



Credits: Audi AG

# LCM 2021

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

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# 1. Introduction

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Power-to-Gas (PtG) is seen as an important instrument for decarbonizing the industry, energy & transport sectors.

Studies and roadmaps expect significant increases of produced & installed PtG systems.



## Research questions (RQ)

### RQ 1

**Will the production/capacity increase affect the environmental impact of these technologies?**

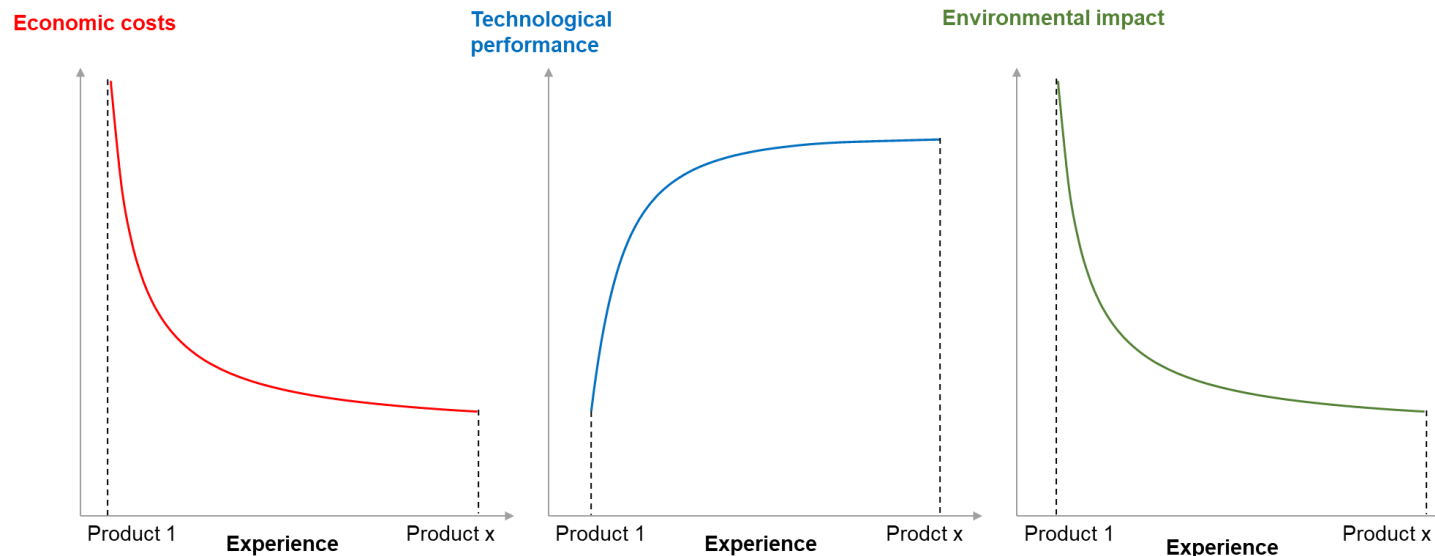
### RQ 2

**How can I quantify the prospective environmental performance and life cycle cost development?**

# 1. Introduction

## Prospectivity and learning

Manufacturing processes & practices develop over time based on learning effects.



Source: Own illustration based on Thomassen et al. (2020)

Method to estimate this prospective economic, technological & environmental progress:

