E3S Web of Conferences **349**, 02004 (2022) https://doi.org/10.1051/e3sconf/202234902004
LCM 2021

Prospective LCA and LCC applied on different Power-to-Gas technologies

Jan Christian Koj[1*], *Freia Harzendorf*[1], *Petra Zapp*[1], *and Klaus Görner*[2]

[1] Forschungszentrum Jülich, Institute of Energy and Climate Research – Systems Analysis and Technology Evaluation (IEK-STE), 52425 Jülich, Germany

[2] Universität Duisburg-Essen, Chair of Environmental Process Engineering and Plant Design, 45141 Essen, Germany

Abstract. Power-to-Gas technologies enable the integration of non-dispatchable renewable energy sources into several sectors and help decarbonize and transform them. This study investigates to which extent an increase in Power-to-Gas technology applications affects their prospective environmental and economic performance. A first combined prospective LCA and LCC for different Power-to-Gas technologies based on the learning curve concept is presented. For the considered case study of future electrolysis and methanation, the applicability of the concept is demonstrated and prospective LCA and LCC results are obtained. Under assumed conditions, highest decreases in environmental impacts and costs occur between the years 2025 and 2030. Polymer electrolyte membrane electrolysis shows prospective advantages over alkaline water electrolysis. All results indicate that an extension of Power-to-Gas deployment and accompanying learning effects until the year 2050 can lead to significant reductions of more than 70 % in terms of environmental impacts and life cycle costs.

1 Introduction

Power-to-Gas (PtG) is seen as an important instrument for decarbonizing the industry, energy and transport sectors [1]. However, technological development, supported by Life Cycle Assessment (LCA) and Life Cycle Costing (LCC) studies, is still needed to unfold its potential and to identify sustainable pathways.

An earlier review of LCAs on this topic revealed that methodological aspects in general and of future-oriented LCA in particular are left out or addressed inconsistently for PtG applications so far [2]. Especially descriptions of the way prospective efficiencies and material consumptions are obtained were mostly missing.

This study aims to answer if and to which extent the expected increase in PtG affects its prospective environmental impacts and life cycle related costs. Within a case study two technologies for Power-to-H_2 (PtH_2) and one for Power-to-CH_4 (PtCH_4) pathways are considered and their current and prospective environmental impacts are calculated and

* Corresponding author: j.koj@fz-juelich.de

compared. For the presented assessments results of the centre of excellence “Virtual Institute - Power to Gas and Heat” project framework are considered. To the authors' knowledge, no combined prospective LCA and LCC based on learning curves of PtG technologies has yet been conducted.

2 Methods and case study description

There is a broad range of quantitative and qualitative methods to analyse prospective technological developments [3], of which the learning curve concept was selected for this study. The learning curve concept is a suitable tool as it is based on learning effects. These effects describe the experience gained within manufacturing processes over time, affecting not only the technological performance but also the environmental impacts and costs.

A publication by Wright in 1936 [4] served as the basis for most of the further work on this subject. Wright analyzed technology costs and their development, using the example of aircraft construction. He discovered that the time required, or unit labor cost, for each aircraft built decreases by a constant percentage as the cumulative number of aircraft produced doubles. A better manufacturing efficiency by increasing production can be considered as the reason [5]. Consequently, learning curves describe the relationship of the increase in production or cumulative capacities of a good and cost reduction [6].

Over the past decades, different models of learning curves have been developed [7]. Eq. 1 has been considered as essential for this study.

$$C_t = C_0 \left(\frac{X_t}{X_0}\right)^{-\beta} \quad (1)$$

C_0 indicates costs (unit costs, investment costs or labour costs) at time t=0. X_0 and X_t stand for capacities of technologies at time t=0 and a prospective time t. β is the applied learning parameter, that can be calculated by a logarithmic equation based on a learning rate. An economic learning rate of 10 % means that for each doubling of cumulative installed capacity, the costs decrease by 10 %. In literature, the terms learning and experience curves are rarely clearly distinguished from each other and are often used synonymously [5, 6]. Thus, in this work, only the term learning curve is used. Additionally, within this study the expression environmental learning curve is used if the concept is applied on LCA.

