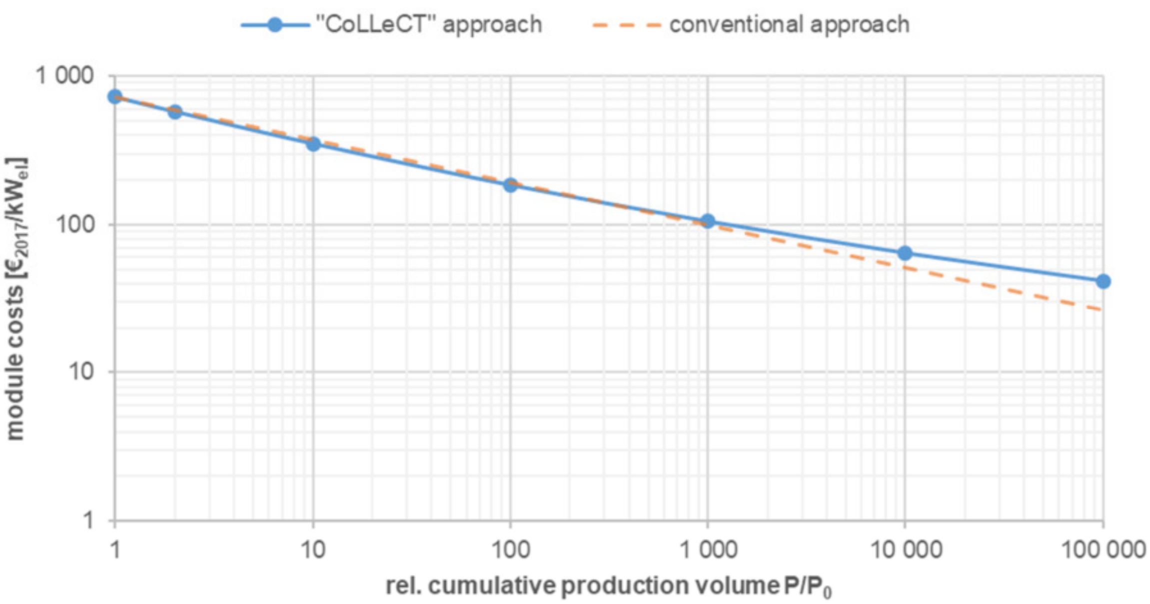


Figure 8-3: Calculated learning curve for PEM cell stack

As it can be seen in Figure 8-3, the learning curve determined with the component-based approach slightly differs from the curve gained by the conventional approach, by using a single learning rate for the whole module (in that case, a learning rate of 18% was used, as it is found in relevant references for electrolysis cells like [46], [83], and [53]). Furthermore, the learning curve is not entirely linear in the log-log graph (logarithmic scale on both axis), as it is the case for a single learning rate. This development of the overall learning rate as a function of cumulative production volumes is shown in Figure 8-4.

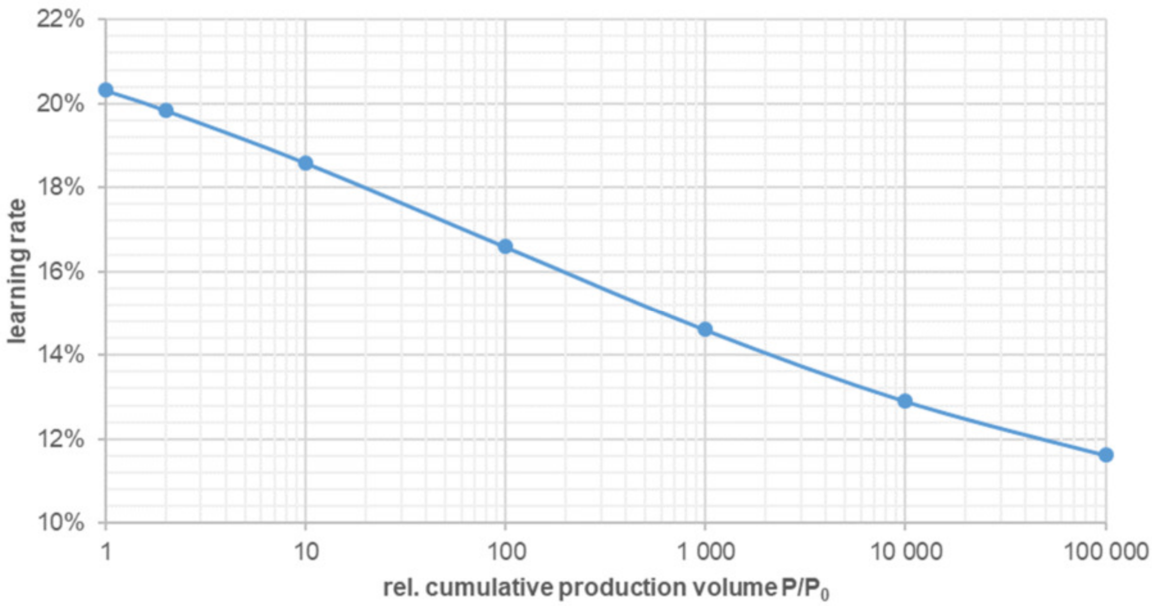


Figure 8-4: Development of the learning rate as a function of cumulative production volume for PEM cell stacks

This can be explained by the circumstance wherein components with high individual learning rates, which often come hand in hand with high-cost shares, reduce faster in costs through technological learning when compared to components with low rates. As a result, their shares on the overall costs decrease, together with their influence on the modules' overall learning rate. By this, the learning curve gains some flexibility when compared to the common theory of technological learning. Eventually, this experience can also be applied to explain some observed decreases in experience rates in different stages of technology readiness, which are hard to determine when using common methods.

As mentioned, defining learning effects on a component basis leads to variance in cost structures as a function of the cumulative number of produced units for the investigated module. Figure 8-5 shows the development for the PEMEC from the initial structure to the values for a cumulative number of produced units of a factor 1,000 (1,000 times more units produced/installed when compared to the initial amount).

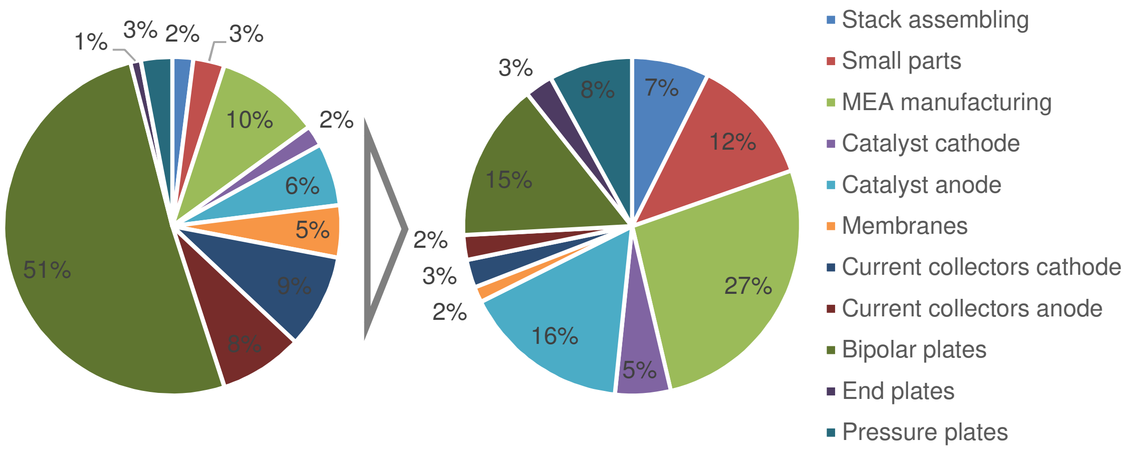


Figure 8-5: Development of the cost structure of PEM electrolysis cells for different cumulative amounts of produced units (left: initial; right: factor 1,000)

This observation does not only have influences on the overall learning curve but also shows an interesting advantage of the described method. By subdividing the modules into components and evaluating their learning curves individually, this approach allows a detailed assessment about which components will be price-dominant at a certain point of technology maturity. This could further allow evaluations like how long it will be reasonable to invest and research for improving technology-critical parts instead of aiming at cost reductions on standard parts.

The results calculated above only describe the development of the cell costs related to the electric power input. To determine the costs per generated product gas, it would be necessary to define an appropriate stack efficiency. As this conversion efficiency will not be constant over time but will improve by technological learning, these additional learning effects must be considered when investigating that topic further.

8.1.2 Transferring results to alkaline electrolysis cells

While alkaline electrolysis cells (AEC) use the same input (water and electric current) and produce the same output (hydrogen and oxygen) flows as PEM electrolysis cells, their technological composition is rather different. Despite that, some individual parts of the alkaline cell share similar functions and are built analogically at a component level when compared to the PEMEC. Considering that, based on the described methods, it would allow a feasible estimation of learning rates for the AEC.

An appropriate component structure is again provided in the study by Bertuccioli, et al. [150], as shown in Figure 8-6. The experience rates, which are summarized in Table 8-4, are chosen by component-wise comparison to similar parts inside the PEMEC. Therefore, standard mechanical parts are again defined by a learning rate of $lr = 0.05$, while peripheral, technology specific components use a rate of $lr = 0.08$. Technology-determining main parts like membranes or electrodes again use significantly higher rates.

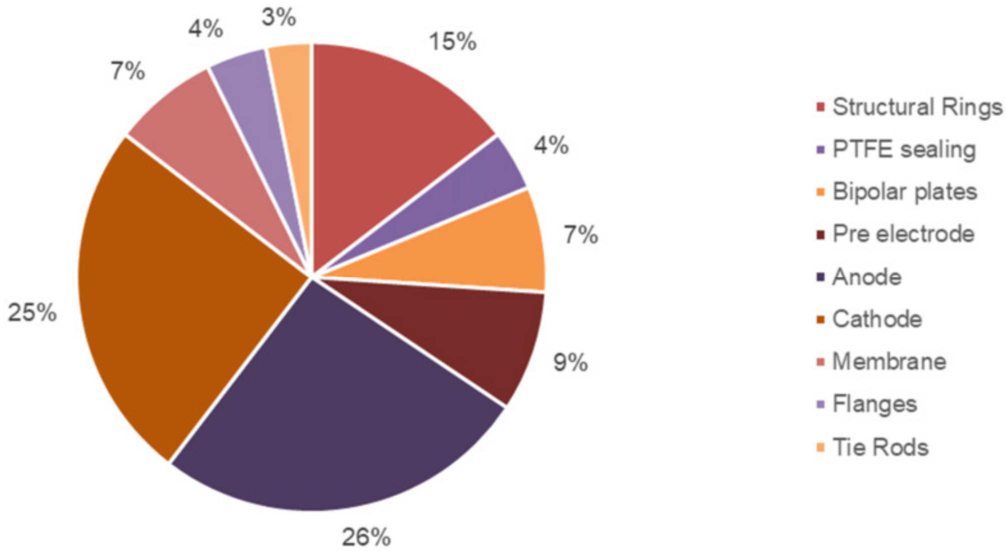


Figure 8-6: Break down of alkaline electrolysis cell stack including initial (2014) cost share of the individual components (source: Bertuccioli, et al. [150])

Table 8-4: Cost shares and learning rates chosen for PEM electrolysis cell analysis

Component	Initial cost share	lr*	pr**
Structural Rings	15 %	5 %	0.950
PTFE sealing	4 %	8 %	0.920
Bipolar plates	7 %	12..**22**..25 %	0.780
Pre electrode	8 %	12..**22**..25 %	0.780
Anode	26 %	12..**22**..25 %	0.780
Cathode	25 %	12..**22**..25 %	0.780
Membrane	7 %	12..**22**..25 %	0.780
Flanges	4 %	5 %	0.950
Tie Rods	3 %	5 %	0.950

** lr = learning rates used in calculations; bold values were effectively used if not stated differently*

*** pr = "progress ratio" =(1 – lr)*

Sources: Initial cost shares based on Bertuccioli, et al. **[150]***; learning rates based on Tsuchiya et al. [49] and analysis of PEMEC, respectively*

While this assumption of the learning rate being applicable from PEM to alkaline electrolysis cells will again be feasible on an area-related basis, this will not be the case when relating costs to different physical values, such as nominal power, for most of the components. This is also explained due to the circumstance wherein a reduction in size often accompanies a reduction in material usage and therefore a reduction in material costs.

To cope with this situation, the flexibility factor given by the power density, which is already introduced as a "Learning Property" for the PEM cell, is being adapted accordingly to make it applicable for the characteristics of the AEC. The used values are again defined by the mid- and long-term predictions given by the NOW study [72], as already shown in Table 8-3, together with iterative calculations. The parameters of the resulting “Learning Property” and the affected components can be found in Figure 8-5.

Table 8-5: Characteristics of the used "Learning Properties" for AEC

Learning Property	Initial value	lr*	Influence exponent	Influenced Components
Power density	8,8 kW_{el}/m^2	-5,5 %	-1	Structural Rings PTFE sealing Bipolar plates Pre electrode Anode Cathode Membrane Flanges Tie Rods

** lr = learning rate*

The initial overall costs for the AEC stack are again defined by using the value evaluated from the literature (cf. section 5.1) on the alkaline technology of 1,100 €/kW_{el}, while the available data range from 870 to 2,530 €/kW_{el}. Schmidt et al. [83] provided similar values as references for the year 2016, generated in an expert elicitation study. As these values describe system costs, the cost breakdown, as shown in Figure 8-7 below, is used to determine the stack costs.

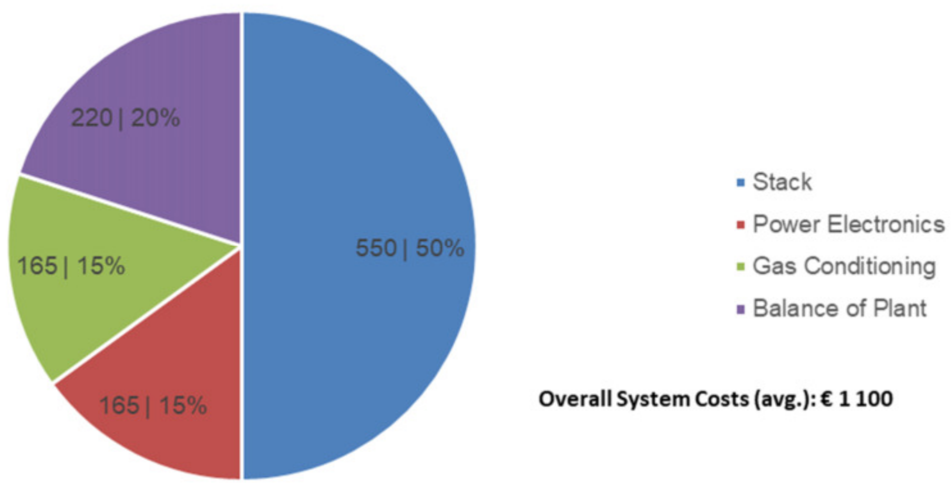


Figure 8-7: Cost breakdown for alkaline electrolysis system (2014) including the cost share for overall cell stack costs (source: Bertuccioli, et al. [150])

The results generated based on those assumptions for alkaline electrolysis cells are illustrated in Figure 8-8 and Figure 8-9. The comparative curve in Figure 8-8 is again calculated by assuming the conventional theory of technological learning with a constant experience rate of $lr = 0.18$, as it was already justified for the PEMEC in section 8.1.1.

The Figure 8-9 reveals that the overall learning rate is generally a little higher when compared to the values calculated for the PEM electrolysis cell (cf. Figure 8-4). Even though the added-up cost shares of the “high-learning” main parts are on the same level for both technologies, the portion of the “low-learning” standard parts is even higher for the AEC. This is due to the fact that the development of the power density (as a “Learning Property”) adds another learning effect, which, as per definition, is significantly higher for the alkaline cell when compared to the PEM.

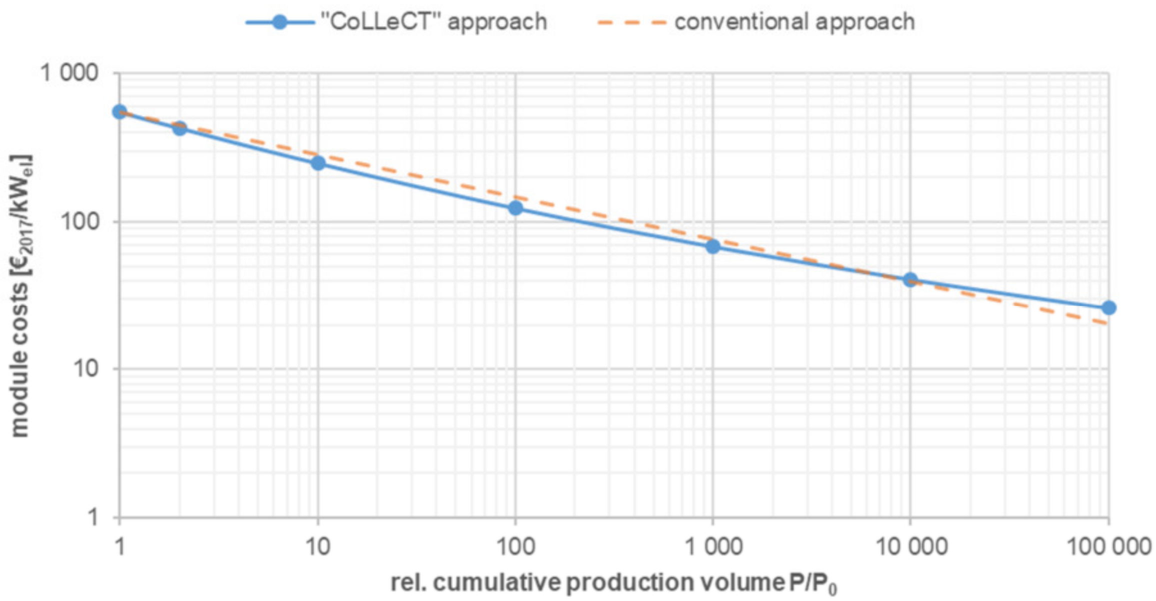


Figure 8-8: Calculated learning curve for alkaline electrolysis cell stack

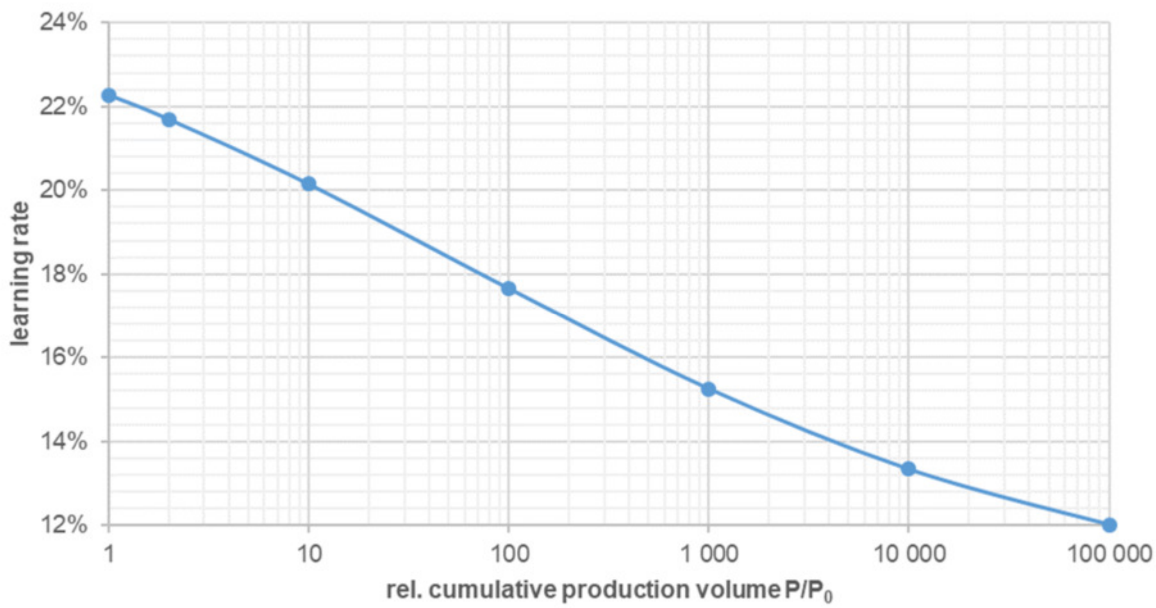


Figure 8-9: Development of the learning rate as a function of the cumulative production volume for alkaline electrolysis cell stacks

During this study, there was an attempt to apply the presented approach to other electrolysis technologies such as SOEC. While this is affordable for PEM and alkaline cells, less-established technology implicates further difficulties. It emerged that the TRL of solid-oxide cells is rather low when compared to the ones investigated, and therefore it was not possible to define a clear and universally valid component or a cost structure. An analysis of the relevant literature, including commonly used materials (cf., [152], [155]), affirmed this conclusion. As a result, it can be concluded that even with the approach described in this study, reaching an appropriate degree of maturity is essential for a technology to allow a generalized assumption on its cost development.