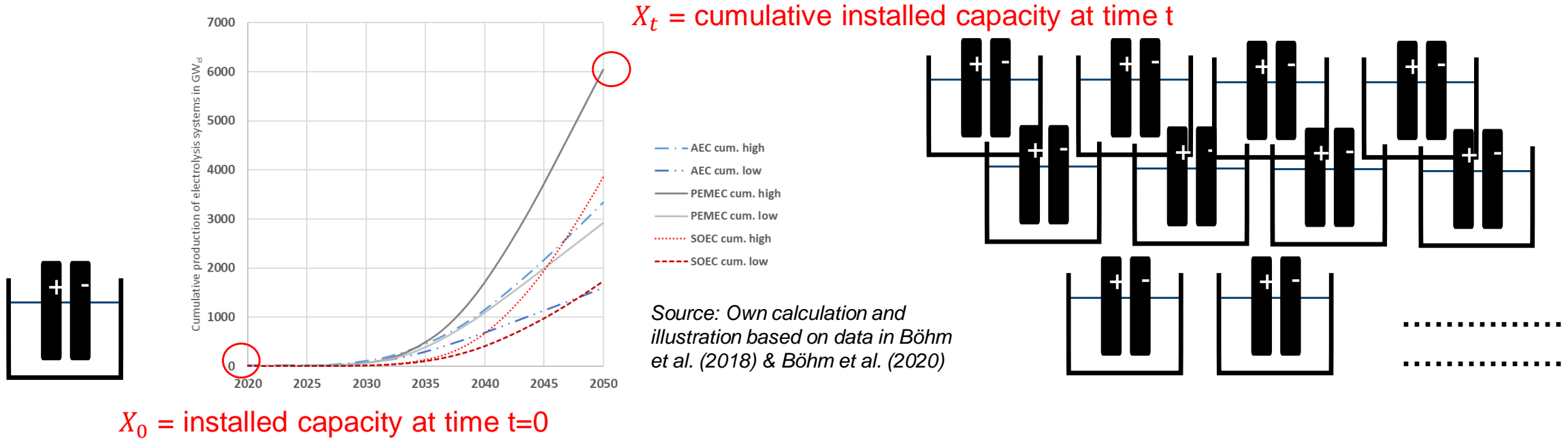
Learning curves



A case study of combined prospective LCA & LCC applied on different PtG technologies is presented – incorporating learning curves

## 2. Methods

### Economic learning curve concept – Example



Capacity values for 2020-2050 are given – what more do I need for prospective cost assessment?

$C_0$  = costs (unit costs, investment costs or labour costs) at time  $t=0$

$C_t$  = costs at time  $t$

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

$\beta =$  learning parameter or degradation factor

$$\beta = \log\left(\frac{1}{1-lr}\right) / \log 2 \quad (lr: \text{learning rate})$$

## 2. Methods

### Environmental learning curve concepts

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E.g. Caduff et al. (2012), Arnold (2015) and Bergesen & Suh (2016) apply the economic learning approach on environmental assessments.