In LCAs, environmental learning curves can be used in the phases Life Cycle Inventory (LCI) and Life Cycle Impact Assessment (LCIA). Environmental learning curve concepts are considered as an option to obtain LCI data for future-oriented LCAs [8]. They can be applied on technology efficiencies or material consumption. Furthermore, an environmental learning curve approach to estimate future inputs (materials or energy) was developed and mathematically formulated by Bergesen et al. [9]. Within this approach the costs of eq. 1 are replaced by the amount of direct inputs and a parameter β, describing learning specifically for these inputs (materials or energy), is used. On the other hand, there are environmental learning curve concepts that have a direct future-oriented effect on the LCIA phase by indicating future trends in environmental impacts [9, 10]. Some authors assumed, that the economic learning rates of an established technology can also be applied for environmental learning curves as a rough approximation [11, 12]. Arnold [11] describes as reason for this assumption, that further influencing factors on the learning diminish as the technology becomes more established. Following this approach, same economic and environmental learning rates are assumed to calculate the learning parameter β for costs and environmental impact forward projection with eq. 1. For the environmental learning curve C_0 indicates the environmental impact (e.g. global warming potential) of a technology at time t=0.

Within the assessed case study, current and prospective conditions until the year 2050 are compared. The spatial scope is Germany. As electricity input wind onshore is assumed. Base are environmental values for the start year of the assessed period provided by the “Virtual

Institute – Power to Gas and Heat" project. Two different electrolysis types for PtH_2 are considered: alkaline water electrolysis cells (AEC) and polymer electrolyte membrane electrolysis cells (PEMEC). Additionally, an integrated $PtCH_4$ system using hydrogen from PEMEC for the catalytic methanation (CM) process is assessed. For each of these technologies a "high" and a "low" capacity increase from the year 2020 until the year 2050 is assumed based on [6, 13]. With regard to the learning curve calculation, information on worldwide capacities, as illustrated in Fig. 1, is required.

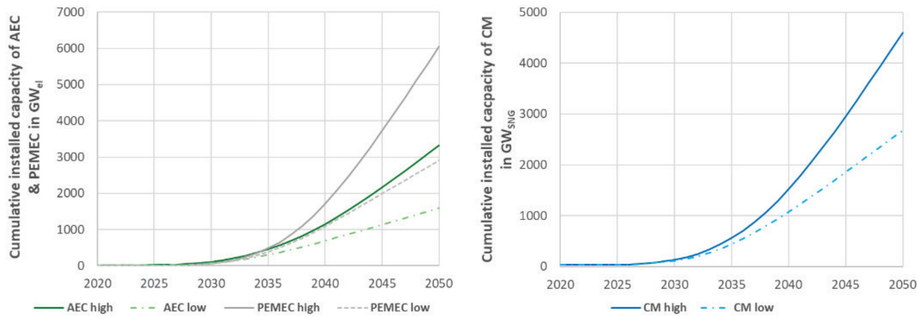

Fig. 1. Assumed cumulative installed global capacities of AEC, PEMEC (left diagram) and CM (right diagram) till the year 2050 based on [6, 13].

While highest absolute increases occur in the distant future, highest relative increases (multiplication rates of capacities) are expected between the years 2025 and 2030. With regard to the different electrolysis technologies higher increases in cumulative installed capacity are assumed for PEMEC compared to AEC. As typical system size 5 MW is considered. For the LCC additionally an up-scaling to 50 MW in 2050 is analysed. The assumed projections are in the range of other projections on a global scale and political hydrogen strategies. Projections expect multi-gigawatt capacities of electrolysis in the year 2030 [14] and multi-terawatt capacities in the year 2050 [15]. Regarding hydrogen strategies Germany and the European aim on multi-gigawatt capacities in the year 2030. Germany has an electrolysis capacity target of 5 GW and the European Union of 40 GW.