8.1.3 Estimations on solid oxide electrolysis cells

While alkaline and PEM electrolyzers have been well-established over the last years for PtG applications, solid oxide cells (SOC) have come up as a promising alternative. SOECs are expected to reach high current efficiencies when compared to common low-temperature electrolysis due to the operation at elevated temperatures and appropriate integrated heat management, especially in combination with exothermal methanation processes [156, 89]. Therefore, this technology is part of many recent research activities, and an investigation on SOEC in this study is reasonable.

Until now, SOCs have been primarily used for fuel cell applications. However, the technology of SOC is expected to allow operation in both electrolysis and fuel cell modes, with the same cell configuration. This is also confirmed by recent research [157, 158]. Thus, for the investigations on the learning effects of SOEC, mostly technology and cost data available for solid oxide fuel cells (SOFC) have been used.

In this study, it was not possible to define a common configuration for SOEC, as cell configurations are very specific to the use case (e.g., steam electrolysis or co-electrolysis) and technology is in a very early development stage. Therefore, the cell stack was defined by a single component module inside the CoLLeCT resulting in a constant learning rate for the module. As a reference value, the results of a recent expert elicitation study [83] were used. The study reveals an experience rate of 28% for SOEC stacks, but also shows a high uncertainty of ±16% due to lacking data. The development of the power density—used as “Learning Property” for other technologies—was also neglected.

To be consistent with the data for alkaline and PEM systems, the same system modules were used, thereby resulting in the following system cost share. As the base data, the values used by Giglio et al. [90] were used and expanded with a share of 15% to ensure that the “Gas Conditioning” is comparable with other systems (costs for “Enclosure,” “Transport and Placement,” and “Foundations” were summed up as “Balance of Plant”).

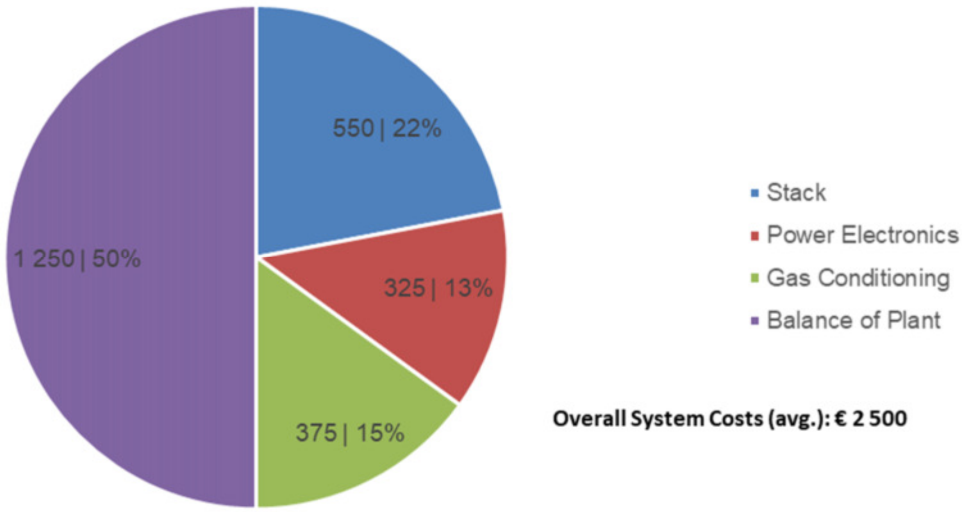


Figure 8-10: Cost breakdown for solid oxide electrolysis system including cost share for overall cell stack costs (based on: Giglio, et al. (2015) [90])

Since only a single component is used in the module for the SOEC stack, the "CoLLeCT" approach coincides with the conventional approach, assuming a constant learning rate, thereby resulting in a linear experience curve in the log-log graph (see Figure 8-11).

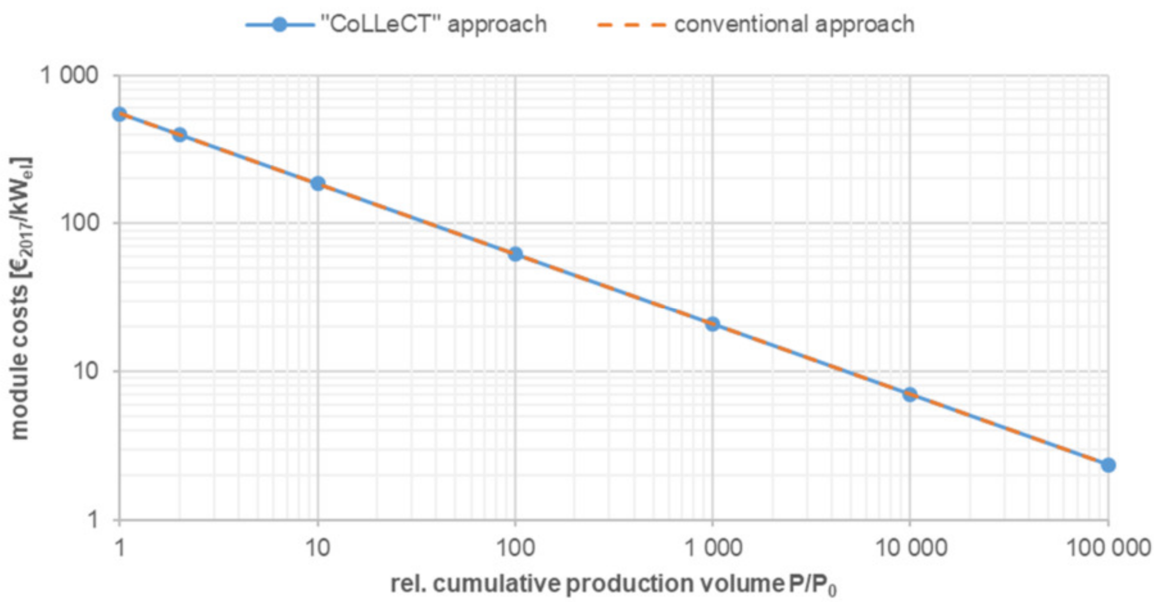


Figure 8-11: Calculated learning curve for solid oxide electrolysis cell stack

With the assumptions given above, it has to be stated that the investigations for SOEC only aim to give a very rough estimation of the technology. To make use of the benefits of the component-based learning curve model, a more specific assembly and cost structure for this application has to be identified and investigated. In the early stage of the development of this technology, this investigation will be essential to facilitate concrete implementations before being able to make relevant predictions.

8.1.4 Comparison with the conventional approach

To prove the quality of the component-based learning curve approach when compared to the conventional theory with constant learning (per technology), the experience curves were also calculated for available historical data on costs of electrolysis cell stacks. Unfortunately, the amount of cost data available, especially together with data on the corresponding cumulative number of produced units (or nominal power), are quite limited. To provide updated information, the data disseminated by Schmidt et al. (paper: [53]; dataset: [159]) was used for reference. Figure 8-12 shows a comparison of the component-based (CoLLeCT) and conventional approaches fitting the curves to the available historical data points.

The curve for the conventional approach was determined by fitting a common experience curve (cf. Eq. 1) to the given set of data points, resulting in a constant experience rate of 18.8%. A comparison of this rate to other available references in relevant literature, such as Schoots et al. [14] or Louwen, et al. [160], shows that this value seems reasonable.

Concerning the component-based theory, the parameters for the AEC presented above were used. Though it is not explicitly stated which kind of technology the historical cost data stands for, it is assumed, from the given time frame and the general development of the water electrolysis technologies at that time, that the major part is about alkaline cells rather than the other types.

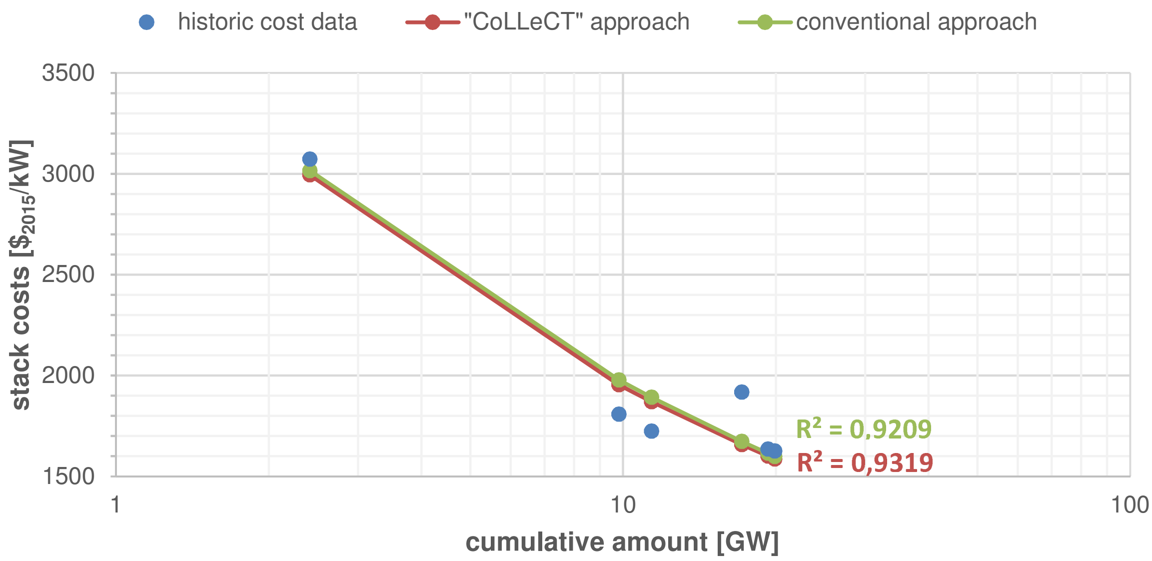


Figure 8-12: Comparison of the component-based and the conventional approach fitting to available historical cost data (data source: Schmidt, et al. [159])

A comparison of both learning curves in Figure 8-12 shows that there are no significant differences. The coefficient of determination (R^2) shows that these approaches are fitting (for the component-based method, it is even slightly better), which leads to the assumption that the presented approach is at least not worse when compared to the common theory for the given data points. Certainly, the small amount of available data points does not allow a well-grounded statement about the goodness of fit.

8.2 Electrolysis Plant System

To evaluate cost reductions for PtG technologies, an observation of the overall system costs is often desired and reasonable. This implies that learning effects for peripheral plant parts, apart from the main technology, which is in this case, the electrolysis cell stack should also be considered.

The estimation of those learning effects entails some difficulties. While the model provides appropriate capabilities on that level (cf. “System Level” in section 7.2.2), the determination of the needed input parameters is complicated. On the one hand, as those peripheral parts are usually not cost-determining or their costs do not vary significantly, respectively, in the early stages of technology development, they are often out of the scope of long-term investigation in techno-economic studies. Therefore, appropriate data about learning rates is usually not available. On the other hand, the second main influencing factor, that is, the number of cumulative produced units for each “module” of the system, is of special interest. As the model includes functions to preclude spillover effects from other technologies by considering the reuses of each module within other systems, a full analysis of the appropriate production amounts is necessary to make full use of the benefits provided by the model.

These circumstances must allow an assessment of whether the benefits derived from accurate calculations are worth the effort invested on data acquisition; this aspect must be determined per use case whether some simplifications in the calculations are reasonable. In the present case of an electrolysis system, some simplifications were made, compensating unknown third-party usages for the peripheral modules by either estimating lower learning rates (despite “direct” dependency, the learning effects for the module are low; refer to Section 7.2.2.2 for definition of dependencies) or completely decoupling the module from system productions (“independent” or “constant” dependency).

8.2.1 Future demand for water electrolysis for hydrogen production

Based on the evaluated potentials for renewable hydrogen for 2050 (cf. section 5), necessary annual production volumes to reach these targets have been estimated. This is done by using the so-called logistic functions for curves of annual production. As a reference for starting values, historical estimations of cumulative electrolyzer production from relevant literature [83, 14] are used. For the three investigated scenarios (high, moderate, and low), the resulting electrolysis production curves (rated power) are shown in Figure 8-13 for yearly and cumulative values.

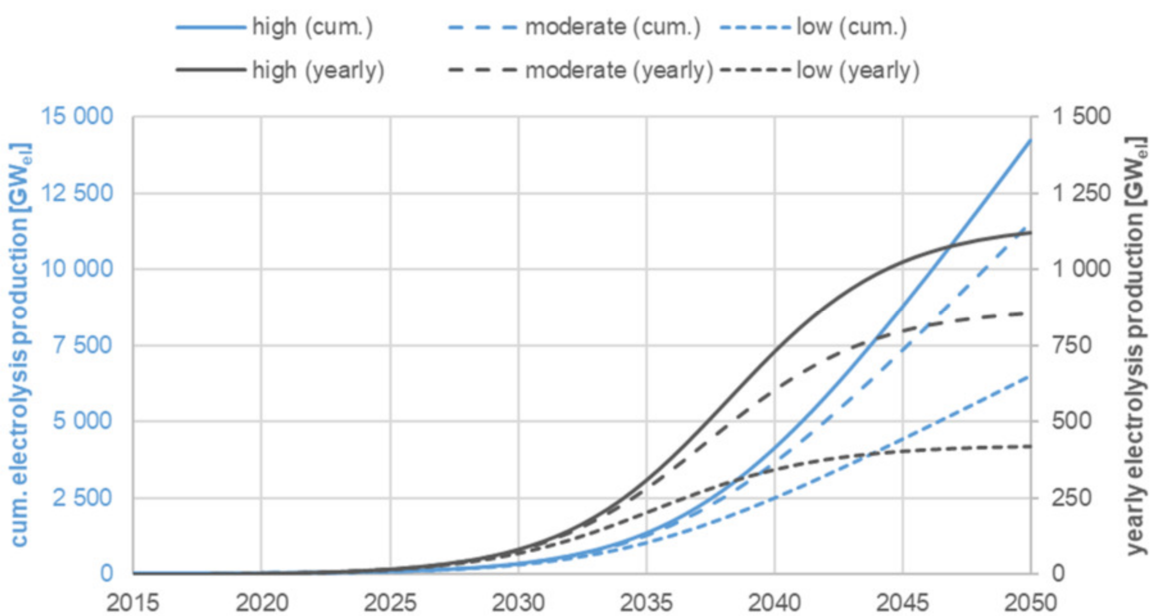


Figure 8-13: Assumed cumulative and annual overall production of electrolysis systems (rated power) based on the evaluated hydrogen demand potentials for 2050

For the estimation of the future production of individual electrolysis technologies (AEC, PEMEC, and SOEC), based on the evaluated production curves above, the following assumptions were made:

- Cumulative production of alkaline electrolysis stacks was assumed to match available data of about 20 GW_{el} in 2014 (referring to [14, 159, 83])
- Cumulative production of PEMEC was estimated to be about 1 GW_{el} and SOEC to be about 0,1 GW_{el} in 2014 (referring to [83])
- Variable shares of produced units for each technology were assumed, starting with 50% (AEC), 40% (PEMEC), and 10% (SOEC) for 2015, and ending with balanced shares in 2050 (cf. Figure 8-14).

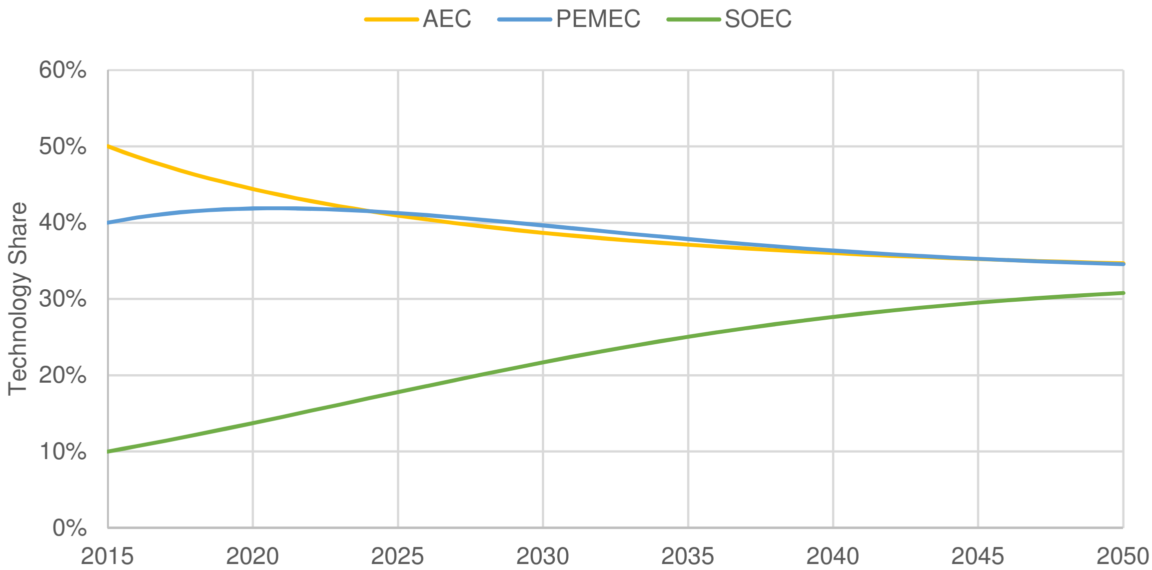


Figure 8-14: Assumption on the development of electrolysis technology share

8.2.2 System definition

To achieve consistency and comparability between the investigated technologies, the electrolysis system was split into four main cost factors, as already described in the cell stack definitions:

- Cell Stack
- Power Electronics
- Gas Conditioning
- Balance of Plant

The assumptions made for the use of the aforementioned four modules within the CoLLeCT-based calculation, including the number of sub-components and dependency on the production volumes (cf. section 7.2.2), are described in the following.

8.2.2.1 Cell Stack

The electrolysis cell stack is the core technology of the electrolysis and therefore the main driver for technological learning. This core technology for each of the three electrolysis technologies (AEC, PEMEC, and SOEC) is defined separately and described in detail in the previous section 8.1. As their learning effects are decoupled from each other through their definitions, they are directly dependent on the cumulative production of each individual technology and therefore "direct" dependency is used on CoLLeCT's "System Level."

8.2.2.2 Power Electronics

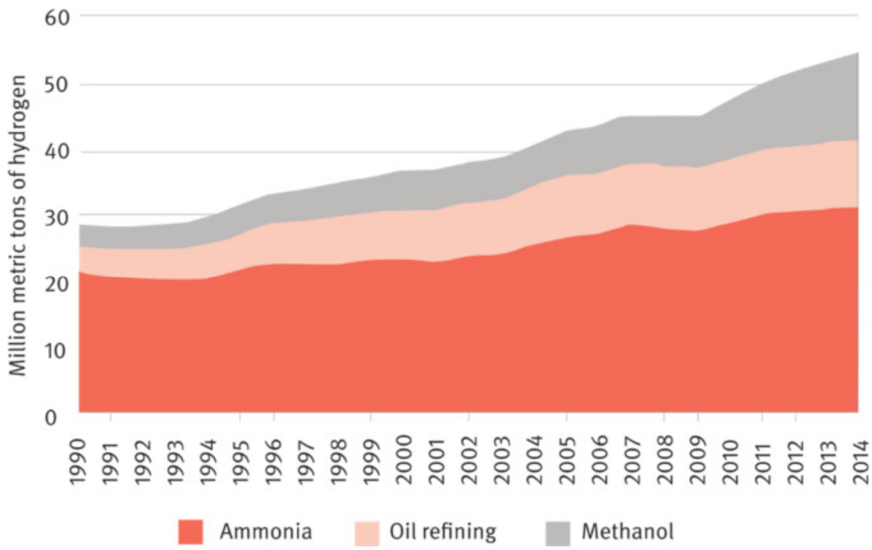
The second module includes power electronics, which is necessary for every electrolysis system. To reduce complexity, only one sub-component was defined, resulting in a single constant learning rate for the module. Since learning curves are usually investigated for complete systems, technologies, or products, learning rates for individual system components lack available data. Therefore, the observed learning effects for different manufacturing processes have to be used as a reference. Referring to the study by Strategos Inc. [161], which shows typical learning rates for repetitive electronics manufacturing at 5%–10% and 15%–25% for electrical wiring, an average learning rate of 12% was chosen for power electronics in the investigated electrolysis systems.