They replace costs by material or energy inputs or environmental impacts

Prospective material input,  
energy input or  
environmental impact

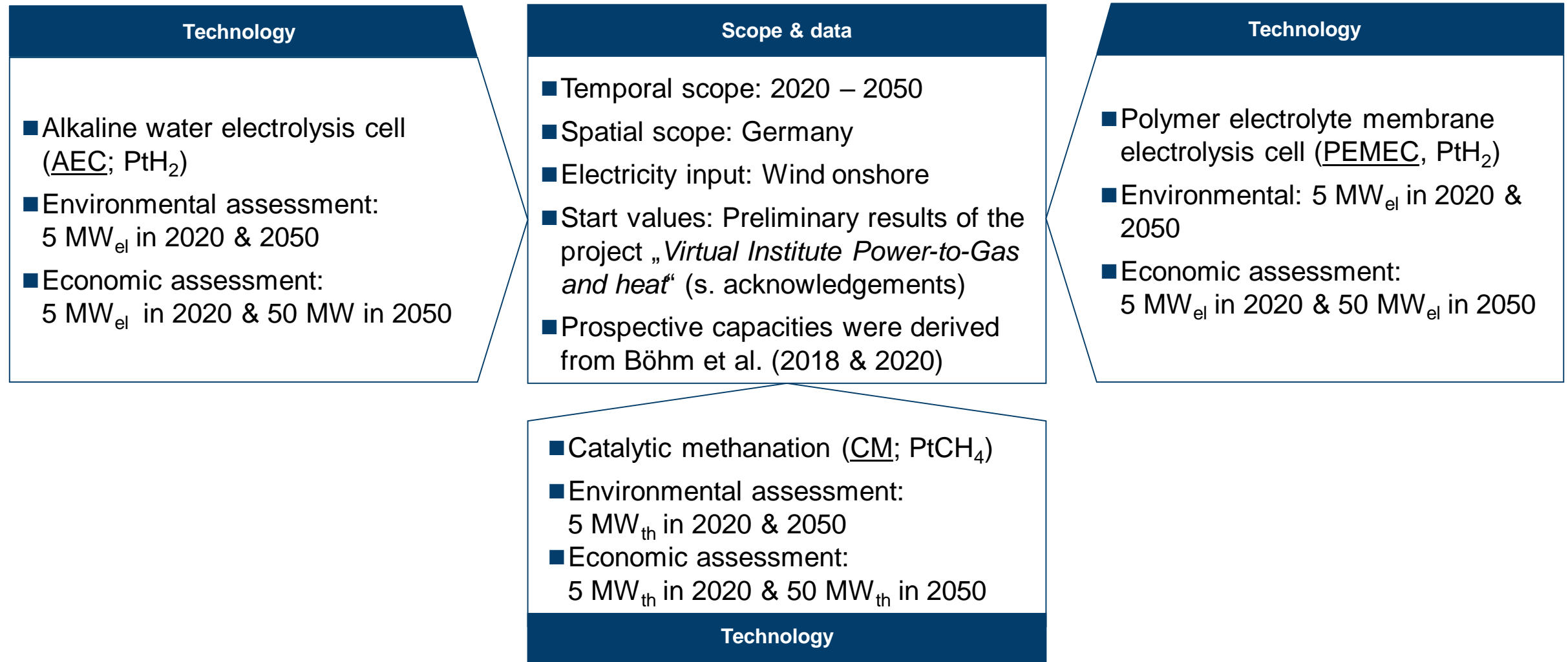
$$I_t = I_0 \left( \frac{X_t}{X_0} \right)^{-\beta}$$

Specific learning parameters and underlying learning rates have to be obtained

Material input, energy input  
or environmental impact at  
time t=0

# 3. Power-to-Gas case study description

## Scope & data



# 3. Power-to-Gas case study description

## Scope & data – learning rate assumptions

Learning rates for electrolysis & methanation for prospective LCA & LCC were based on literature.

Following approach of Arnold (2015) & Simon et al. (2020) was applied:

(economic) learning rates of an established technology can be applied for environmental learning curves.

### Overview on learning rates of whole PtG systems in literature

Learning rate in %	Technology	Notes	Reference
8	AEC		Gül et al. (2009)
9	AEC	2020-2030	Hydrogen Council, 2020
9.6 +/-5.5	Electrolysis		Böhm et al. (2018)
12	Electrolysis	No calculations - judged as conservative lr	Alverà (2019)
13	PEMEC	2020-2030	Hydrogen Council (2020)
13	Electrolysis & Methanation		Thema et al. (2016)
18 +/-6	AEC	1956-2014	Schmidt et al. (2017)
18 +/-13	Electrolysis	1972-2004	Schoots et al. (2008)