For calculating prospective environmental impacts, learning rates for established PtG technologies had to be obtained. In a literature research for electrolysis, different learning rates between 8 % [16] and 18±13 % [17] were identified. For CM only one publication with same learning rates (13 %) for methanation and electrolysis was found [18]. A trend was observed that highest values are given in publications of the distant past of the last century, when the technologies were less mature. To present more current conditions and a range of developments, three different learning rates for PtG systems were taken into account, 8 %, 9.6 %, and 12 %.

The geographic and temporal scope of the case study and life cycle-based assessments have been already mentioned. There are some more assumptions related to the goal and scope of the LCA and LCC. For this study an attributive cradle-to-gate LCA approach is chosen. The assessment is related to the functional unit "1 kg gas". The LCA software used is openLCA in version 1.10.3. Background data for the life cycle inventory preparation are taken from the LCA database ecoinvent (version 3.7.1) in the system model "cut-off by classification". The considered LCA methodology for the impact assessment is ReCiPe in version 2016 v1.1 Midpoint (hierarchist). Due to its significance the LCA in this study analyzes the global warming potential (GWP)/climate change in particular. With regard to the global warming potential, the reference to a period of 100 years was chosen (GWP100).

The economic assessment is linked to assumptions within the project "STORE&GO" ([6, 13]). Besides values for whole systems, also learning rates for individual components are pointed out, which were taken into account for the current study. The learning rates of system components reach from 7 – 13 %.

3 Results

First, results of the prospective environmental assessment for AEC, PEMEC, and CM supplied with hydrogen from PEMEC are illustrated in Figure 2 exemplarily for the impact category climate change.

A main outcome is that the highest environmental impact reduction between time steps is given between 2025 and 2030. This is because highest relative multiplication rates of installed capacity are assumed for this period. The impact reductions from the year 2025 to the year 2030 depend on the learning rate and technology considered and reach up to more than a third. From the year 2040 onwards calculation no longer show significant reductions in environmental impacts as capacity multiplication rates decrease. Highest impact reductions of the assessed PtG technologies until 2050 are projected for PEMEC, reaching up to more than 80 %, due to the highest assumed capacity increase. Moreover, increasing impact reductions can be observed for higher learning rates. In comparison to the variation between high and low capacities, the learning rate variation between 8 % and 12 % affects higher impact reductions.