As power electronics is needed for all investigated electrolysis systems, and the use of power electronics between these systems is assumed to be comparable, there will be spillover effects on the technological learning across the different systems. To include these effects in our calculations, it was assumed that learning effects are not directly dependent on the cumulative production of the individual technology but more or less dependent on the overall production of electrolysis systems. Therefore, the dependency parameter for the power electronics module was set to "independent" by using the overall cumulative electrolysis production, as shown in Figure 8-13.

8.2.2.3 Gas Conditioning

The overall investment costs for product gas treatment in the electrolysis plant is covered in the gas conditioning module. Similar to the Power Electronics module, it contains a single sub-component with a constant learning rate. As this section mainly consists of purchased parts (e.g., compressors), electronics and electrics (e.g., controls and measurement and power supply), machining and assembly and components, which are far beyond R&D, the learning rate is set relatively low at 7%, following [52] and [161].

Gas treatment for further processing does not only have to be done for hydrogen production by electrolysis but also for conventional ways of H_2 generation like steam methane reforming (SMR). As a result, learning effects on this module will not only be influenced by the production of electrolyzer units but will also spillover from other forms of H_2 generation. Particularly, cumulative production and therefore learning that has happened in the past must be considered in the calculations. To take that into account, cumulative hydrogen production from 1990 to 2014, as shown in Figure 8-15, is used as a base value. This means that the gas conditioning module uses "independent" as the dependency parameter inside the CoLLeCT calculations by using cumulative processing of hydrogen from electrolysis on top of those conventional production values from the past. Figure 8-16 shows the resulting curves for the three investigated PtG distribution scenarios (high, moderate, and low).



Source: Brown (2014) [162]

Figure 8-15: World captive hydrogen production

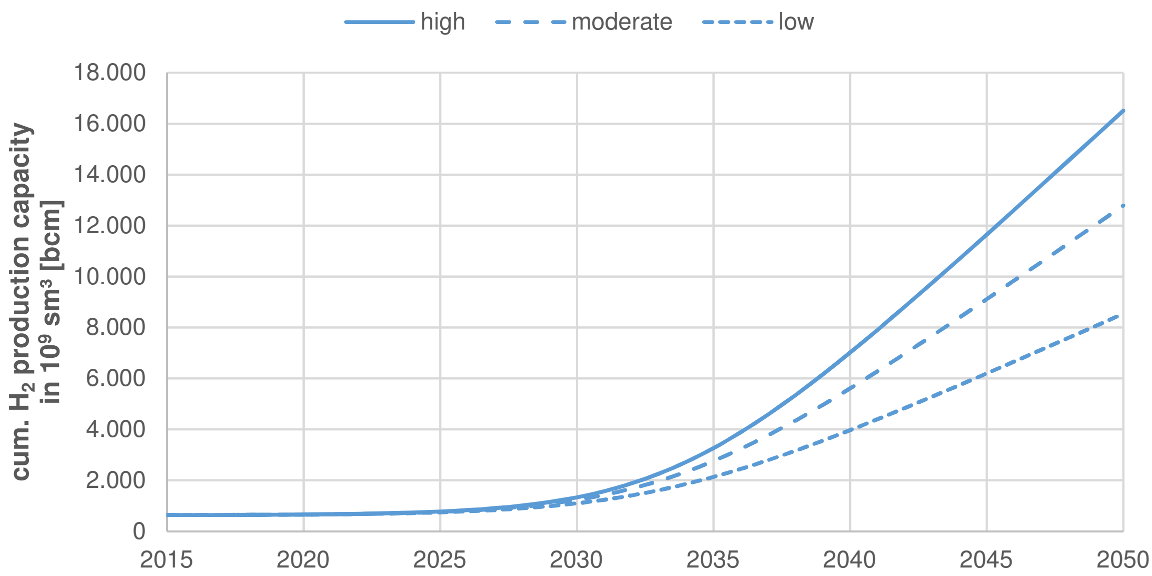


Figure 8-16: Assumed cumulative production capacity of hydrogen from 2015–2050

8.2.2.4 Balance of Plant

Costs of peripheral components and implementation tasks of the electrolysis system that are not covered by other modules are summed up in the Balance of Plant (BoP). As there is a wide variation in included sub-components between different implementations of electrolysis plants (even within the same technology), a valuable allocation of a cost structure for this module would have to be done individually for certain implementations in the considered case. To allow an assessment in this study, a reduction to a single sub-component with a constant learning rate was done. Referring to Strategos Inc. [161], a moderate learning rate of 13% was assumed, mostly a composition of purchased parts (12%–15%), machining (5%–10%), assembly (10%–20%), welding (10%), and comparable cost factors in a similar range.

Since there is a high individuality per technology, especially for pressure levels and heat management, spillover effects were neglected for this module. Hence, a "direct" dependency between the technological learning of BoP and the cumulative production of each individual electrolysis technology was chosen for the calculations.

Table 8-6 sums up the modules and assumptions used for the calculation of the technological learning potential for electrolysis systems based on AEC, PEMEC, and SOEC stacks.

Table 8-6: Summary of calculation parameters for electrolysis system

Module	**# components**			**initial cost share**			**dependency**		
	AEC	**PEMEC**	**SOEC**	**AEC**	**PEMEC**	**SOEC**	**AEC**	**PEMEC**	**SOEC**
Cell Stack	9 1)	11 1)	1 (lr=28%)	50%	60%	22%		direct	
Power Electronics	1 (lr=12%)	1 (lr=12%)	1 (lr=12%)	15%	15%	13%		independent	
Gas Conditioning	1 (lr=7%)	1 (lr=7%)	1 (lr=7%)	15%	10%	15%		independent	
Balance of Plant	1 (lr=13%)	1 (lr=13%)	1 (lr=13%)	20%	15%	50%		direct	

1) variable learning rate calculated by CoLLeCT

8.3 Methanation System

Alongside the electrolysis system, methanation comprises the second major capital costs for the implementation of a PtG plant producing SNG. While technological learning on PtG systems as a whole and electrolysis as a sub-technology have already been a topic of a few individual research studies, experience curves for methanation appliances are even harder to determine (cf. section 4.2), as there is hardly any relevant literature available. An aggravating factor is that the development of methanation plants is still at a very early stage, and therefore no consistent and verifiable data about cost structures is publicly available (cf. [158, 159, 14, 160]). As a result, the approach for using the learning curve theory along with methanation technologies will only be possible at a coarse level ("System Level"). Additionally, the composition of the methanation reactor is very specific to the application, considering processing parameters (pressure, temperature, and catalyst carrier structure), and therefore it is difficult to estimate the needed cost structure.

In the following sections, the configurations used to apply the CoLLeCT model to the methanation part of the PtG plant are described for catalytic and biological methanation. These estimations are mainly based on the data retrieved from the STORE&GO demo plant manufacturing as well as the reviewed literature data.

8.3.1 Future demand for methanation applications for SNG production

The amounts of annually produced methanation applications, valued as the rated power of SNG output (GW_{HHV}), are estimated based on the evaluated potentials for SNG demand in 2050, as shown in section 5. For this purpose, logistic functions were used again as an assumption to describe the production volumes per year. There is hardly any literature data about cumulative capacity for methanation available. Thus, the compilation of current methanation projects given by [69] was used as a referende resulting in a starting value of about 33 GW_{SNG} for the cumulative production for 2015. This includes applications for catalytic methanation of CO_2 as well as CO, considering that both types show no significant difference in the main reactor concept. Figure 8-17 shows the resulting production curves (rated power SNG output) for annual and cumulative values for the three investigated scenarios (high, moderate, and low).

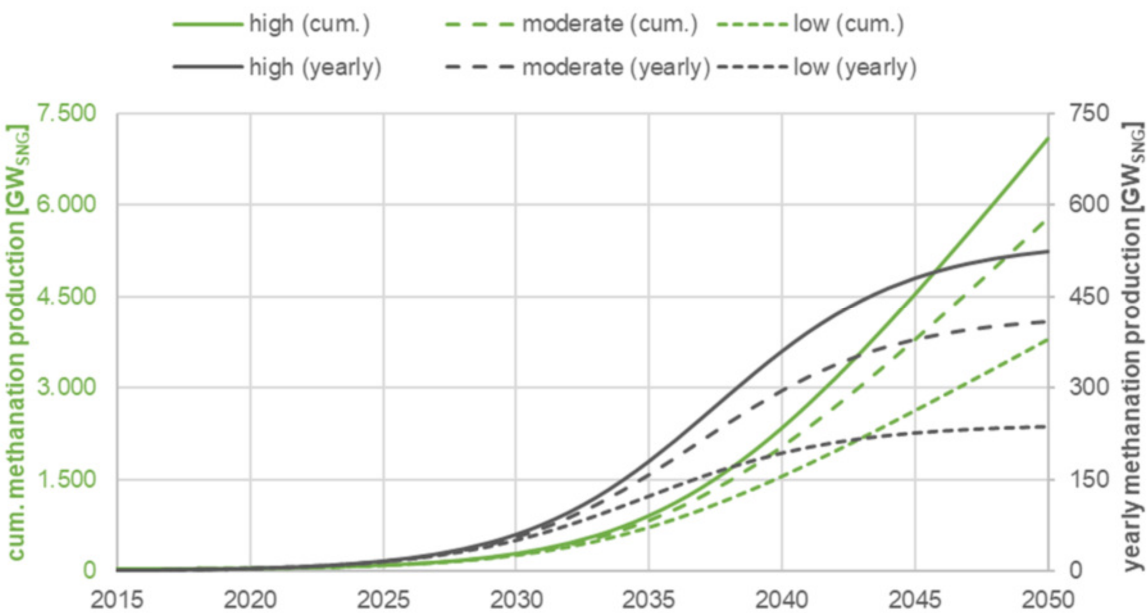


Figure 8-17: Assumed cumulative and annual overall production of methanation systems (rated power SNG output) based on evaluated renewable SNG demand potentials for 2050

For the subdivision of these overall production amounts into individual investigated methanation technologies—catalytic and biological—the following assumptions were made:

- The separation of actual technology shares for both methanation concepts shows some difficulties. If considering methanation technologies solely, biological methanation reactors are only marginal. Though, it has to be taken into account, that similar concepts are already widely used in biogas productions, which increases the base volume for learning effects. As a compromise, catalytic methanation was estimated to have a total share of 95% of cumulative productions up to the year 2015, and biological methanation was presumed to be equivalent to 5% in the same period.
- The technology shares in annual production were assumed to start at 90% for catalytic methanation and 10% for biological methanation, reaching shares of 60% vs. 40% in 2050, following the curves in Figure 8-18.

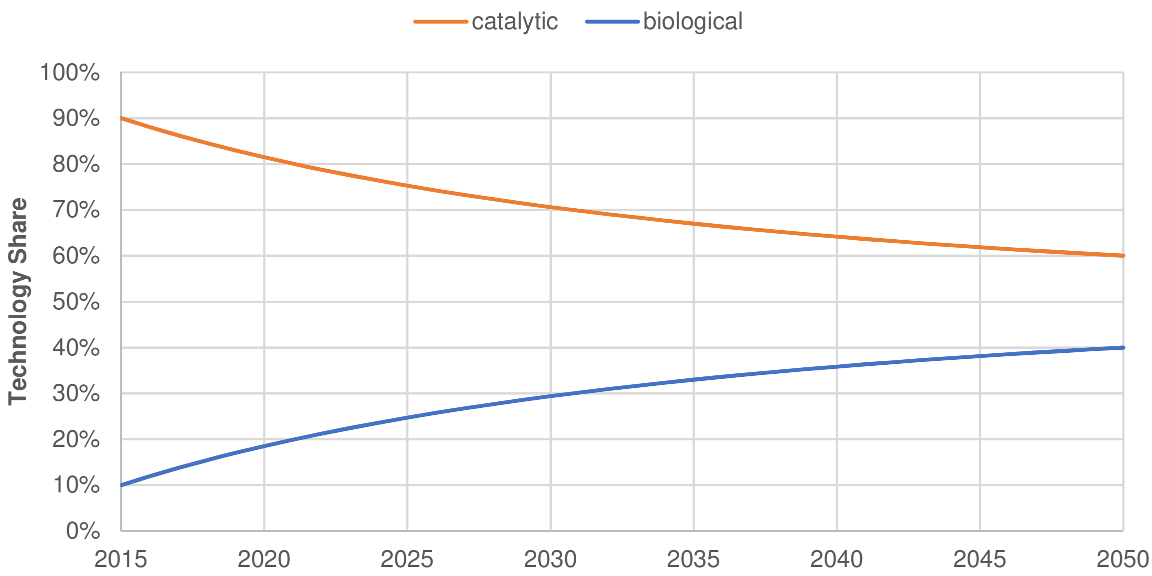


Figure 8-18: Assumption on the development of methanation technology share

8.3.2 System definition “catalytic”

The catalytic methanation system was split into the following four main subdivisions (modules) representing the main cost structure:

- Methanation Reactor
- Electric Installation and Control System (ICT)
- Gas Conditioning
- Balance of Plant

The compositions and parameters of these modules used in the CoLLeCT calculation model are described in the following section. This includes cost shares and the number of sub-components and their dependencies on the production volume (according to section 7.2.2). The cost breakdown and allocation to the modules stated above was done in reference to the available cost data of the STORE&GO demonstration plants.

8.3.2.1 Methanation Reactor

The methanation reactor represents the core component of the methanation system, with the highest potential for technological improvements and cost reductions. For the catalytic methanation, this module is split into three sub-components provided with different learning rates.

The first component is given by the reactor itself, representing the reacting volume and structure for the methanation process. According to Rönsch et al. [69], different methanation concepts are usable, which can be roughly classified into fixed-bed, fluidized-bed, structured reactors, and slurry reactors. Due to this high bandwidth of technologies, the reactor is not further classified in our investigations. To allow an estimation of learning rates for catalytic reactors, a literature review on comparable technologies and applications was performed (cf. section 4.2), without significant results. Therefore, to predict future cost reductions for methanation appliances, only very rough estimates on learning rates will be possible. While the steam methane reforming shows learning rates of 11%±6%, Anandarajah et al. [163] suggest using learning rates from 15% to 20% for novel technologies in general. As a result, a moderate learning rate of 15% was assumed as a starting value for the methanation reactor.

While the methanation reactor contains the carrier material for the catalytic material, the catalyst itself is treated independently within our model. This component can be roughly compared to the catalyst used in the definitions for the electrolysis cells, at least in terms of learning rates. While the catalyst material itself is different (methanation uses Ni-catalysts primarily), cost reduction effects will be similar, assuming, as it was worked out for electrolyzer catalysts, that material costs will stay constant, while only coating thickness is reduced (cf. section 8.1). In this case, the same learning rate of 8%, which provided good results for electrolysis cells, can be used for the methanation catalyst as well.

The third major component that is essential in the methanation reactor is heat management. As the methanation process is highly exothermal, an operation at a controlled temperature is mandatory for the functioning process and appropriate methane yield. As heat management is highly dependent on the operation mode used in the individual reactors [69] and therefore tightly integrated with the reactor concept itself, a learning rate of 15% was assumed in this case, referring to the values used for the reactor component and provided by Anandarajah et al. [163] for developing technologies.

Table 8-7 shows an overview of the values used for the calculations elaborated on the catalytic methanation reactor. Initial cost shares are based on data retrieved from the STORE&GO demonstration plants.

Table 8-7: Cost shares and learning rates chosen for catalytic methanation reactor

Component	Initial cost share	lr*	pr**
Reactor	57%	15%	0.850
Catalyst	26%	8%	0.920
Heat Management	17%	15%	0.850

** lr = learning rates used in calculations*

*** pr = „progress ratio“ = (1 – lr)*

Since the methanation reactor, as a module, represents the main technological part of the complete methanation system associated with technological improvement, the technological learning effects will be directly coupled with production amounts of the catalytic methanation technology. This is considered with a “direct” dependency within the CoLLeCT calculation module.

8.3.2.2 Electric Installation and Control System (ICT)

This module includes electrical wiring as well as the implementation of necessary measurement and control systems for the operation and monitoring of the methanation plant. In order to reduce complexity in the calculation model, this module was defined with only a single sub-component and hence a single, constant learning rate. A comparison of the parts allocated to this module to typical representative learning rates given by Strategos Inc. [161] shows that the values for repetitive electronics (5%-10%) and electrical wiring (15%-25%) both are reasonable. Relating to the values used for “power electronics” in the electrolysis system (cf. section 8.2.2.2), a central learning rate of 12% was assumed for the calculations.

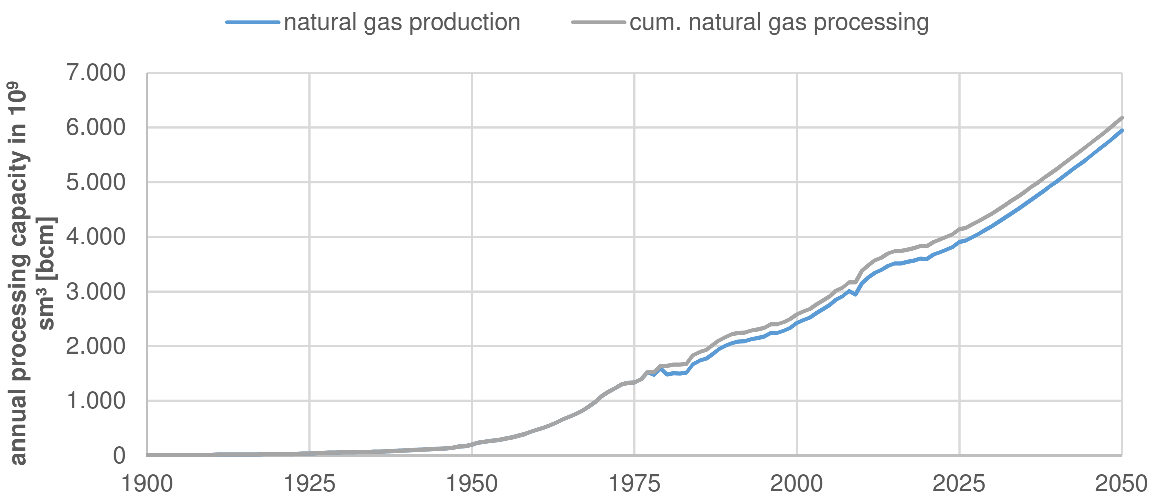
Since the electric connection and interconnection and the measurement and control systems are needed in catalytic and biological methanation systems in the same manner, spillover effects from one technology to the other must be expected in this module. Therefore, it was assumed that the technological learning effects covered by this module are more or less dependent on the distribution of methanation systems as a whole and not directly dependent on the production of each individual technology. However, this can still be an underestimation because many purchased parts used for measurement and control purposes for gas processing and heat management are widely used in different sectors, resulting in additional cost reduction effects on those elements, which cannot be considered in this investigation.

8.3.2.3 Gas Conditioning

The treatment of input (H_2, CO, and CO_2) and output (SNG) gasses of the methanation process is a necessary processing step to ensure relevant operating conditions—in terms of eliminating unwanted gas impurities and pressures—and to ensure that the requirements for the product gas, such as for feed-in to the gas grid, are met. Compared to how this module was implemented for the electrolysis system (cf. section 8.2.2.3), it will be treated the same way for methanation in terms of learning rates, by using a constant (single sub-component) rate of 7%. This seems reasonable because devices, such as compressors, and implementation works are quite transferable between those two technologies, mostly differing in gas compositions and amounts.