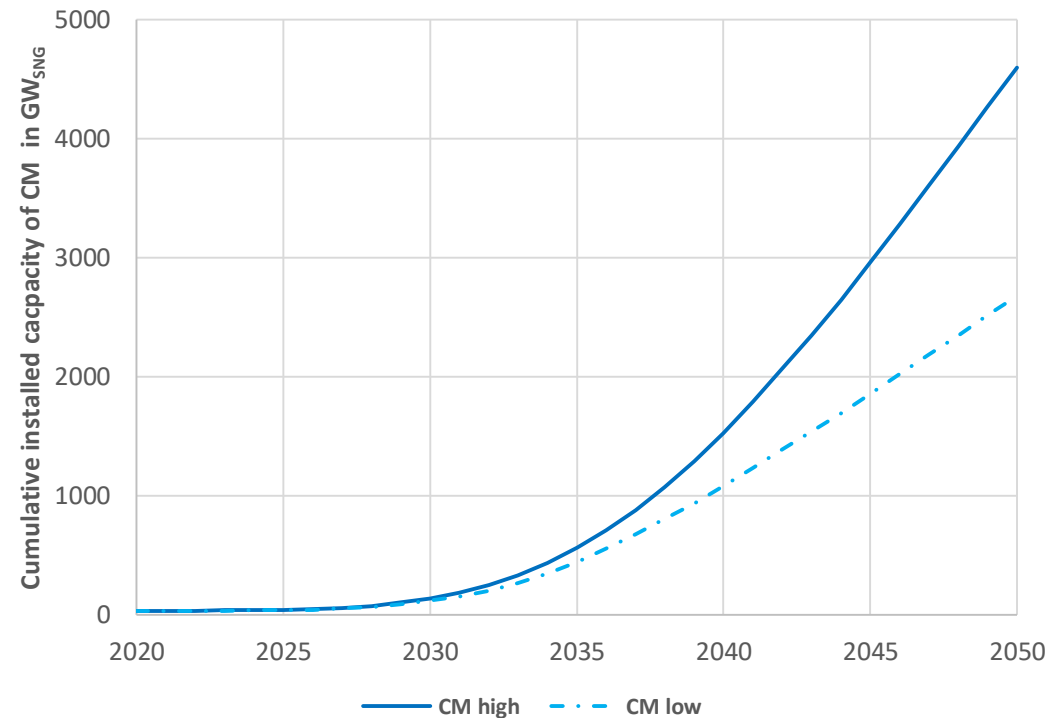
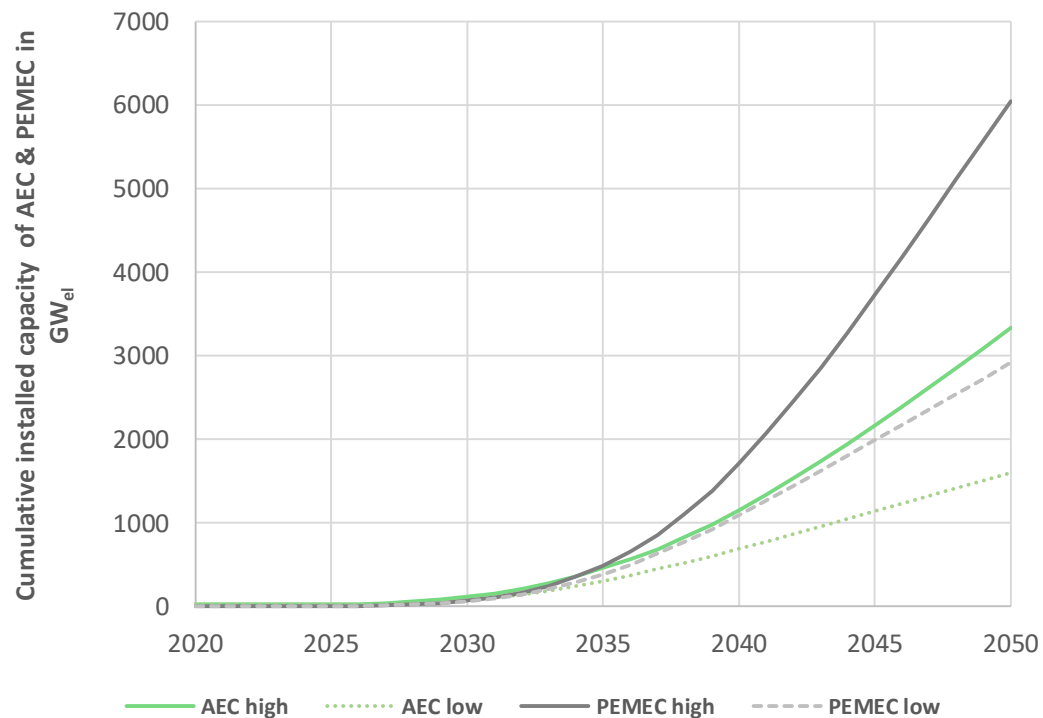
Assessment of environmental learning effects: 8 %, 9.6 & 12 % were chosen as range for learning rates (lr) for electrolysis & methanation.