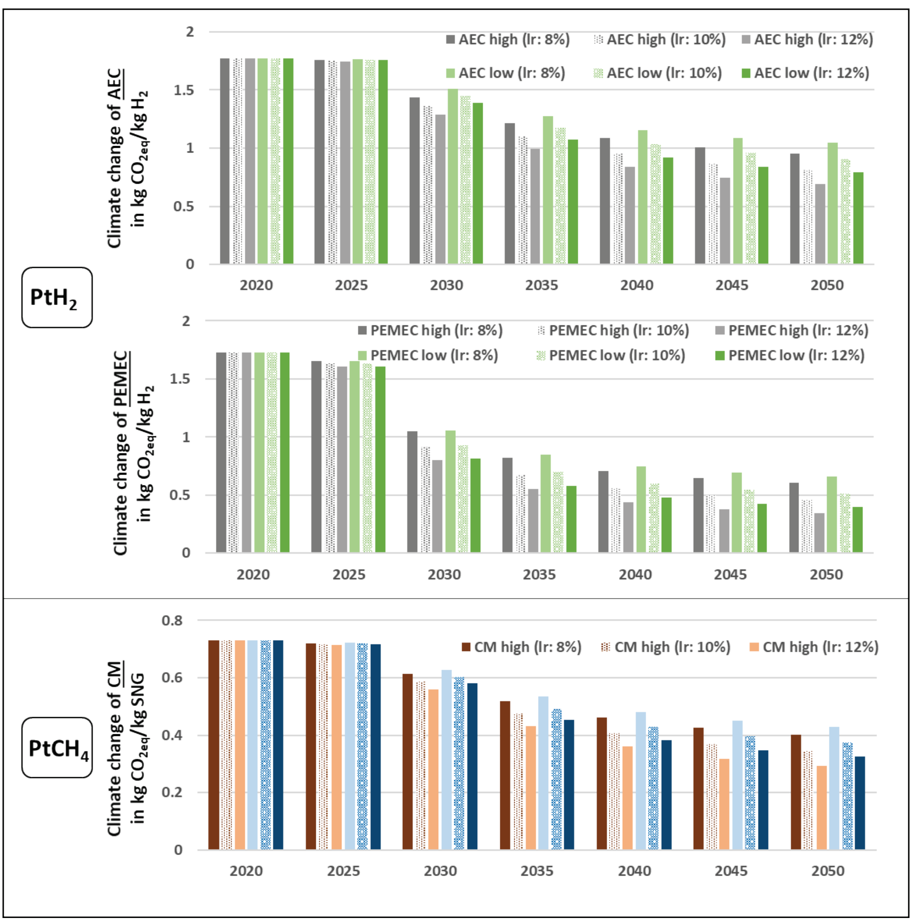

Fig. 2. Developments of climate change impacts for PtH_2 (AEC & PEMEC) and $PtCH_4$ (CM) until the year 2050 (lr: learning rates).

For the same technologies and period prospective economic results are calculated and illustrated in Fig. 3, showing the capital expenditures (CapEx). In the LCC variations of learning and additional up-scaling are combined. Additionally, contributions of different system components with different learning rates are considered. Variations of learning rates and capacity increases, as shown in Fig. 2, are not considered. With regard to the contribution of individual components, stacks reveal highest CapEx contributions for AEC. In comparison to AEC lower costs are calculated for PEMEC in 2050 due to a significantly higher capacity multiplication rate between 2025 and 2030 and a constant learning rate.

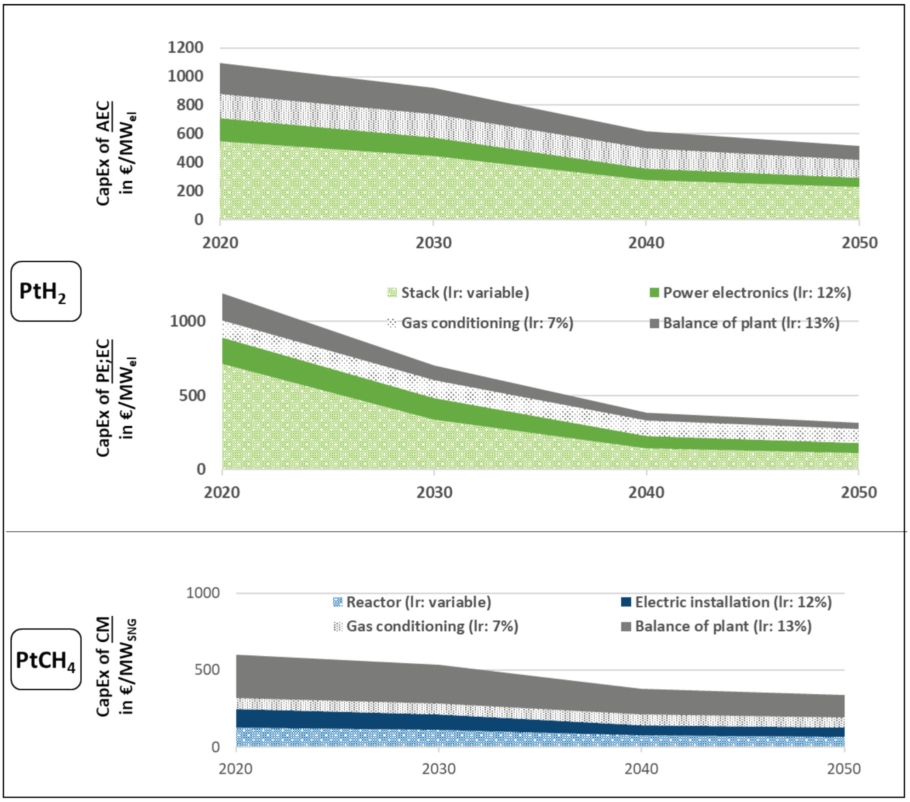

Fig. 3. CapEx developments for PtH_2 (AEC & PEMEC) and $PtCH_4$ (CM) (lr: learning rates) until the year 2050 based on [6, 13].