Presuming that conditioning of the input gases is handled separately, such as hydrogen treatment is already addressed in the appropriate electrolysis unit, this module mainly deals with the synthetic natural gas (SNG) produced by the methanation unit. Since the properties of this gas match those of fossil natural gas, comparable equipment is expected to be used for both fossil and renewable gas treatment. Therefore, a major part of technological learning can be attributed to the processing of natural gas (fossil and synthetic) in the future as well as in the past. To take this into account, the historical and future trends of natural gas processing[8] were investigated (cf. Figure 8-19). For the consideration of learning effects, including technological learning that already happened in the past, this cumulative amount of gas processing (with the exclusion of capacity reductions) was used as production time series for gas conditioning in methanation plants, and therefore was “independent” of the direct productions of the methanation unit.

[8] Remark: In this context, natural gas includes fossil as well as synthetic (green) resources. Therefore, the estimated future demands are expected to be in large parts (or completely) be covered by SNG from renewable sources to reach climate goals for 2050.



Sources: https://ourworldindata.org/fossil-fuels [164] & https://www.statista.com [165]

Figure 8-19: Worldwide annual processing capacity of natural gas from 1900-2050 (gray: reductions in capacities excluded)

8.3.2.4 Balance of Plant

By analyzing the data on costs available from the STORE&GO demo plants, it can be seen that a major share of the overall plant costs is driven by peripheral components and engineering that are not specific to the technology. Hence, methanation systems, as some kind of chemical plants, require individual engineering, planning, and equipment; however, in reality, these systems lack standardizations between different implementations. Therefore, a detailed analysis of the included sub-components and their specific experience curves would not be feasible in a harmonized way in this study. Therefore, all these peripheral cost factors are summed up in the Balance of Plant that is implemented as a single component module in the CoLLeCT model. In reference to the Balance of Plant module of the electrolysis system (cf. section 8.2.2.4), the same moderate learning rate of 13% was assumed, keeping in mind the higher significance due to substantially higher share on total system costs (47% for catalytic methanation).

Due to the high individuality of non-standardized methanation facilities, which is also dependent on boundary conditions like further processing of the product gas, spillover effects from other technologies on the Balance of Plant module were neglected. Consequently, the experience driving the cumulative production volume was assumed to be directly dependent on distribution of the technology itself, setting the parameter to “direct” in the calculation model.

8.3.3 System definition “biological”

As a counterpart to the catalytic methanation process, biological methanation is another way to generate SNG from hydrogen and CO/CO_2. While the process is quite similar to biogas production by the fermentation of biomass, the actual usage as part of a PtG plant is marginal when compared to the chemical conversion. According to Götz et al. [103], biological methanation is only an option for small plant sizes due to the requirement of large specific reactor volumes and fewer possibilities for the waste heat utilization (as a result of lower operating temperatures).

As a result, information about the structure of investment costs for biological methanation plants is rather rare in relevant literature. To stay consistent with the other systems in this study, especially with catalytic methanation, the CoLLeCT modules were implemented in the same way as follows:

- Methanation Reactor

- Electric Installation and Control System (ICT)
- Gas Conditioning
- Balance of Plant

Compared to the catalytic system, this composition only differs by the modules' shares in the overall system costs and the sub-level definition of the methanation reactor, which is described in the following section. Due to the lack of detailed cost data, which is still not available at the appropriate STORE&GO demonstration plants, the subdivision of costs into those modules was done by referring to the available data for catalytic facilities, excluding the costs for the catalyst. Therefore, the calculations done for the technological learning on biological methanation plants include high uncertainties that must be considered when interpreting the results. However, they can still give an idea about potential cost reductions through technology distribution.

8.3.3.1 Methanation Reactor

The CoLLeCT module for the biological methanation reactor basically consists of two components—the reactor, representing the reaction volume for the fermentation process, and heat management to handle thermal operating conditions. Compared to the catalytic model, only the component for the catalyst was removed, resulting in an adjustment of cost shares of the other two components, as shown in Table 8-8. In the absence of other significant data, the aforementioned components were assumed to show the same learning rates (15% both) as defined for their catalytic counterparts.

Even though biological methanation reactors are technologically related to biogas production by fermentation, spillover effects from these installations were neglected. Therefore, the learning effects are coupled to the specific production volumes of the technology itself by a "direct" dependency.

Table 8-8: Cost shares and learning rates chosen for biological methanation reactor

Component	Initial cost share	lr*	pr**
Reactor	77%	15%	0.850
Heat Management	23%	15%	0.850

** lr = learning rates used in calculations*

*** pr = „progress ratio" = (1 – lr)*

8.3.3.2 Electric Installation and Control System (ICT), Gas Conditioning, and Balance of Plant

The other three modules implemented are assumed to be quite similar for both catalytic and biological methanation in their compositions and operational functions. Hence, the assumptions made and parameters set for catalytic methanation systems have been defined the same way for the biological counterpart by learning rates and production volume dependencies. Of course, their shares on overall system costs are different.

Table 8-9 sums up the modules and assumptions used for the calculation of the technological learning potential for catalytic and biological methanation systems. The initial cost shares are elaborated in reference to the data available from STORE&GO demonstration plants for catalytic methanation; subsequently, these cost shares are transferred to biological methanation by considering the omitted catalyst material.

Table 8-9: Summary of calculation parameters for electrolysis system

Module	# components		initial cost share		dependency	
	catalytic	biological	Catalytic	biological	catalytic	biological
Methanation Reactor	3[1)]	2[1)]	21%	17%	direct	
Electric Installation & Control System (ICT)	1 (lr=12%)	1 (lr=12%)	20%	21%	independent	
Gas Conditioning	1 (lr=7%)	1 (lr=7%)	12%	13%	independent	
Balance of Plant	1 (lr=13%)	1 (lr=13%)	47%	49%	direct	

[1)] variable learning rate calculated by CoLLeCT

9 Potential for cost reductions through technological learning

Unless otherwise mentioned, cost predictions for the PtG technology in this deliverable are stated as **real costs** (reference year 2017, €$_{2017}$). This means that the inflationary effects that are anticipated and will lead to rising nominal costs have not been considered. Additionally, **no significant changes in technology**, such as an implementation of additional functions, control elements and safety devices or efficiency improvements, have been taken into account for calculating the future investment costs.

In the following sections, the results from calculations on the technological learning on PtG systems are shown. Sections 9.1 and 9.2 show the results based on the assumptions and definitions described in the previous chapter 8. Section 9.3 deals with the sensitivity of the used models to a variation of their parameters. Unlike the calculated real costs (year 2017) in this deliverable, chapter 9.4 examines the evolution of nominal prices by considering inflation.

While common PtG systems, especially those investigated in STORE&GO, usually consist of electrolysis and methanation, the two systems were evaluated separately to allow detailed investigations and reduce the number of combinations. Of course, overall PtG plant investment costs, for each combination of electrolysis and methanation technology, can simply be calculated by summing up the individual system costs.

9.1 Cost predictions for electrolysis systems

The graphs given below show the calculated experience curves for the PEM (Figure 9-1 and Figure 9-3), alkaline (Figure 9-3), and solid oxide (Figure 9-4) electrolysis systems, as defined in section 5. The curves are shown for all the three scenarios of electrolysis deployment defined in sections 5 and 8.2.1. The results are summed up in Table 9-1:

Table 9-1: Summary of the calculated cost reduction potential for 5 MW$_{el}$ electrolysis systems

Electrolysis system	Calculated costs [€$_{2017}$/kW$_{el}$]			
	initial (2017)	2020	2030	2050
PEMEC	1,200	971 – 973	522 - 532	265 – 303
AEC	1,100	1,058 – 1,059	754 - 767	408 – 464
SOEC	2,500	1,850 – 2,100	1,031 – 1,266	560 – 751

The cost reduction potential of PEMEC systems shows that the underlying scenario for future deployments of PtG only has a marginal influence on the resulting investment costs for high production volumes. The resulting costs for 2050 are in a range of 270–300 €$_{2017}$/kW$_{el}$. This can be explained by the resulting development of the systems' overall learning rate, as shown in Figure 9-2. The learning rate decreases at an accelerated pace with increasing production volumes in the beginning, whereas this effect reduces for higher cumulative volumes. Conversely, the experience rate of the alkaline system is more harmonized over the whole period. This effect is supported by the assumed development of the technology shares defined in Figure 8-14, through which the production capacities for PEMEC can grow at a rapid pace in the near future.

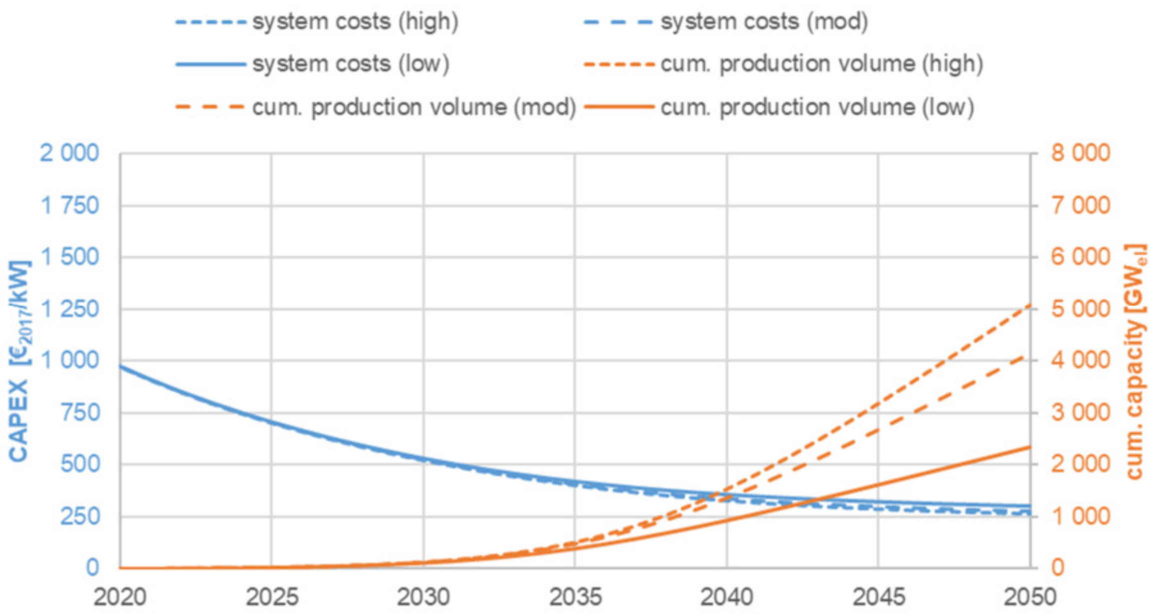


Figure 9-1: Investment cost development for PEM electrolysis systems (rated power 5 MW) depending on their potential future production volumes

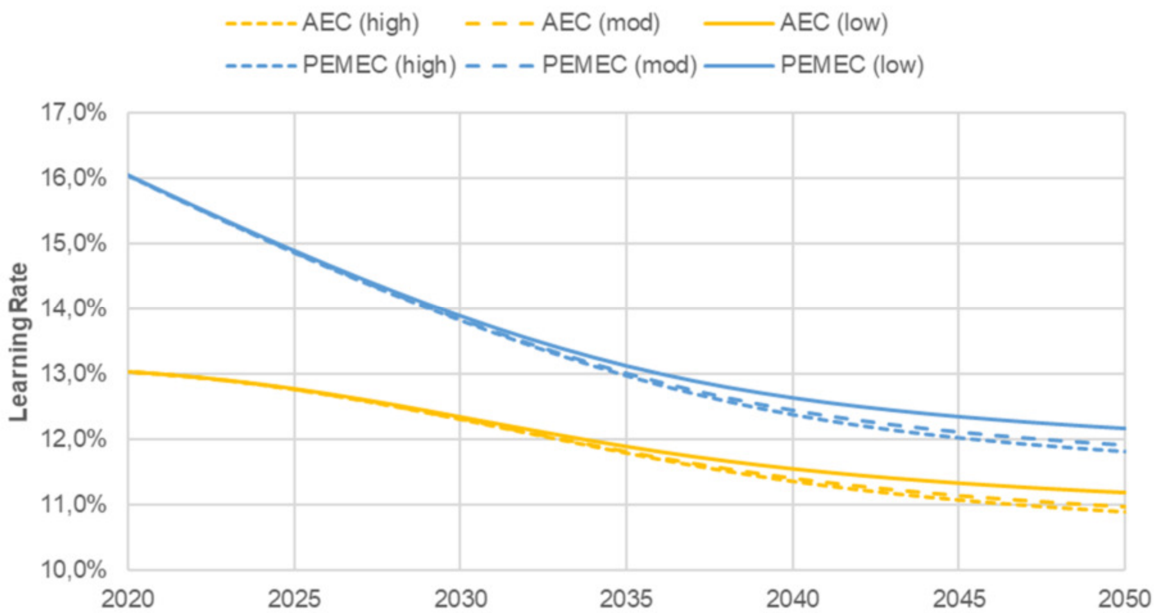


Figure 9-2: Learning rate development for PEMEC and AEC systems depending on their potential future production volumes

AEC Systems show lower potential for cost reductions when compared to the other investigated electrolysis technologies. With a calculated range of 410–470 $€_{2017}/kW_{el}$, the costs are expected to be even significantly higher than stated for PEMEC systems. Besides the lower overall learning rate, this can be explained by the substantially higher starting value of cumulative productions, which means that significant learning effects have already happened in the past.

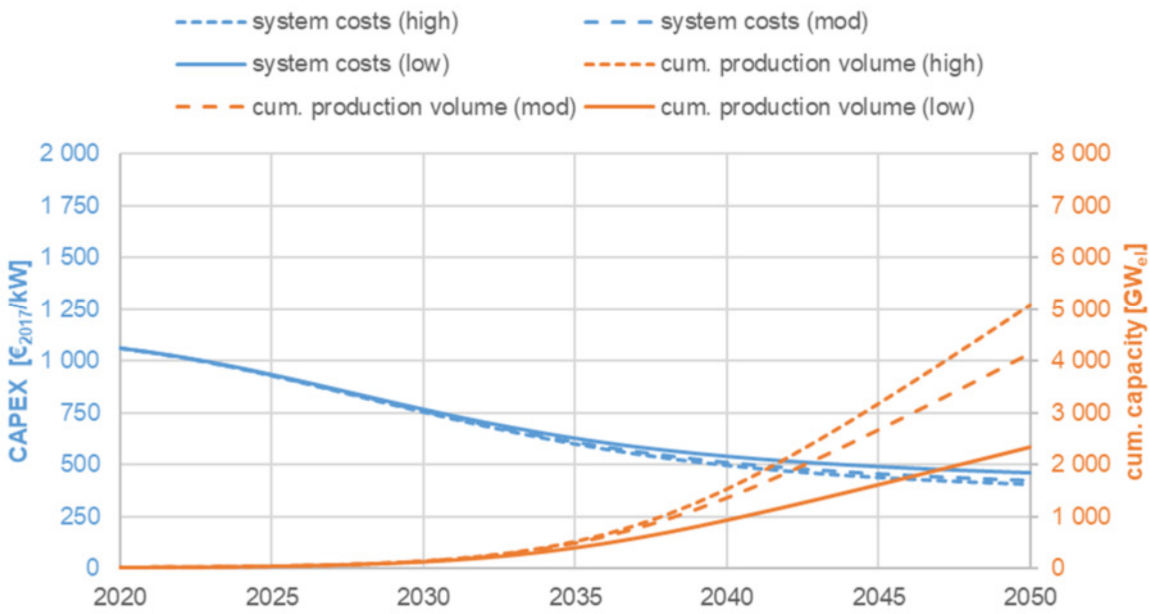


Figure 9-3: Investment cost development for alkaline electrolysis systems (rated power 5 MW) depending on their potential future production volumes

The results calculated for SOEC show highest cost reduction potential of all the three investigated electrolysis technologies. This follows from the high learning rate that was defined for the SOEC, based on relevant literature and compared to AEC and PEMEC a significant lower cumulative production volume as an initial value. By taking the relatively high uncertainty for this value of ±16 percentage points into account (cf. [83]), the bandwidth of expected future costs can be significantly higher, as it can be seen in Figure 9-5. This would primarily affect the upper boundary as module costs for the cell stack itself are already extremely low due to the high base value for the learning rate, which would further increase the gain through additional cost reductions in the long term. Especially, for this technology, further investigations on cost structure and experience rates are necessary to allow reasonable estimations on future investment costs.

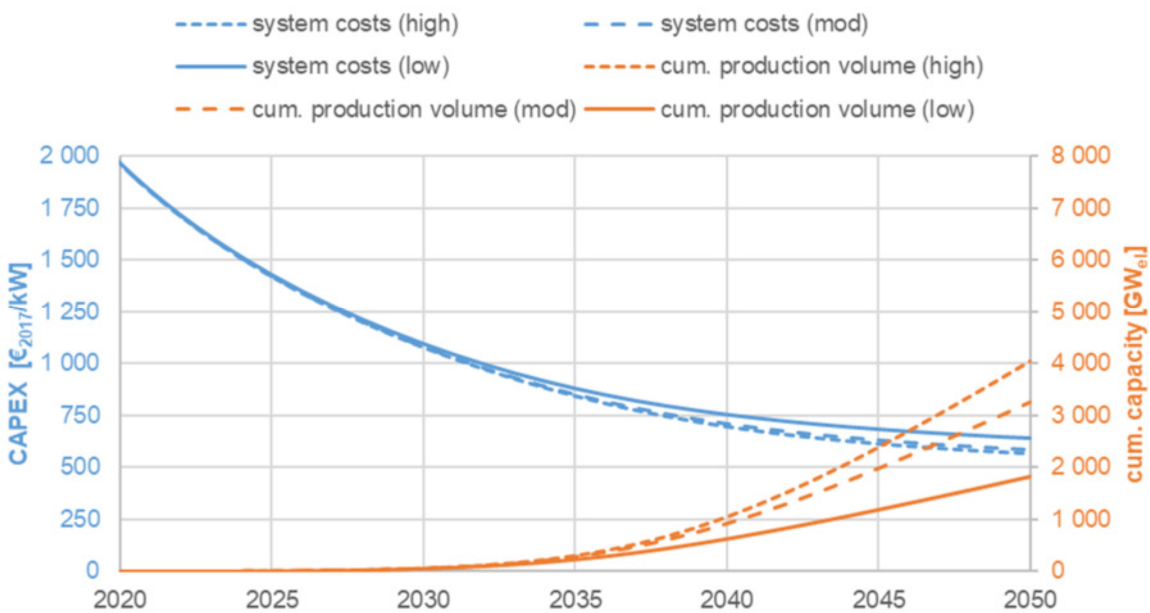


Figure 9-4: Investment cost development for solid oxide electrolysis systems (rated power 5 MW) depending on their potential future production volumes

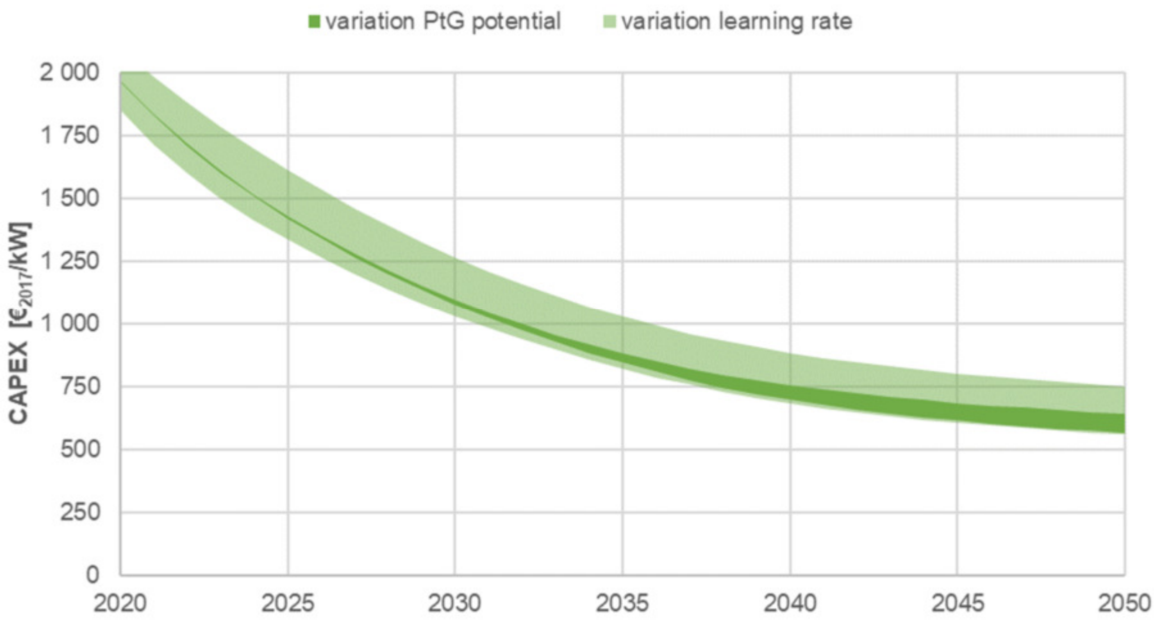


Figure 9-5: Influence of learning rate uncertainty for solid oxide electrolysis cell (LR=28%±16%)

9.2 Cost predictions for methanation systems

This section analyzes the results calculated for the methanation part of the PtG plants. The resulting ranges of the investment cost (high and low deployment scenarios) are summed up in Table 9-2 for the years 2020, 2030, and 2050:

Table 9-2: Summary of calculated cost reduction potential for 5 $MW_{SNG\text{-}output}$ methanation systems

Methanation system	Calculated costs [$€_{2017}/kW_{SNG}$]			
	initial (2017)	2020	2030	2050
Catalytic	600	579 – 579	437 – 444	270 – 295
Biological	600	551 – 552	357 – 363	213 – 232

The experience curves for catalytic (Figure 9-6) and biological (Figure 9-7) methanation systems show similar trends for cost reductions. The investment costs for biological methanation reach lower levels in the long-term. This is mainly driven by the aspect that the relative increase in cumulative produced units (or rather rated power) has to be substantially higher when compared to the catalytic application to reach presumed technology production share levels (from 5% initially to 40% in 2050), as defined in Figure 8-18. Contrary to the catalytic reactor, another factor is that biological methanation misses the catalyst component, wherein this component is implemented with a relatively low learning rate (8%) when compared to other components in the reactor module.