Assesment of economic learning effects: values from Böhm et al. (2020) considering learning effects from 7 – 13 % for different components were chosen.

# 3. Power-to-Gas case study description

## Scope & data – assumed installed capacity development

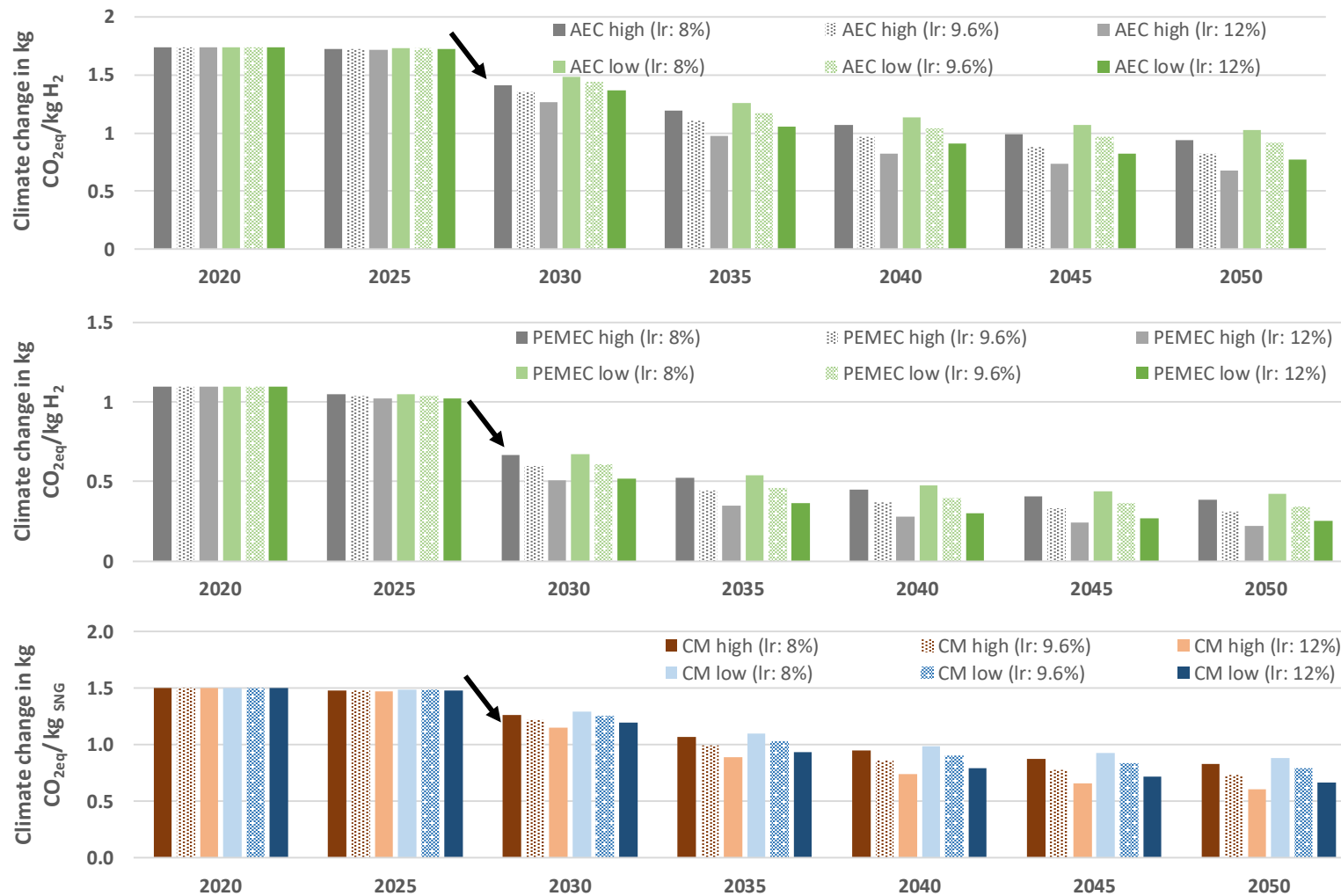


Source: Own calculation and illustration based on data in Böhm et al. (2018) & Böhm et al. (2020)