For the $PtCH_4$ system costs decrease but to a lower extent compared to the electrolysis technologies. For this technology balance of plant shows highest CapEx contributions.

4 Discussion and conclusions

This study demonstrates a decrease in life cycle environmental impacts and costs of PtG technologies if their capacities are significantly expanded. Capacity increase and learning rates affect the environmental impacts and life cycle costs of these technologies. The learning could cause environmental impact decreases of more than 80 % and CapEx reductions of more than 70 % until 2050 for highest assumed learning rates and capacity increase.

Compared to results of conventional technologies, the results for PtH_2 and $PtCH_4$ operation based on wind energy indicate clear environmental advantages. A former study

[19, 20] calculated around 10.6 kg CO_{2eq}/kg (88 g CO_{2eq}/MJ) for hydrogen from steam reforming of natural gas as well as 3.2 kg CO_{2eq}/kg (63 g CO_{2eq}/MJ) for natural gas including upstream impacts. If the first value is compared with the PtH_2 results, a significantly better environmental performance is already evident in 2020. The environmental advantages also apply to $PtCH_4$ compared to conventional natural gas as a reference. For PtH_2 impact reductions of over 95 % compared to the reference are possible in the year 2050. In the best case for $PtCH_4$ impacts can be reduced by around 90 % in comparison to the reference.

It was shown that learning curves are a quantitative method applicable for a combined prospective LCA and LCC. The combined LCA and LCC has a common basis, the assumed cumulative installed capacities (Fig. 1). However, there are disparities that must be highlighted. The system level has been considered for LCA and the component level for LCC. Furthermore, the presented LCC takes up-scaling into account, while it is not yet considered for LCA. Future work should constitute a uniform approach.

The LCA results were shown for the indicator “climate change”. Literature indicates that the approach can also be applied on further impacts. Consideration of additional impact categories would provide a more complete picture of the environmental impacts. LCC results are limited to CapEx values. Thereupon the levelised costs of PtG technologies [21, 22] could be assessed as a more common indicator of LCC.

The approach to use economic learning rates from established technologies [11, 12] for environmental learning curves is a possible but facilitated approach. However, it needs further analysis of its robustness and applicability. An analysis with own calculations of learning rates and their application on environmental learning curves, especially to obtain prospective LCI data for construction and operation of PtG, would deliver further insights about environmental contributions of different life cycle stages. A comparison of the different environmental learning curve approaches is intended to identify strengths and weaknesses of different approaches.

For all kinds of prospective life cycle-oriented assessments, uncertainty is a challenge and has to be addressed. In this study, the uncertainty of results was reduced by considering many time steps (one-year steps rather than ten-year steps) for the capacity increase. Additionally, different learning rates and prospective capacities were used within the environmental assessment to show ranges of prospective results. However, different kinds of uncertainty analysis, that could be applied in further work, would improve the accuracy of results.

Funding of the center of excellence “Virtual Institute - Power to Gas and Heat” (EFRE-0400151) by the “Operational Program for the promotion of investments in growth and employment for North Rhine–Westphalia from the European fund for regional development” (OP EFRE NRW) through the Ministry of Economic Affairs, Innovation, Digitalization and Energy of the State of North Rhine-Westphalia is gratefully acknowledged.

References

1. M. Sterner, *Power-to-Gas*, in *Handbook of Climate Change Mitigation and Adaptation*, W.-Y. Chen, T. Suzuki, and M. Lackner, Editors. 2016, Springer New York: New York, NY. p. 1-51.
2. J.C. Koj, C. Wulf, and P. Zapp, *Environmental impacts of power-to-X systems - A review of technological and methodological choices in Life Cycle Assessments.* Renewable and Sustainable Energy Reviews, 2019. **112**: p. 865-879.
3. S.I. Olsen, M. Borup, and P.D. Andersen, *Future-Oriented LCA*, in *Life Cycle Assessment: Theory and Practice*, M.Z. Hauschild, R.K. Rosenbaum, and S.I. Olsen, Editors. 2018, Springer International Publishing: Cham. p. 499-518.