Despite this, investment costs for both technologies are on a similar level throughout the investigated time frame, reaching values of 270–300 $€_{2017}/kW_{SNG}$ (catalytic) and 210–230 $€_{2017}/kW_{SNG}$ in 2050 under the presumed conditions.

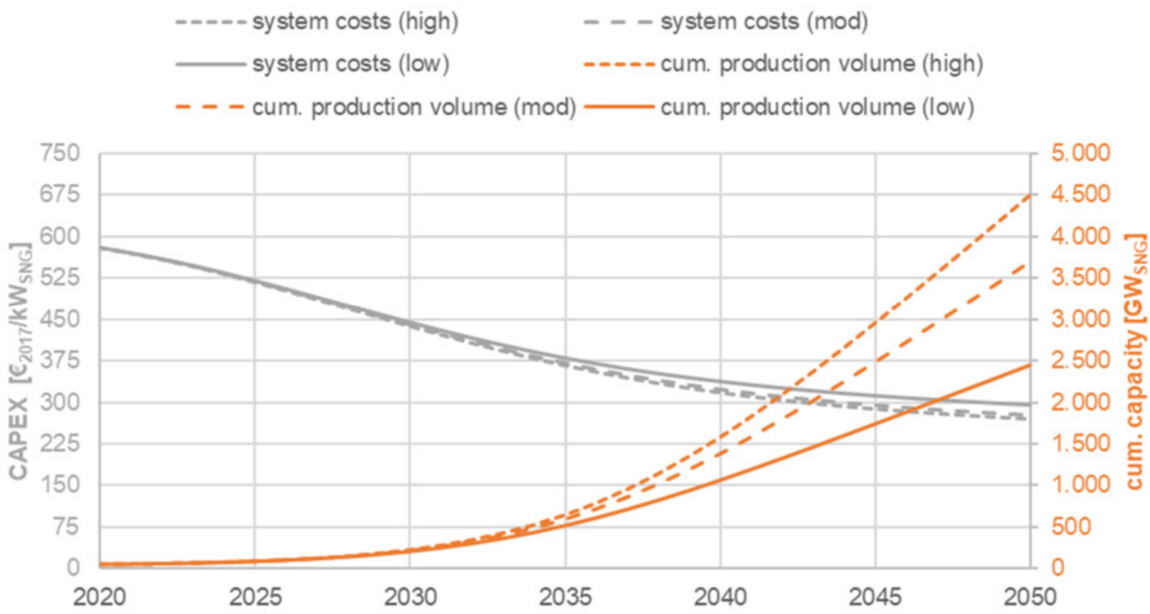


Figure 9-6: Investment cost development for catalytic methanation systems (5 MW SNG output) depending on their potential future production volumes

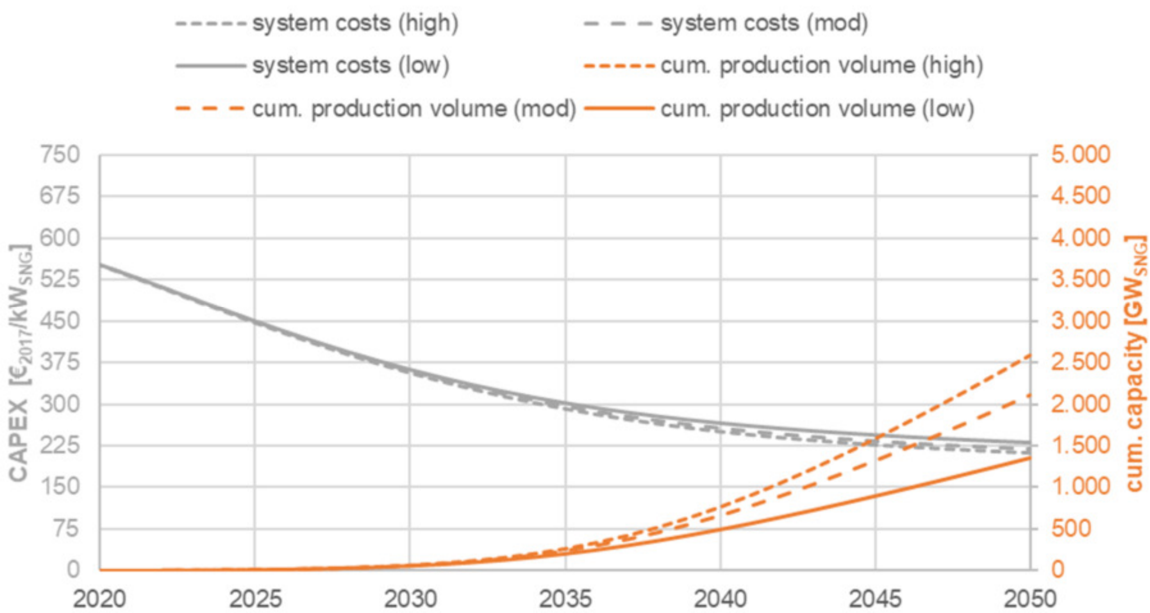


Figure 9-7: Investment cost development for biological methanation systems (5 MW SNG output) depending on their potential future production volumes

Since assumptions made for biological methanation (cf. section 8.3.3) include high uncertainties, the resulting overall learning rate calculated by the model was examined in detail. As it can be seen in the trend in Figure 9-8, it stays in a small range of about 11.5%–12.5% over the investigated period. To assess this value, the process of biogas production by the fermentation of biomass was taken as a comparable technological conversion process due to missing reference values for biological methanation. Junginger et al. [166] investigated the technological learning of bioenergy systems in 2006, finding an experience rate of 12% on the investment costs per daily digester capacity. Even though this value is not significant (R^2=0.69), the results for the biological methanation are exactly in that range (assuming a continuous production and static efficiencies throughout the investigated period). Therefore, the evaluations can at least serve as guiding values for forthcoming investigations.

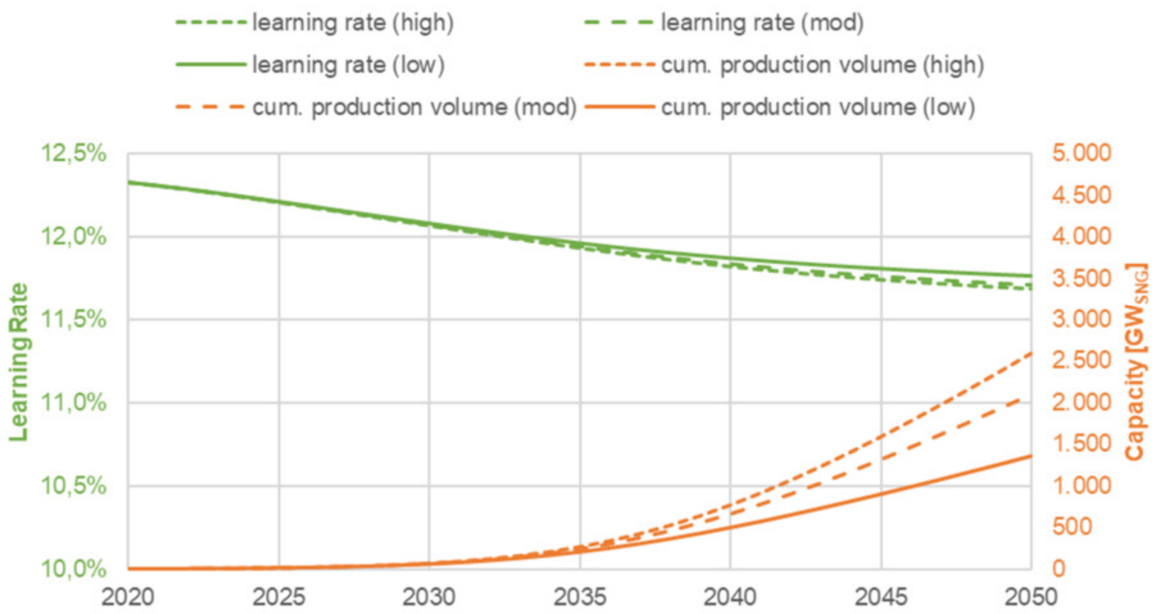


Figure 9-8: Learning rate development for biological methanation systems depending on their potential future production volumes

9.3 Sensitivity to parameter variation

Since the models defined to estimate learning curve effects for PtG technologies imply uncertainties in some degree—in addition to the uncertainties given by the presumed potentials for future deployments of the individual technologies—this chapter is used to evaluate the influence of the variation of model parameters on the predicted cost reduction potentials. As this is primarily meant to be a qualitative analysis, this is done for selected models only to keep the number of variations low. Therefore, if not stated differently, PEMEC electrolysis and catalytic methanation are used for sensitivity analysis as they are the most verified systems of each sub-unit of the PtG plant. Additionally, the considerations were limited to the two “high” PtG deployment scenarios; however, it can be easily transferred to the other scenarios.

9.3.1 Considering replacements

While cumulative production volumes are thoroughly investigated and include spillover effects by considering past and future processing demands for hydrogen and natural gas, the calculated volumes do not include necessary replacements of those units at end of lifetime. Hence, following assumptions were made:

- PEM electrolysis cells are expected to operate for 10 years, on average, for continuous operation (95% yearly work load), based on lifetime trends stated by Bertuccioli et al. [73]
- Electrolysis system as a whole is set with a lifetime of 25 years, based on relevant literature [73]
- Natural gas (fossil and SNG) processing units are expected to run on an average of 25 years before being replaced
- Catalytic methanation reactors are presumed to reach an average lifetime of 10 years
- Since different lifetimes for PEMEC stack and system were defined, the stack production is now decoupled from the system production and dependency parameter is set to “independent” accordingly. This also applies to the reactor module in the methanation system.

Even though the total cumulative production volumes of the implemented modules increase significantly, considering replacements due to limited lifetimes, the observed impact on the learning curves is negligible for both electrolysis and methanation systems, as shown in Figure 9-9 (electrolysis) and Figure 9-10 (methanation). This is mainly caused by the long lifetimes in relation to the observation period.

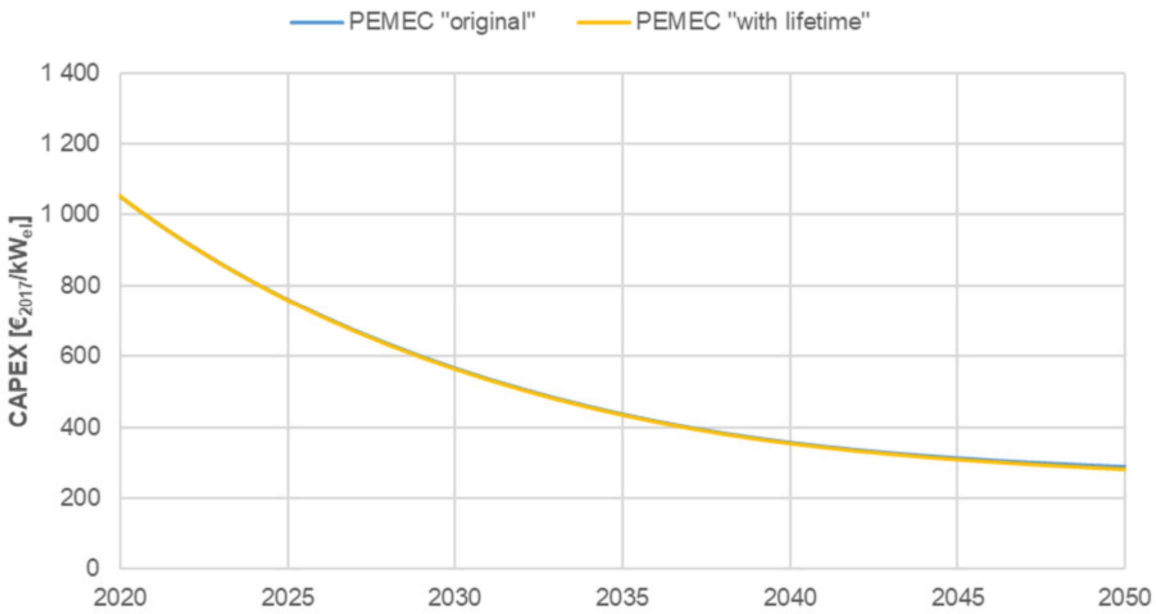


Figure 9-9: Influence of component replacement on the experience curve for PEM electrolysis systems

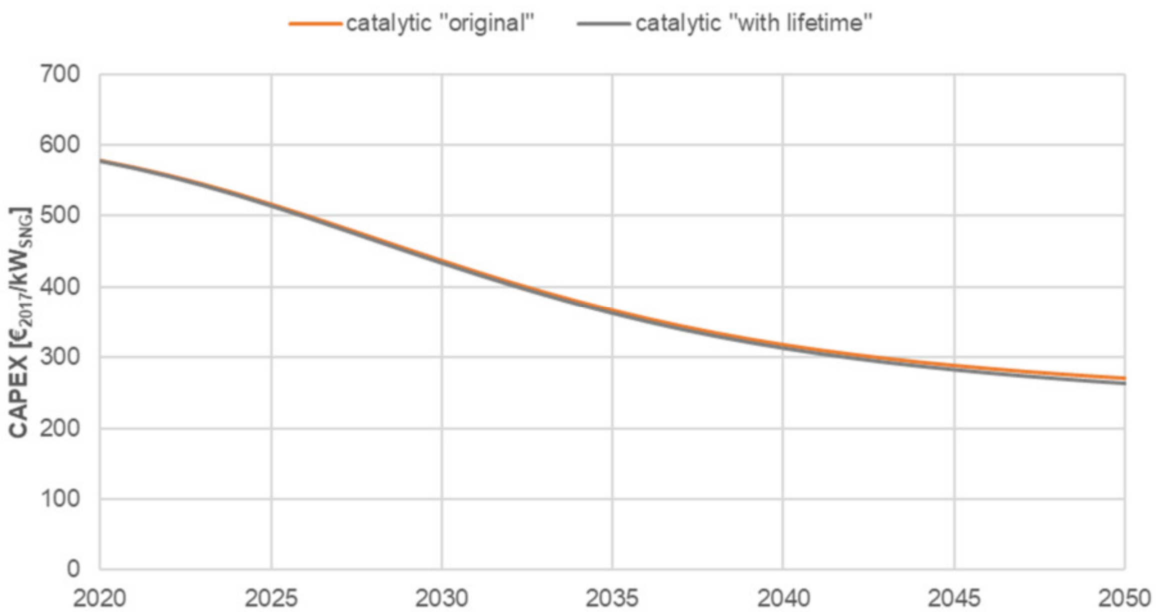


Figure 9-10: Influence of component replacement on the experience curve for catalytic methanation systems

9.3.2 Learning rate variation

Since learning rates presumed for peripheral components could not be verified by comparing them with data in the existing literature, they carry a high potential for uncertainties. To evaluate their influence on the overall learning curve, they have been varied by ±25% off their base values, as defined in Section 5 in the sensitivity analysis. As already mentioned, only peripheral components are affected, including the following:

- Electrolysis:
  - Power Electronics
  - Gas Conditioning
  - Balance of Plant
- Methanation:
  - Electric Installation and Control System (ICT)
  - Gas Conditioning
  - Balance of Plant

For the PEM electrolysis, the observed influence is relatively low, considering the high underlying production volumes. By increasing the learning rates by +25%, the calculated costs for 2050 would decrease by about 13%, whereas a reduction of learning effects would lead to an increase in costs by 17% when compared to the base case. A variation by ±50% would have a significantly higher effect, influencing the outcome by -23% or +38%, respectively.

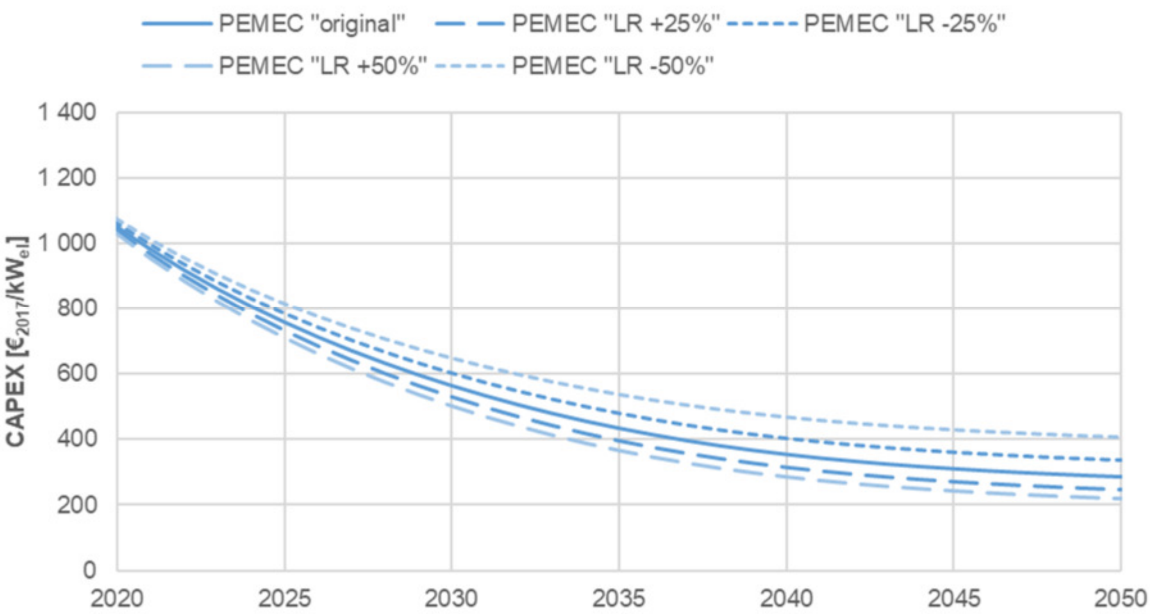


Figure 9-11: Influence of learning rate variation of peripheral components for PEM electrolysis systems

For the catalytic methanation system, the effects are almost comparable to the results above, influencing costs by -14% and +18%, respectively. This is an interesting behavior as the peripheral components take a significantly higher share on the total costs of the whole system when compared to the PEM electrolysis. Therefore, the impact of their learning rates was expected to be higher. This behavior is more observable at higher variations, such as by ±50%, which shows an impact of -25% or rather +42%.