# 4. Results

## Prospective LCA: learning curve based environmental impact reduction

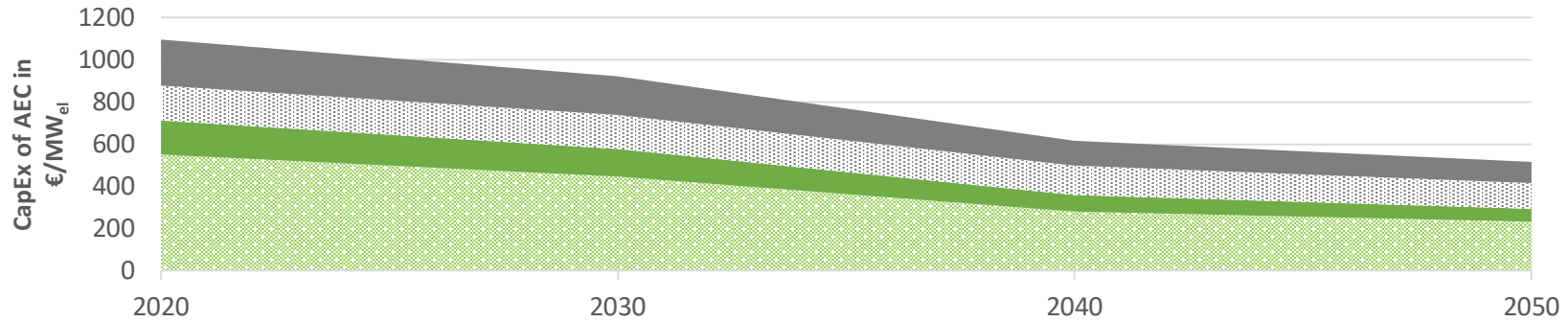


Highest multiplication rate occurs between 2025 and 2030 – provoking highest decrease between periods

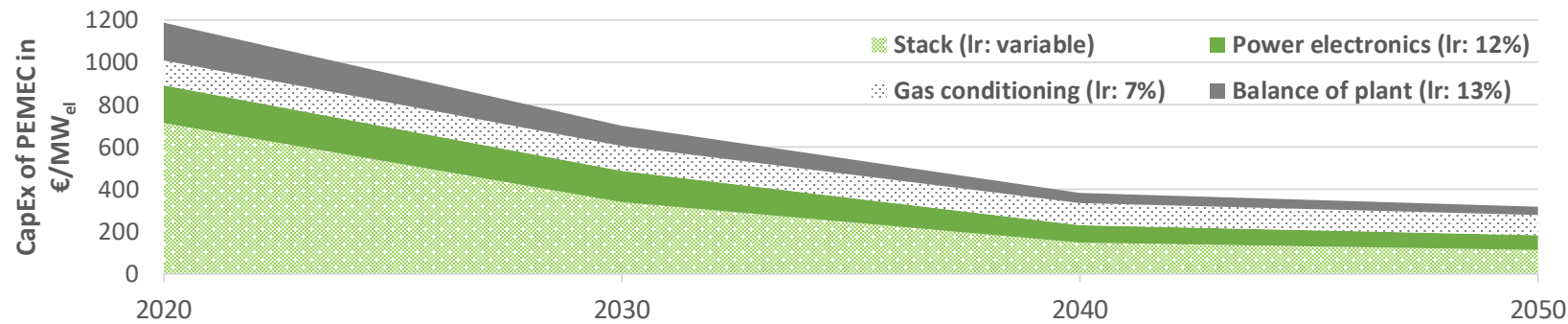
Highest capacity increase assumed for PEMEC – Leading to highest relative impact reductions of the assessed PtG-technologies