4. T.P. Wright, *Factors Affecting the Cost of Airplanes.* Journal of the Aeronautical Sciences, 1936. **3**(4): p. 122-128.
5. G. Thomassen, S. Van Passel, and J. Dewulf, *A review on learning effects in prospective technology assessment.* Renewable and Sustainable Energy Reviews, 2020. **130**: p. 109937.
6. H. Böhm, et al., *D7.5 Report on experience curves and economies of scale*, in *Innovative large-scale energy storage technologies and Power-to-Gas concepts after optimisation*. 2018.
7. C.H. Glock, et al., *Applications of learning curves in production and operations management: A systematic literature review.* Computers & Industrial Engineering, 2019. **131**: p. 422-441.
8. A. Louwen and J.S. Lacerda, *Chapter 2 - The experience curve: concept, history, methods, and issues*, in *Technological Learning in the Transition to a Low-Carbon Energy System*, M. Junginger and A. Louwen, Editors. 2020, Academic Press. p. 9-31.
9. J.D. Bergesen and S. Suh, *A framework for technological learning in the supply chain: A case study on CdTe photovoltaics.* Applied Energy, 2016. **169**: p. 721-728.
10. M. Caduff, et al., *Wind Power Electricity: The Bigger the Turbine, The Greener the Electricity?* Environmental Science & Technology, 2012. **46**(9): p. 4725-4733.
11. K. Arnold, *Treibhausgas-Optimierung des Einsatzes von Technologien zur Erzeugung und Nutzung von Biomethan auf Basis nachwachsender Rohstoffe als Baustein eines zukunftsfähigen Energiesystems*, in *Fakultät für Ingenieurwissenschaften, Abteilung Maschinenbau und Verfahrenstechnik*. 2015, Universität Duisburg-Essen: Essen.
12. S. Simon, K. Arnold, and T. Targiel, *Synoptische Auswertung von Szenarien und Lernkurven - Endbericht AP 3. BioEnergieDat - Bereitstellung einer aktuellen und harmonisierten Datenbasis als Beitrag zur Weiterentwicklung einer nachhaltigen Bioenergiestrategie*. 2013: Stuttgart; Wuppertal.
13. H. Böhm, et al., *Projecting cost development for future large-scale power-to-gas implementations by scaling effects.* Applied Energy, 2020. **264**: p. 114780.
14. C. Wulf, P. Zapp, and A. Schreiber, *Review of Power-to-X Demonstration Projects in Europe.* Frontiers in Energy Research, 2020. **8**(191).
15. IRENA, *Green Hydrogen Cost Reduction: Scaling up Electrolysers to Meet the 1.5°C Climate Goal*. 2020: Abu Dhabi.
16. T. Gül, et al., *An energy-economic scenario analysis of alternative fuels for personal transport using the Global Multi-regional MARKAL model (GMM).* Energy, 2009. **34**(10): p. 1423-1437.
17. K. Schoots, et al., *Learning curves for hydrogen production technology: An assessment of observed cost reductions.* International Journal of Hydrogen Energy, 2008. **33**(11): p. 2630-2645.
18. M. Thema, et al., *Necessity and Impact of Power-to-gas on Energy Transition in Germany.* Energy Procedia, 2016. **99**: p. 392-400.
19. A. Liebich, et al., *Detailed analyses of the system comparison of storable energy carriers from renewable energies - Final report*, G.E. Agency, Editor. 2021: Dessau-Roßlau.
20. A. Liebich, et al., *Detailed analyses of the system comparison of storable energy carriers from renewable energies - Annex*, G.E. Agency, Editor. 2021: Dessau-Roßlau.
21. W. Kuckshinrichs, T. Ketelaer, and J.C. Koj, *Economic Analysis of Improved Alkaline Water Electrolysis.* Frontiers in Energy Research, 2017. **5**(1).

22. S. Morgenthaler, et al., *Site-dependent levelized cost assessment for fully renewable Power-to-Methane systems.* Energy Conversion and Management, 2020. **223**: p. 113150.