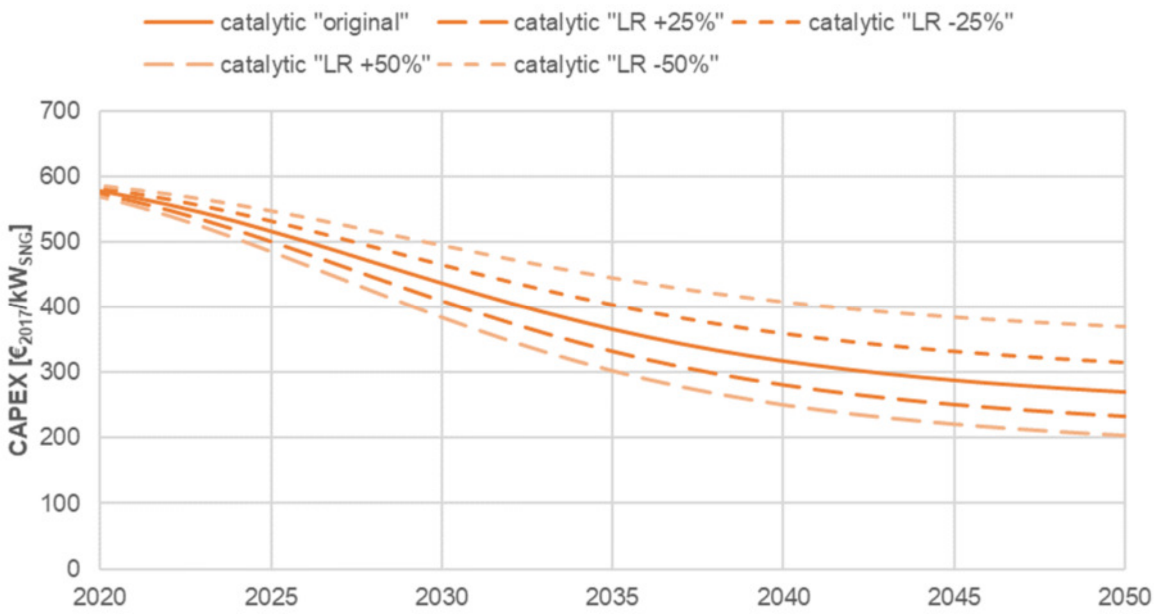


Figure 9-12: Influence of learning rate variation of peripheral components for catalytic methanation systems

9.3.3 Variation of technology share

Since only assumptions can be made for the technology shares in future production volumes of PtG systems, the influence of this aspect on the experience curves has also been investigated as part of the sensitivity analysis. Therefore, the technology shares for electrolysis have been adapted to reach about 40% / 45% / 15% (AEC / PEMEC / SOEC) in 2050, as illustrated in Figure 9-13. The resulting experience curves for the investigated electrolysis systems in Figure 9-14 shows that the influence, when compared to the base case (cf. Figure 8-14), is negligible, even if the technology share is reduced by more than 50%, as it is the case for SOEC.

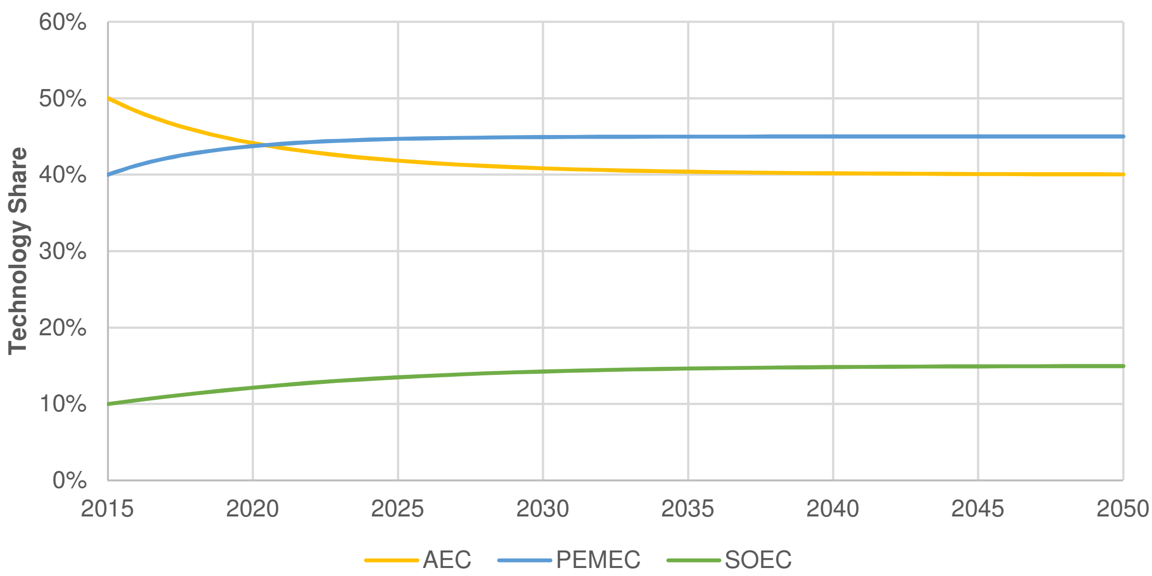


Figure 9-13: Adapted technology shares for electrolysis systems

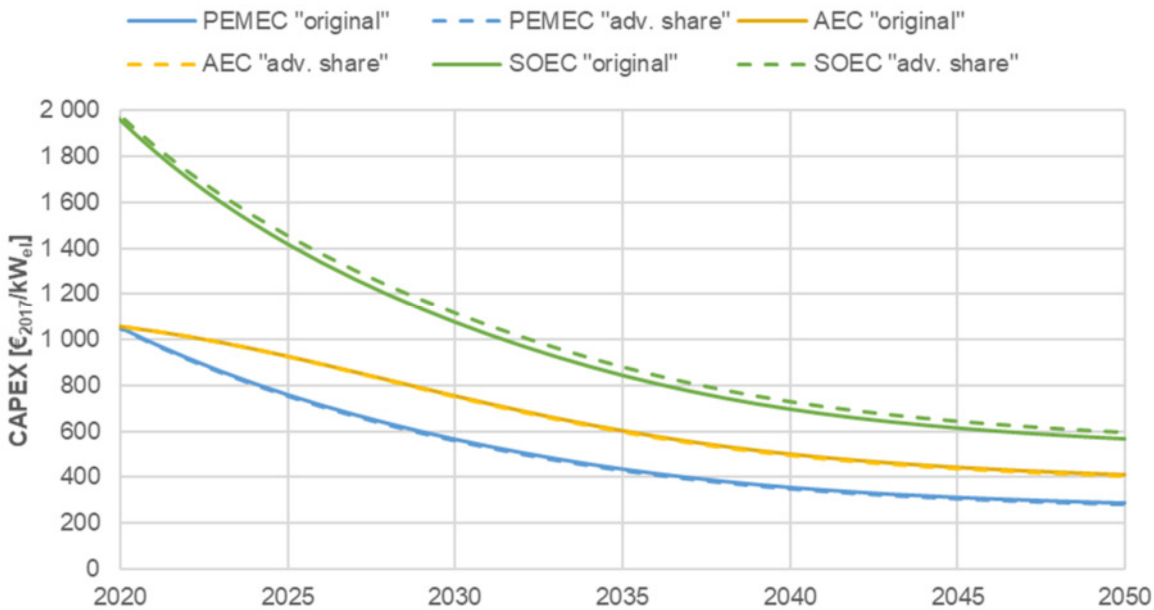


Figure 9-14: Influence of technology share variation on learning curves for electrolysis systems

The same analysis is also done for methanation on the basis of a significant variation in the technology shares from 75% / 25% (catalytic / biological; shown in Figure 9-15). The results in Figure 9-16 show that the effect on the experience curve is marginal, which means that the errors on the calculated results indicated by these parameters are low.

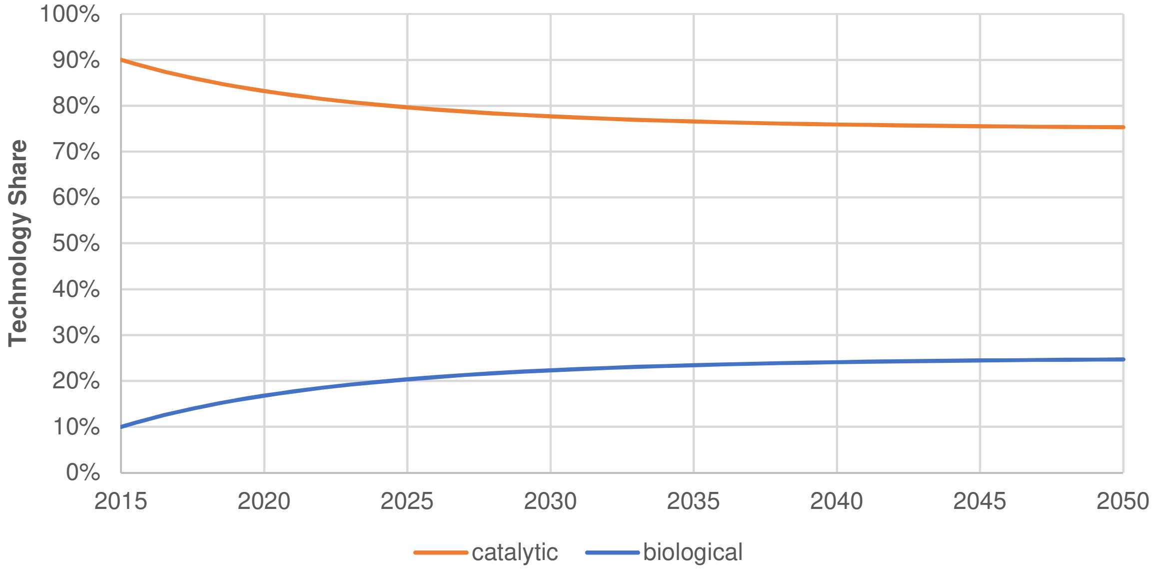


Figure 9-15: Adapted technology shares for methanation systems

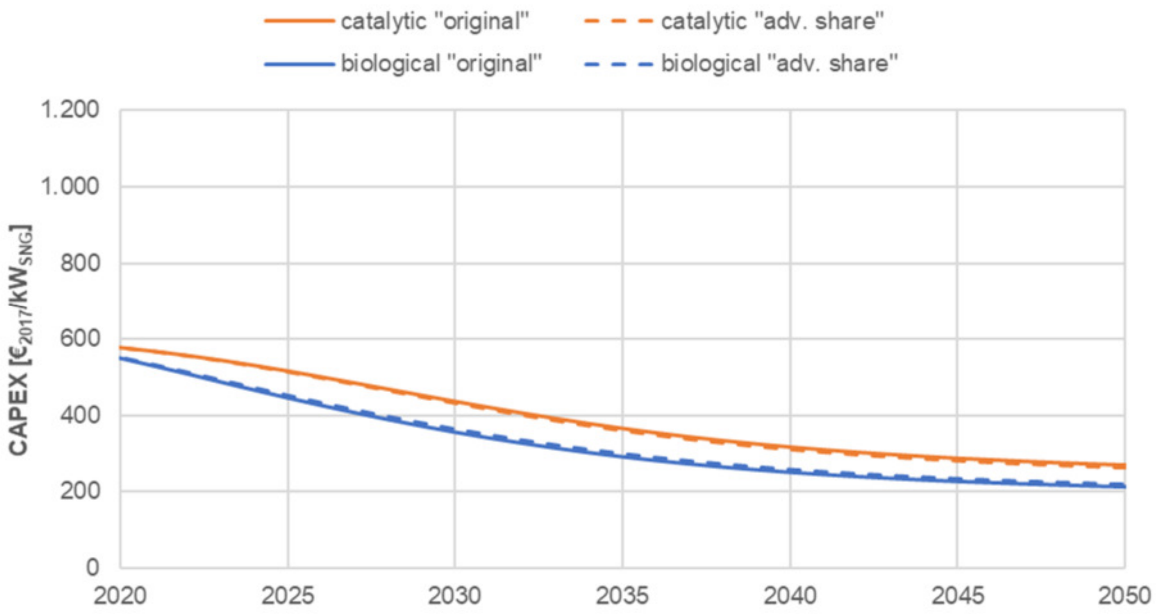


Figure 9-16: Influence of technology share variation on learning curves for methanation systems

9.4 Cost predictions with nominal prices

When comparing monetary amounts or costs at different times, the inflation—the change in the general price level over time—must be considered. The inflation rate represents the percentage that indicates the change in the general price level in an economy when compared to the previous year. In the European Union, the inflation is measured with the harmonized index of consumer prices (HICP). The European annual inflation was fluctuating in the last 10 years between approximately -0.5% and 4% and was, on average, about 2 %, see Figure 9-17. It must be noted that, in chemical engineering, it is also quite common to use a construction price index (e.g., ProcessNet Chemieanlagenindex Deutschland PCD) for calculating investment costs.

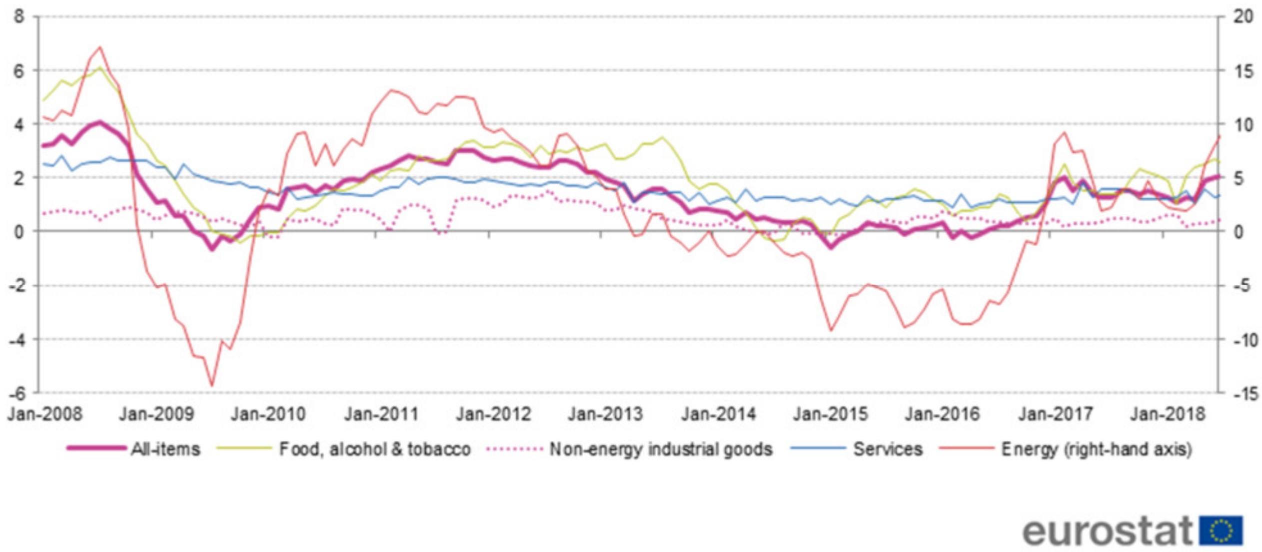


Figure 9-17: Euro area annual inflation and its main components (%) from January 2008 to July 2018 [167]

In this context, also the price development of the materials used for the production of the components must be briefly discussed. In general, the prices of materials will not decline but rather increase in the future, when considering the nominal price developments and thus taking into account the consumer price index. However, the analyzes in the report regarding experience curves and economies of scale refer to real price developments, which does not take into account global market price increases (for example, oil price fluctuations or the normally controlled volatilities of central banks over their interest rate policy). Certainly, the real prices of some materials (such as platinum, lithium) will potentially increase in the future, especially if they are subject to a foreseeable rapid shortage, but In the case of a rapid development of new mining areas in a global context, the real prices might also decrease.

With regard to labor costs, it should be noted that the development of labor costs is not itself a relevant aspect of technological learning. Rather, reducing labor costs per produced unit is responsible for the learning curve effects through increased productivity (increased efficiency due to work experience) and changing manufacturing processes. However, it should also be noted in a global context, that the future demand for PtG products requires the production of enormous quantities of PtG plants and thus new production regions must be opened in the coming decades, whereby some of them have much lower labor costs than for example Germany.

In the following figures, the development of the specific investment costs of electrolyzers and methanation units until 2050 for real costs (the reference year 2017, $€_{2017}$) and the nominal costs (assumed inflation 1 % and 2 %) are shown. The specific investment costs (real cost, $€_{2017}$) are taken from the cost predictions in chapter 9.1 for different electrolyzer systems with 5 MW, and chapter 9.2 for methanation units with 5 MW SNG-output power.

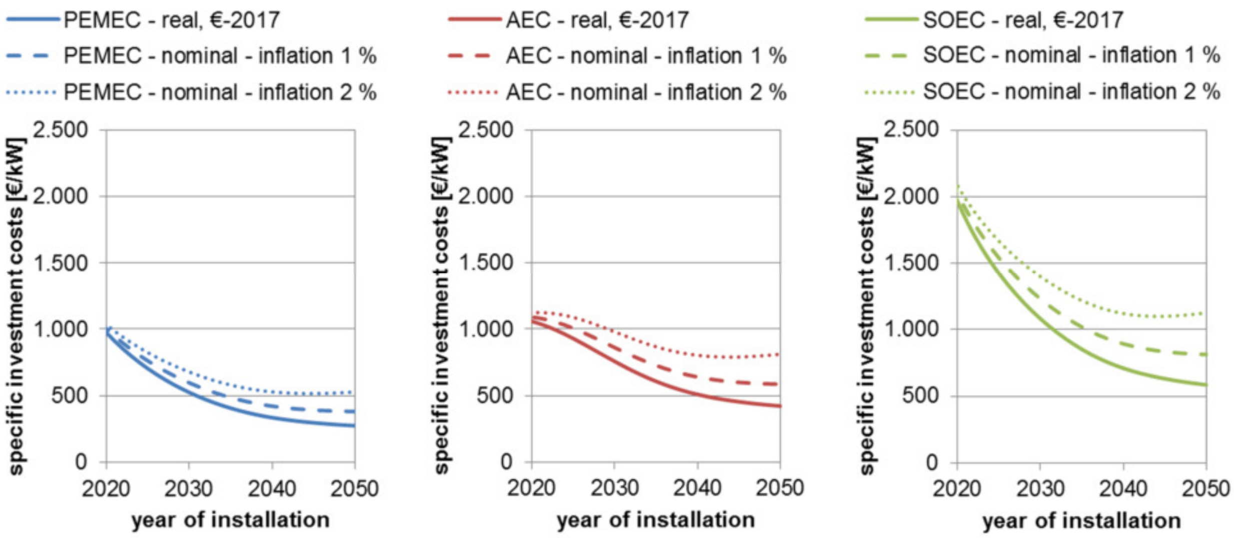


Figure 9-18: Development of specific investment costs of electrolyzers until 2050 for real costs ($€_{2017}$) and nominal costs (inflation 1 % and 2 %)

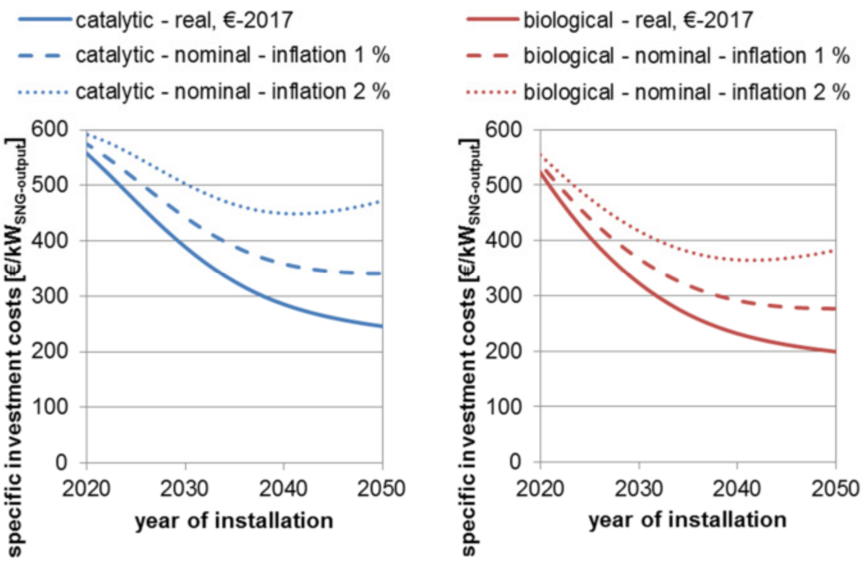


Figure 9-19: Development of specific investment costs of methanation units until 2050 real costs (€$_{2017}$) and nominal costs (inflation 1 % and 2 %)

The nominal costs in the year 2050 are about 40% higher (inflation rate 1%) as real costs (€$_{2017}$). If the inflation rate is assumed to be 2%, then the nominal costs would be about 90% higher as real costs. This means that, depending upon the inflation rate in the year 2050, up to 90% higher costs, when compared to 2017 values, must be expected to obtain the same electrolyzer or methanation system. However, the cost reduction due to learning curve effects is more pronounced than the general price increase (inflation) and counteracts the inflation, resulting in a reduction in nominal costs for components of the PtG system.