# 4. Results

## Prospective LCC: CapEx development for AEC, PEMEC and CM

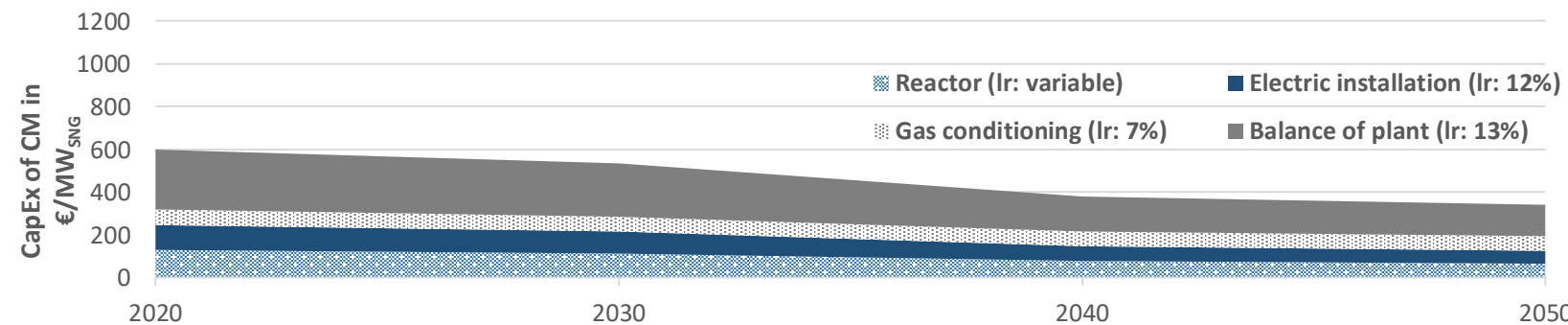


- **Costs decrease** due to learning and scaling
- Stack with highest CapEx contributions



**PEMEC with lower costs in 2050** due to:

- higher learning rates of the stack &
- higher capacity multiplication rate between 2025 and 2030



- **Costs decrease** due to learning and scaling
- BOP with highest CapEx contributions
- Comparative reductions due to lower capacity multiplication rates

Source: Own calculation and illustration based on data in Böhm et al. (2018) & Böhm et al. (2020)

## 5. Discussion & conclusion

### ■ Answer to RQ 1:

→ Capacity increase affects the environmental impact of all considered technologies

### ■ Answer to RQ 2:

→ Learning curves can be used to quantify the prospectively changing environmental performance and development of life cycle costs

■ Decreases of environmental impacts and life cycle costs can be expected till 2050 – due to significant capacity increase and accompanying learning effects

### ■ Requirements:

- detailed data about prospective capacity/production increase
- learning rates or historic data to calculate them

## 5. Discussion & conclusion

- Ways to reduce uncertainties:

- many points in time should be considered (better one-year steps as ten-year steps)
- ranges of learning rate & prospective capacities help to show ranges of possible developments

- The environmental learning curve approach of Arnold (2015) and Simon et al. (2012) helps to give an idea of prospective environmental impacts based on learning curves. However, this is a simplified approach.

- Learning curves of prospective material use for construction and energy requirements are more appropriate.  
→ More detailed insights about environmental contributions & developments of different life cycle stages.

- Our work on learning curve concepts for prospective LCA curves continues – especially for electrolysis & methanation – aiming on further develop better solutions.

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KoVI SGW Project description on IEK-STE website:

[https://www.fz-juelich.de/iek/iek-ste/DE/Forschung/Projekte/KoVI\\_SGW/KoVI\\_SGW\\_node.html](https://www.fz-juelich.de/iek/iek-ste/DE/Forschung/Projekte/KoVI_SGW/KoVI_SGW_node.html)

Official project website:

<http://strom-zu-gas-und-waerme.de/>