Additionally, no significant change in technology, such as the implementation of additional functions, was taken into account for calculating the future investment costs. If additional functions are considered, this would lead to an increase in real costs, since it is no longer the reference plant from 2017, but a further developed plant with additional functions. Therefore, the cost reduction due to learning curve effects may be offset by the implementation of additional features (and thus additional costs), and the real cost of the PtG may only slightly decrease, remain the same, or even increase over time.

10 Conclusions

The use of experience curves is an important measure to evaluate potential future production costs for emerging technologies. Especially in terms of the transition of the global energy system to renewable energy sources, the learning curve theory can help to estimate the learning investment, which is necessary for renewables to be competitive with incumbent technologies. Furthermore, this allows recommendations on regulatory frameworks as a driving factor for the enforcement of novel technologies. The elaboration of this deliverable D7.5 “Report on experience curves and economies of scale” shows the potential effects of the technological learning on the future investment costs of PtG technologies available and researched today.

In general, the formal concept of **experience curves** describes the decline of real costs by a constant percentage (learning rate) for every cumulative doubling of its produced volume and therefore represents a relationship between the costs of a product and the experience, expressed in cumulative production of that product. Also the term economies of scale in this deliverable refers **solely to the effect of real cost reductions through an increase of the production volume** and not to cost reductions in consequence of an increase in size in form of upscaling (e.g. of nominal power).

Since common approaches for the estimation of learning effects, which define a single learning rate for a certain technology, require an observation of the production cost development over several magnitudes of cumulative production volumes, they are obviously unsuitable for emerging technologies, which have not yet reached a certain market penetration. Additionally, an intense literature review, which was performed on various technologies established in the energy sector, revealed a lack of comparison of experience curves between similar technologies in a macroscopic manner.

The approach in this deliverable to investigate the effects of technological learning at a component or production process level allows circumventing the difficulties mentioned above. It provides possibilities to incorporate experiences on direct production processes, while the low-level view enables interchangeability between different products and technologies with minimal adaptions. Furthermore, the stiffness of the learning curve following the conventional theory of constant learning rates at a macro level suspends the possibility of allowing an easier adaptation of the learning curve to the various stages of technology readiness.

However, in order to use the advantages of the CoLLeCT model, a fundamental knowledge on the investigated technologies, and thus a general study on their characteristics, is necessary to reveal the relevant cost structures and incorporated materials and processes. While this task was quite successful for alkaline and PEM electrolysis cells, the results have shown that further improvements will be needed, based on the data gathered for SOEC and methanation reactors. This can be handled either by a more detailed analysis of individual applications or by a harmonization of the technological structure of those devices. Following the former approach allows assessments in the early R&D stages but requires a high adaptation to an individual application; however, the latter one becomes potentially self-fulfilling to a certain extent by increasing the technology readiness.

Alongside the experience rate itself, an increase in the cumulative production volumes is the driving parameter for cost reductions by technological learning. Although high-cost reductions primarily encourage decisions on future investments in certain technologies, these cost reductions cannot be achieved without early investments (=learning investment). To propel renewable energy technologies to an extent where they are competitive with incumbent fossil counterparts, an enforcement of such early investments would be a key factor. The estimated potentials for PtG products (hydrogen and SNG), which are elaborated in this deliverable, assume different amounts of renewable energy sources, and thus appropriate amounts of renewable gases, to be reached in 2050. These amounts require a drastic increase in production of PtG components, which can only be achieved with a mass production. This, however, call for a standardized and mass production-ready design of the components. The resulting production curves to meet the estimated PtG demand provide a rough assessment of the necessary efforts driven not only by manufacturers but also by regulatory frameworks.

Unless otherwise mentioned, cost predictions for the PtG technology in this deliverable are stated as **real costs** (reference year 2017, $€_{2017}$). This means that the inflationary effects that are anticipated and will lead to rising nominal costs have not been considered. Additionally, **no significant changes in technology**, such as an implementation of additional functions, control elements and safety devices or efficiency improvements, have been taken into account for calculating the future investment costs.

The results for future investment costs summarized in Table 10-1 and shown in Figure 10-1 (electrolysis) and Figure 10-2 (methanation) clarify that the determination of current costs has a significant influence on the quality of resulting forecasts. Therefore, the evaluation of initial system costs based on currently available technology is a mandatory task, preceding considerations on experience curves. The literature elaborated on this topic revealed broad bandwidths on available costs data for each investigated technology. While these differences in specific cost data complicate the determination of a starting value, they can be decreased by scaling the data to a common plant size for each technology. On the one hand, this step involving scaling is necessary to harmonize the calculation and clearly distinguish between cost reduction effects from technological learning and scale-up of plant implementations. On the other hand, it presumes additional knowledge on scaling effects for each investigated technology. The determination of those scaling effects is out of the scope of this deliverable and will be examined in detail as part of deliverable D7.7 “Future technology and techno-economic optimization,” incorporating findings from equipment manufacturers and other project partners. Therefore, the scaling factors assumed for the harmonization of the initial product cost used in this study are covered with a relevant uncertainty.

Table 10-1: Summary of calculated cost reduction potential for 5 MW_{el} electrolyzer and 5 $MW_{SNG\text{-}output}$ methanation systems for the years 2030 and 2050 as well as the corresponding learning rates

Technology (System)	Calculated costs			Calculated learning rates (avg.)		
	initial (2017)	2030	2050	initial (2017)	2030	2050
Electrolysis		€/kW_{el}			%	
PEMEC	1,200	530	290	16,8	13,8	12,0
AEC	1,100	760	440	13,1	12,3	11,0
SOEC	2,500	1,090	610	15,6	12,4	11,2
Methanation		€/kW_{SNG}			%	
Catalytic	600	440	280	12,1	12,0	11,7
Biological	600	360	220	12,3	12,1	11,7

Comparing the results of the learning curve analysis, it can be concluded that the influence of the presumed production potential is rather low (e.g. if the cumulative produced volume of electrolyzers produced in 2050 would only reach half of the estimated quantity, the calculated costs would only increase by 12%; this would correspond to an increase from about 290 €/kW to 325 €/kW), especially when compared to the variations given for current technology costs (e.g. an deviation of plus 15% of the initial CAPEX of PEMEC’s would lead to an increase in 2050 of about 5%; this would correspond to an increase from about 290 €/kW to 305 €/kW). Considering the sensitivity analysis that was performed to assess the influences of individual parameters of the calculation model, it becomes clear that the determination of learning rates for peripheral components of the PtG process (e.g., gas conditioning or BoP) are a relevant factor in the future CAPEX development. Regarding the relevant literature on technological learning on PtG systems, this determination is often neglected because only the technological main parts (electrolysis stacks/methanation reactors) are investigated. Therefore, the observation of learning effects on commonly used peripheral components is a relevant topic for upcoming studies, even though they are already highly established and cost reductions on observed short-term are expected to be low, as emerging technologies can re-enable such mechanisms.

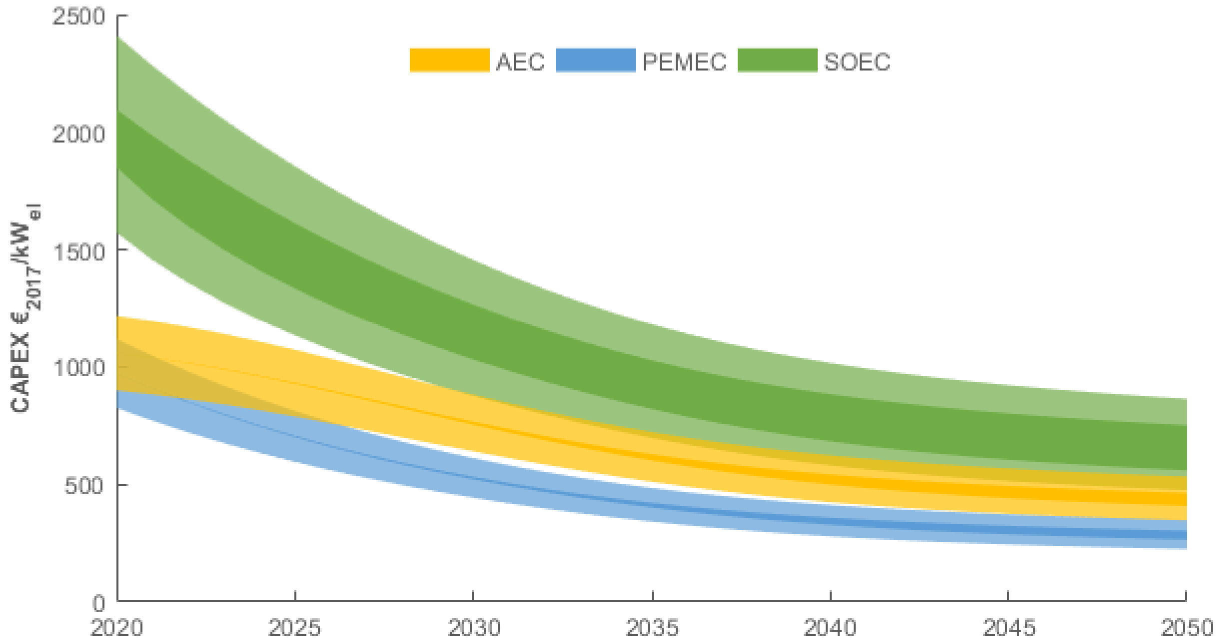


Figure 10-1: Resulting learning curves for electrolysis systems with an uncertainty of ±15% on initial CAPEX (light-colored areas)

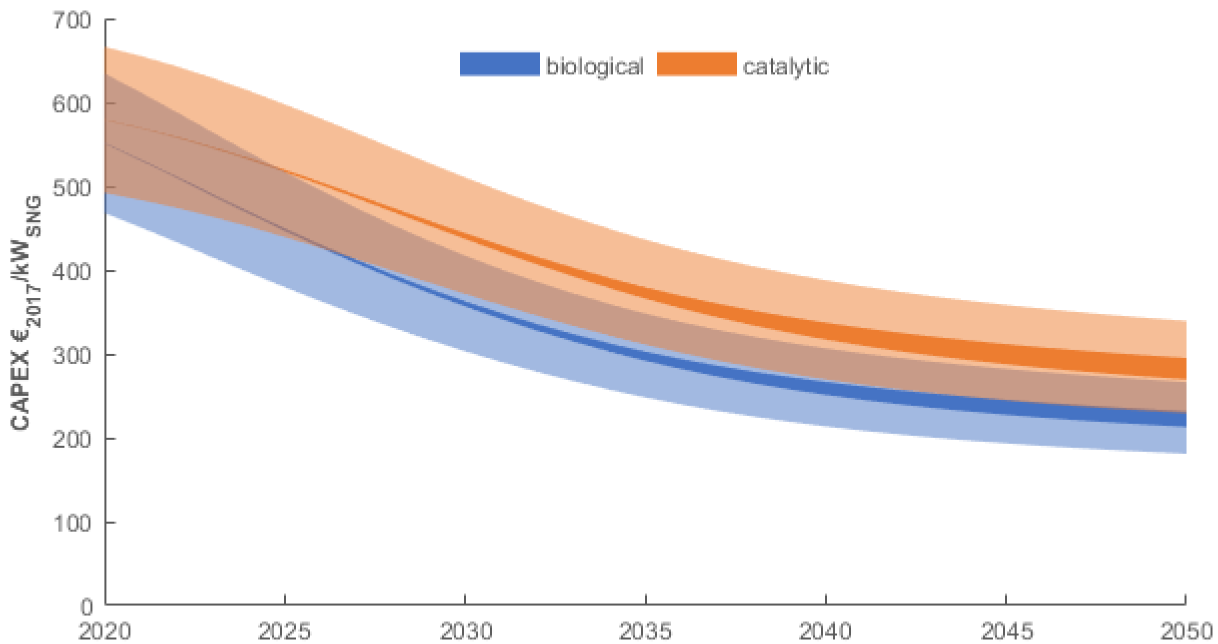


Figure 10-2: Resulting learning curves for methanation systems with an uncertainty of ±15% on initial CAPEX (light-colored areas)

Despite all cost reductions in this deliverable derived from technological learning (resulting from e.g. fix cost degression, reduction of production time, increased specialization, variation in the used resources, improvement of existing production technologies, and optimization of product design with respect to simplify the production process), it has to be kept in mind that the evaluated costs for the whole investigation period represent real costs referenced to the year 2017. This means that the inflationary effects that are anticipated and will lead to rising nominal costs have not been considered. Additionally, no significant changes in the technologies themselves (e.g., increasing efficiencies) or improvements in function or quality, which have no direct effect on the related output, have been considered. As all calculations are specific to the rated power, these improvements will influence the nominal cost reductions through technological learning. Summing up those effects will potentially reduce the effects gained from technological learning or even result in increasing nominal costs in the long-term.

The evaluation of learning curves for novel and established technologies requires the analysis of an adequate amount of historical cost data. Therefore, the availability of this data is mandatory to allow reasonable predictions on the future cost development. While the component-based approach of the CoLLeCT model tries to circumvent this limitation by comparing learning effects on similar sub-components between independent technologies, the collection of base data is still unavoidable, even necessary in a more detailed view, especially in this early stage of model development. Nevertheless, the use of a component-based calculation model allows the incorporation of learning effects at a much lower level, wherein these can be determined more precisely and narrowed down to certain adaptations of the production process for single parts. This would allow the use of experience values for process improvements or the reduction of raw material costs from a unit to mass production, which is usually less obvious for a full technology view.

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Appendix

Appendix 1: Main components of the PtG-process

The main parts of a PtG-technology are the electrolyzer, methanation unit, and CO_2 capturing. The electrolyzer is the main and hence the most important component of a PtG system.

Electrolyzer

In an electrolyzer, water is split into hydrogen and oxygen through a redox reaction. The total reaction is [149]:

$$H_2O \rightarrow H_2 + \frac{1}{2}O_2 \qquad \textbf{Eq. 1}$$

The partial reactions of the redox reaction are different, depending on the electrolyzer construction. Currently, there are three different types of electrolyzers available. All the three types are explained in the following sections.

Alkaline electrolyzer (AEC)

The AEC is widely used and established in industrial applications. It does not need limited materials, and hence it incurs a relatively low CAPEX. Owing to its low current and operating pressure, further research is focusing on improving these parameters [83]. The AEC is operated with temperatures between 80 and 90°C and ambient pressure.

This type of electrolyzer uses caustic potash (KOH) as electrolyte, a nickel anode, and an activated cathode. The following partial reactions occur [168]:

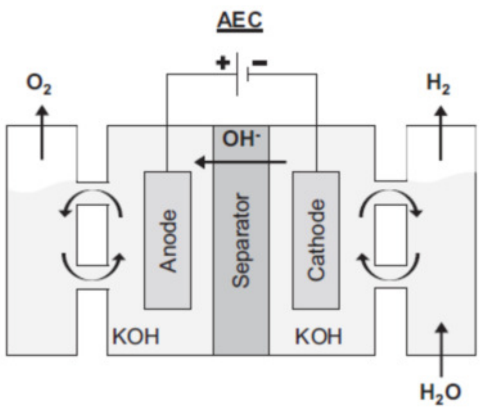
Anode reaction:

$$2\,\mathrm{OH^-} \rightarrow \frac{1}{2}\,\mathrm{O_2} + \mathrm{H_2O} + 2\,\mathrm{e^-} \qquad \textbf{Eq 2}$$

Cathode reaction:

$$2\,\mathrm{H_2O} + 2\,\mathrm{e^-} \rightarrow \mathrm{H_2} + 2\,\mathrm{OH^-} \qquad \textbf{Eq 3}$$

The electrolyzer consists of three parts—the case in which the cathode area and the anode area is separated by a diaphragm and filled with the electrolyte. Appendix - Figure 1 shows the schematic of an AEC.



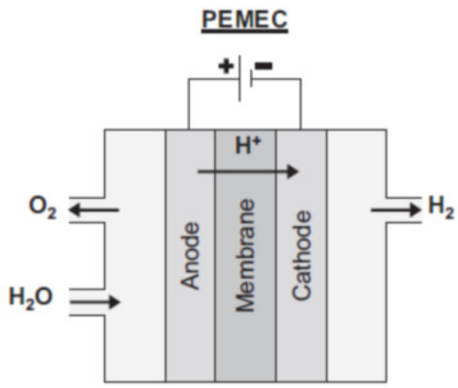
Appendix - Figure 1: Schematic of an AEC [83]

Proton exchange membrane electrolyzer (PEMEC)

PEMECs are mostly used in small-scale applications. When compared to AEC, its advantages include a high cell efficiency, high power density, and flexible operating conditions. However, the materials used for the system (e.g., platinum), its complexity, and later introduction have led to a higher CAPEX than AEC. Another disadvantage of PEMEC is its shorter lifetime when compared to AEC [83].

Further research is focused on material optimization, reducing complexities, and scaling-up the technology. All these three areas would lead to a reduction of CAPEX [83].

A PEMEC uses a proton-conducting membrane as an electrolyte. It also separates the anode and cathode areas. As shown in Appendix - Figure 2, the water enters and the oxygen leaves the system at the anode side, while the hydrogen leaves the system at the cathode side. Appendix - Figure 2 also shows that H^+-ions are exchanged through the polymer membrane [169].



Appendix - Figure 2: Schematic of a PEMEC [83]

The used material for the membrane is normally a perfluoro sulfonic acid polymer (e.g., Nafion). PEMEC is mostly operated with temperatures slightly above 100°C and a pressure of 1atm.

The following partial reactions occur:

Anode reaction:

$$2\,\mathrm{H_2O} \rightarrow 4\,\mathrm{H^+} + \mathrm{O_2} + 4\,\mathrm{e^-} \qquad \textbf{Eq 4}$$

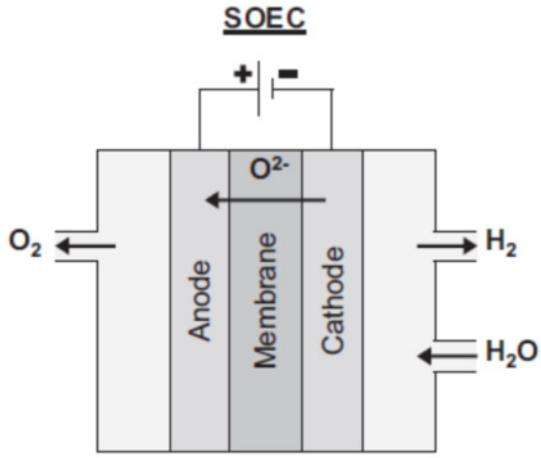
Cathode reaction:

$$4\,\mathrm{H^+} + 4\,\mathrm{e^-} \rightarrow 2\,\mathrm{H_2} \qquad \textbf{Eq 5}$$

Solid oxide electrolyzer (SOEC)

The SOEC uses Y_2O_3 electrolyte, which is stabilized with ZrO_2. The water enters the electrolyzer and the hydrogen leaves it at the cathode side while the oxide leaves it at the cathode side. An SOEC differs from the AEC and PEMEC especially due to its operating conditions. It is a high-temperature electrolyzer and therefore operated at temperatures around 900°C and a pressure of 1–10 bar. Beside these advantageous conditions it has low material costs, high electrical efficiency and is operable in reverse mode as fuel cell [83], [170].

Appendix - Figure 3 shows the basic construction of SOEC. The O^{2-}—Ions conduct through the electrolyte.



Appendix - Figure 3: Schematic of a SOEC [170, 83]

The following partial reactions occur:

Anode reaction:

$$O^{2-} \rightarrow \frac{1}{2}\, O_2 + 2\, e^- \qquad \textbf{Eq 6}$$

Cathode reaction:

$$H_2O + 2\, e^- \rightarrow H_2 + O^{2-} \qquad \textbf{Eq 7}$$

Summary - Electrolyzer

Appendix - Table 1 shows an overview of the different parameters of AEC, PEMEC, and SOEC systems.

Appendix - Table 1: Technological characteristics of AEC, PEMEC, and SOEC systems [83]

	AEC	PEMEC	SOEC
Current densitiy (A/cm²)	0.2-0.4	0.6-2.0	0.2-2.0
Cell voltage (V)	1.8-2.4	1.8-2.2	0.7-1.5
Voltage efficiency ($\%_{HHV}$)	62-82	67-82	<110
Cell area (m²)	<4	<0.3	<0.01
Operating temperature (°C)	60-80	50-80	650-1000
Operating pressure (bar)	<30	<200	<25
Production Rate (m^3_{H2}/h)	<760	<40	<40
Stack energy (kWh_{el}/m_{H2}^3)	4.2-5.9	4.2-5.5	>3.2
System energy (kWh_{el}/m_{H2}^3)	4.5-6.6	4.2-6.6	>3.7
Gas purity (%)	>99.5	99.99	99.9

	AEC	PEMEC	SOEC
Lower dynamic range (%)	10-40	0-10	>30
System response	Seconds	Milliseconds	Seconds
Cold-start-time (min)	<60	<20	<60
Stack lifetime	60,000-90,000	20,000-60,000	<10,000
Maturity	Mature	Commercial	Demonstration

Methanation

A key factor in the project STORE&GO is the methanation process, which contributes toward maintaining natural gas or SNG in the existing European infrastructure as a clean energy source, but with an already advantageous and continuously improving environmental footprint.

First, the gas input in STORE&GO is not syngas[9], the normal source for methanation, but a mixture of H_2, CO_2, and, depending on the source, CO. Hence, the focus will be on information with this input. Second, in the project, three processes will be used. Work package 2 (WP2) and WP4 both demonstrate a cooled-reactor methanation. A biological methanation will be demonstrated in WP3.These three processes are of special interest within the data collection and can be compared with a “commercial standard” of fixed bed methanation.

In this chapter, the most common methanation processes are described based on the available data on the current situation. This includes available data on technological parameters and costs. Since scale effects and cost reduction developments (learning effects) differ for different parts of the installations, as far as possible, costs are split up.

The catalytic or chemical methanation processes are subdivided into the following three different technologies [103]:

- Fluidized bed
- Fixed bed
- Three phase reactor
- Structure reactors

The biological methanation is subdivided into the following:

- In-situ
- Ex-situ

<u>Chemical methanation</u>

The methanation process is exothermic and releases a substantial amount of heat, which will increase the gas temperature [103]:

$$CO_2\,(g) + 4\,H_2\,(g) \rightleftharpoons CH_4\,(g) + 2\,H_2O\,(g) \qquad \Delta H_{ro} = -165.1\ \text{kJ/mol}$$

$$CO\,(g) + 3\,H_2\,(g) \rightleftharpoons CH_4\,(g) + 1\,H_2O\,(g) \qquad \Delta H_{ro} = -206.3\ \text{kJ/mol}$$

[9] Syngas, or synthesis gas, is a fuel gas mixture consisting primarily of hydrogen, carbon monoxide, and very often some carbon dioxide.

The equilibrium of a gas reaction can be influenced by pressure if the number of molecules on both sides is different. If the pressure is increased, then the position of the equilibrium would move in the direction of the least number of molecules. Since the number of molecules in the product site (methane on the right-hand side of the double arrow) is lower, high pressure helps to shift the reaction to methane. Considering that the reaction is exothermic, a higher temperature has the opposite effect. It can accelerate the reaction and lower the equilibrium concentration of methane. There are two other important reactions. The first reaction comprises the water gas shift reaction, balancing the amount of several gasses:

$$CO\ (g) + H_2O\ (g) \rightleftharpoons CO_2\ (g) + H_2\ (g) \qquad \Delta\ H_{ro} = -41.2\ kJ/mol$$

The second is the Boudouard reaction, which can deactivate the catalyst by covering it with a carbon layer:

$$2\ CO\ (g) \rightleftharpoons C\ (s) + CO_2\ (g) \qquad \Delta\ H_{ro} = -172.5\ kJ/mol$$

Hence, this catalytic process faces several problems—the increasing gas temperature caused by the exothermic reaction of the gas and the decline in activity of the catalyst by carbonaceous coke deposition. Hence, cooling of the gas is an important issue, which emerges in all the chemical processes. Coke deposition can be suppressed to a certain extent by a small excess of hydrogen[10]. Several reliable catalysts have been developed and made commercially available for the methanation reaction. They have such a high activity that further development has no priority. Hence, mass and heat transfer limit the reactor performance [171].

General commercial process

Chemical or catalytic methanation is already a commercially available technology used in several industrial applications. However, the general commercial process uses syngas and not hydrogen and CO_2, as in the STORE&GO project. Syngas can also be diluted with other gasses like nitrogen.

- Catalyst:
  In most cases a nickel-based catalyst is used because of its relative high reactivity, good CH_4 selectivity, and the low cost when compared to more precious metals like Ni, Ru, Rh, and Co. However, a nickel-based catalyst requires a clean syngas with respect to halogeneous and sulphurous compounds, among others [103].

- Carrier:
  A metal oxide, such as alumina oxide, is usually the carrier metal because of its high specific surface, but other materials are also mentioned.

- Temperature:
  Low temperature methanation takes place in the range of 200–550 °C and high-temperature methanation between 550–750 °C [172]. The carrier metal is usually a metal oxide, such as alumina oxide, because of its high specific surface.

- Efficiency:
  The energetic efficiency of the methanation process is in the range of 70% to 85%, with the remaining 15%–30% being emitted as a high-temperature heat (with respect to the energy in the outgoing gas stream relative to the energy in the incoming gas stream) [172].

[10] The presence of ethene and ethyne can also cause carbon formation. Hence, in the gasification processes, which produce SNG, those components has to be removed first.

Since natural gas also contains higher alkanes, such as ethane, propane, and butane, high concentrations of methane are needed to reach the same combustion value. To reach a conversion of 98% of the CO_2, a temperature of 225°C is needed at 1 bar and 300°C at 20 bar [103].

Demo plant Falkenhagen (STORE&GO WP2)

In Germany, a lot of surplus sustainable energy is available. There is already an existing 2 MW_{el} hydrogen production unit, and the hydrogen is injected in the gas grid with a 1.6 km hydrogen pipeline. A small 60% of the output will be used for methanation, which would be equivalent to 1.1–1.2 MW_{el}. The methanation plant in Falkenhagen will be provided with a honeycomb or structured wall reactor methanation technology. CO_2 would be generated from a biomass related process (biogas or bioethanol plant) under the following conditions: <0.1 ppmv H_2S and about 9 bar. The output is connected to the high-pressure transport gas grid of 55 bar(g). The optimal operating conditions are neither isothermal nor adiabatic, and a high-pressure steam might be produced. Thermal heat integration with other industrial facilities is an option. The involved partners are E.ON Gas Storage (EGS), the Karlsruhe Institute of Technology (KIT), ThyssenKrupp Industrial Solutions (TKIS), and DVGW (Deutscher Verein des Gas- und Wasserfaches). The target of the methanation plant is to convert 210 Nm^3/h H_2 to 57 Nm^3/h SNG at 280-320 °C and 10 bar with an efficiency of 80%. The 630 $kW_{thoutput}$ plant will produce 2.2 to 2.3 GJ_{SNG}/h.

The isothermal structured wall/honeycomb methanation reactor, mainly developed by KIT and TKIS will be erected and commissioned by TKIS, together with all the necessary gas upgrading facilities near the electrolyzers in two container modules. This reactor concept uses metallic honeycombs as catalyst carriers and an in-situ heat extraction system. After 15 years of research, this concept was converted into a demo scale in 2014 (container module). The structure has a low-pressure loss, and the metal gives a good heat transfer. For catalytic applications like methanation, the metallic honeycomb structure is impregnated with a catalytic washcoat. In the project, the reactor concept can go up to 20 bar and 350 °C. For the methanation-specific catalyst types, based on innovative Ni and Ru based catalysts, it must be adapted to be suitable for the developed coating technology.

Demo plant Troia (STORE&GO WP4)

A 200 kW_{el} $PtCH_4$ plant will be built in Troia in Italy at the existing INGRID PtG demonstration site. INGRID is an ongoing FP7 European R&D project (large-scale demonstration project). The location is designed for a 1.2 MW_{el} alkaline electrolyzer, producing a maximum of 240 m^3/h H_2. The electrolyzer will use intermittent electricity from PV and wind farms in the region Puglia through an electric grid, which will provide a modular load from 0 to 1.2 MW. The CO_2 is generated through an adsorptive CO_2 enrichment from the atmosphere; this process is facilitated by Climeworks (CWKS). The target is 16 kg CO_2/h. The industrial partners for this plant will be *ATMOSTAT Alcen (ATM), Engineering (ENG), Hystech (HST), IREN Energia SPA (IREN), studio BFP (BFP), Municipality de Troia, Politecnico di Torino (POLITO),* and *CEA (Commissariat à l'énergie atomique et aux énergies alternatives*). The excess heat of the new PtG unit will be used in the CO_2 capture process for releasing captured CO_2 at 95 °C. The SNG will be liquefied and distributed to regional customers with a tank-truck. The liquefaction step will also help to clean the methane from the not reacted hydrogen.

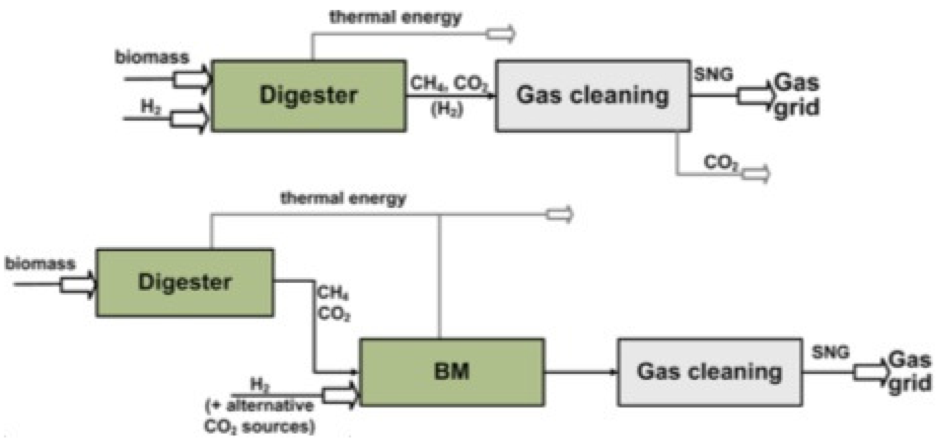
The modular milli-structure reactor based catalytic methanation concept is developed and commissioned by ATMOSTAT Alcen (ATM) and CEA. Heat carrier oil (Dowterm A) will be used for the heat recovery (oil temperature 300 °C). The Heat EXchanger-Reactor (HEX reactor) has longitudinal direction channels for the reaction and the transverse direction channels for cooling; refer to Appendix - Figure 4. This allows a higher mass and heat exchanges. The catalyst powder of nearly 200–300 µm is inserted in reactive channels. The gas goes in plug flow through the reactor and has a high conversion rate. The reactor is tested at pressures up to 50 bar and space velocities of 1000/h to

10000/h has been demonstrated. The plant will have parallel reactors each with an inlet flow of 8-10 Nm^3/h. The startup time would be within 15 minutes, and the load may vary from 20 to 100%.

Appendix - Figure 4: Methanation heat exchanger reactor of 0,8 Nm3/h of CH4 (Picture from Lacre http://www.hex-reactor-lacre.com/en/technologies/)

Biological methanation

In a conventional process, biogas is produced with about 60% of methane and about 35% of carbon dioxide. This existing carbon dioxide can also be methanized by using a surplus of hydrogen. There are two ways for implementing methanation. They are shown in Appendix - Figure 5. Besides the ex-situ pathway whereby methanation is carried out with thermophilic archaea with hydrogen and carbon dioxide (lower one), there is a second method that is the same as the last stage in the digestion phase of biogas production (upper one). This is referred to as in-situ methanation in the digester.



Appendix - Figure 5: Two ways for biological methanation

In-situ methanation

Because for in situ methanation the methane formation rate depend on the CO_2 production rate only low methane formation rates (MFRs) of < 0.1/h are possible. The investments costs are low because an existing digester can be used. The circumstances in the digester are not optimal for methanation. Therefore, it is very difficult to facilitate a total conversion of the CO_2. According to MicorbEnergy Gmbh (Germany), it is possible to increase the methane concentration in biogas from 52% to 75% with in-situ methanation. A laboratorial scale experiment with a 3.5 L continuous stirred-tank reactor (CSTR), in 2011, in a manure digester facilitates the conversion of 80% of hydrogen to methane and a reduction in the CO_2 concentration from 38 % to 15 % (Gang, 2012). The gas output also contained

20% H_2. The experiment was done under ambient pressure and 55 °C. The improvement options could involve mixing (stirring) to improve the gas liquid mass transfer.

Conclusions:

- Low cost because existing digester can be used.
- CO_2 removal would still be needed for injection into the gas grid.
- H_2 removal would still be needed for high injection rates into the gas grid. However, when compared to pure hydrogen, five times more gas can be injected.
- Capacity limited to digester capacity.
- Location must be the digester location (no free choice for optimal location in electricity and gas infrastructure).

Ex-situ methanation

In the ex-situ situation, optimal reaction conditions can be chosen. Two publications mentioned that the methane formation rates (MFRs) of 21.3 to 28.7 per hour are measured with a reactant gas flow rate per reactor volume (GSVH) of 120 and 300 per hour in a continuous stirred-tank reactor (CSTR). However, with 60% and 13.4 vol.-%, the methane concentration is too low for injection into the gas grid. When the GSVH was lowered with a factor 4, the methane concentration increased to nearly 75% (but the MFR also decreased with a factor 4). In a trickle bed reactor and a GSVH of 0.3 per hour, a methane concentration of 98% was reached. The methanation was implemented by using the Methanothermobacter spp[11]. In all the reactor designs, the supply of hydrogen to the microorganisms is a limiting factor. Hence, this is the main improvement option. Additionally, it is mentioned the reactor design (e.g., the use of membrane reactors) and research in microorganisms

Conclusions:

- A methanation reactor is needed. Hydrogen gas transportation to the microorganism is considered a limiting factor. High methane concentration can only be reached with very (too) low gas loads.
- CO_2 removal is still needed for injection into the gas grid.
- H_2 removal is still needed for high injection rates into the gas grid.
- Capacity is limited to digester capacity, if this is the CO_2 source.
- Dependence on the CO_2 source
- More possibilities for an optimal location in electricity and gas infrastructure.

<u>Demo plant Solothurn (STORE&GO WP3) – ex situ</u>

The Swiss demonstration site (WP3) at Solothurn will witness a 700 kW_{el} PtG plant. In April 2015, a 350 KW_{el} PEM electrolyzer (and hydrogen storage) was installed for making hydrogen for the (5 bar) gas; today, the maximum hydrogen content is 2%. The limiting factor for the hydrogen injection is the gas demand in the summer. The target is to convert PV electricity in the summer into methane, which can be stored in the gas infrastructure, to be used as a fuel in the winter. Since electricity from the grid will be expensive most of the time, for this installation electricity from a CHP (Combined Heat and Power) unit, the same location will be used. The CO_2 is generated from a nearby wastewater treatment plant. The plant will be connected to the local electricity and gas distribution grid and to a

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[11] Methanothermobacter marburgensis is a thermophilic and obligatory autotrophic archaeon. Thermophilic means that the microbe survives at a higher temperature of 40+°C when compared to other microbes. Autotropic means that it is used as an inorganic substance (or sunlight) to convert CO_2 into glucose. It is an archaeon because it has no cell nucleus and it is not a bacteria; the single cell microbes are divided in Bacteria, Archaea, and Eukaryota.

district heating system. Regio Energie Solothurn (RES), the local utility, will be the operator. The plant is commissioned by Electrochaea (ELEC). The other research partners are the *Hochschule Rapperswil (HSR), EMPA (Eidgenoessische Materialpruefungs- und Forschungsanstalt), EPFL (Ecole Polytechnique Federale de Lausanne),* and *SVGW (Schweizerische Verein des Gas- und Wasserfaches).* RES will double its electrolysis power and install a 120 m^3/h hydrogen methanation (about 330 $kW_{thoutput}$).

The biological methanation is commissioned by Electrochaea (ELEC). The target is to reach a methane formation rates (MFRs) of 8.3 L/L reactor/h, but with a gas conversion rate of 98%. A specific energy consumption in the range of 7 kW/m^3 reactor is aimed while reducing the specific costs by 20%, when compared to the state-of-the art technology.

CO_2-separation

Investment costs for CO_2 sequestration are not easy to define in general. It is reasonable to set a reference for specific costs, according to the used CO_2 source. Affordable sequestration rates strongly depend on concentration of carbon dioxide in the, usually gaseous, source stream and the underlying emitting process. As the CO_2 sources and the reference values for assessing investment costs differ a lot, it seems more practical—at least for the usage of carbon dioxide in the methanation process— to value the needed CO_2 as an operating supply, and therefore represent its costs as per ton CO_2 depending on its source and sequestration technology, respectively.

Technology

In this section, the three most important CO_2 capturing technologies within the project STORE&GO will be discussed—CO_2 from biogas or bioethanol plants, CO_2 from wastewater treatment plant, and direct air capture.

CO_2 from biogas or bioethanol plant

Biomethane plants—biogas plants with gas treatment and feeding into the gas grid—are a good option for using unused CO_2 as a biogenic gas source. The produced CO_2 mostly shows a high concentration (up to 99 vol.-%); additionally, since it has been captured from the atmosphere during the formation of the biomass, it is by definition climate neutral [111].

For the extraction from CO_2 from bioethanol production, the same conditions as explained above can be applied. Based on the assumption that the gas stream of the fermentation process only contains pure CO_2, the only necessary processing would be the dehydration and compression [113].

CO_2 from wastewater treatment plant

Since the sewage gas, which is released during the treatment of water, contains 50-60% methane and 40-50% CO_2 plus small amounts of attendant materials, a high amount of CO_2 is produced. Due to the gas composition, which is similar to the described biogas from biogas plants, the sewage gas can be directly methanized and the same costs can be used [173].

Direct air capture

Another way of producing synthetic natural gas (SNG) from a CO_2 neutral source is by using CO_2 captured from the atmospheric air. If a CO_2 capture process follows the combustion of the produced SNG, it can also facilitate atmospheric CO_2 reduction. However, since air contains only a small amount of CO_2 of approximately 400 ppm, this technology is more complex.

There are different processes for CO_2 air capture: absorption in solvents, adsorption on solids condensation in a cryogenic distillation process, and the separation of air with membranes. Due to the small amount of CO_2 in the atmosphere and the needed water/CO_2 separation in the adsorption, the cryogenic and membrane process is considered energy intensive and therefore not suitable for PtG plants. The absorption in solvents is considered as the only option for PtG plants [111], [174].