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Impacts of enhanced learning rates for clean energy technologies on global energy system scenarios

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ENERGY SYSTEM MODELLING FOR CLEAN ENERGY TECHNOLOGY SCENARIOS

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Contents

Abstract

This study examines the impacts of enhancing technology progress in clean energy technologies on the global energy system and economy. The analysis focuses on eight thematic technology groups, including wind, solar, batteries, hydrogen and fuel cells, carbon capture, direct air capture and synfuels, biofuels, and heat pumps. Two policy scenarios are considered: a *2°C scenario* with stringent carbon policies and a *Reference scenario* driven primarily by market forces.

The study examines the technology adoption patterns within each technology group for the two scenarios, highlighting the differences in the evolution of costs, capacities and production. Moreover, the study analyses the overall impacts in terms of CO_2 reduction, investment needs and energy supply costs of enhanced learning within each technology group, as well as for combining enhanced learning across multiple technology groups. The results show that enhanced learning can lead to significant reductions in greenhouse gas emissions, investment needs, and energy supply costs. Moreover, enhanced learning results in favourable in socio-economic outcomes (e.g., economy-wide investments, consumption and energy prices). However, the study suggests that enhancing technology progress is not at all a substitute for stringent climate policies to reduce CO_2 emissions.

Foreword on the Clean Energy Technology Observatory

The European Commission set up the Clean Energy Technology Observatory (CETO) in 2022 to help address the complexity and multi-faceted character of the transition to a climate-neutral society in Europe. The EU's ambitious energy and climate policies create the necessity to tackle the related challenges in a comprehensive manner, recognising the important role for advanced technologies and innovation in the process.
CETO is a joint initiative of the European Commission Joint Research Centre (JRC), which runs the observatory, and Directorate Generals of Research and Innovation (R&I) and Energy (ENER) on the policy side. Its overall objectives are to:

- monitor the EU research and innovation activities on clean energy technologies needed for the delivery of the European Green Deal
- assess the competitiveness of the EU clean energy sector and its positioning in the global energy market
- build on existing Commission studies, relevant information & knowledge in Commission services and agencies, and the Low Carbon Energy Observatory (2015-2020)
- publish reports on the Strategic Energy Technology Plan (SET-Plan) SETIS online platform

CETO provides a repository of techno- and socio-economic data on the most relevant technologies and their integration in the energy system. It targets in particular the status and outlook for innovative solutions as well as the sustainable market uptake of both mature and inventive technologies. The project serves as primary source of data for the Commission's annual progress reports on competitiveness of clean energy technologies. It also supports the implementation and development of EU research and innovation policy.
The observatory produces a series of annual reports addressing the following themes:

- Clean Energy Technology Status, Value Chains and Market: covering advanced biofuels, batteries, bioenergy, carbon capture utilisation and storage, concentrated solar power and heat, geothermal heat and power, heat pumps, hydropower & pumped hydropower storage, novel electricity and heat storage technologies, ocean energy, photovoltaics, renewable fuels of non-biological origin (other), renewable hydrogen, solar fuels (direct) and wind (offshore and onshore).
- Clean Energy Technology System Integration: building-related technologies, digital infrastructure for smart energy system, industrial and district heat & cold management, standalone systems, transmission and distribution technologies, smart cities and innovative energy carriers and supply for transport.
- Foresight Analysis for Future Clean Energy Technologies using Weak Signal Analysis
- Clean Energy Outlooks: Analysis and Critical Review
- System Modelling for Clean Energy Technology Scenarios
- Overall Strategic Analysis of Clean Energy Technology Sector

More details are available on the CETO web pages.

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Rafael Garaffa is the main author of the Chapter 4 of this report.
Ana Díaz Vázquez wrote substantial parts of the biofuel description in Section 2.7.

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Executive Summary

This study analyses impacts of enhancing technology progress of clean energy technologies. The impacts are analysed from a global and long-term perspective (until 2100) using the global energy system model POLES-JRC and the global economic model JRC-GEM-E3.
The analysis relies on two *base case* scenarios, which are described in detail in *Chapter 1*:

- The *Reference scenario* describes a world without ambitious long-term carbon policies and where the evolution of the energy system is mainly driven by market forces.
- The *2°C scenario* describes a world with stringent climate policies, which lead to a 2°C temperature increase by 2100 above the pre-industrial era. The stringent climate policies are simulated by a single global carbon value trajectory. In the *2°C scenario* the carbon value triggers the need for decarbonisation and the deployment of low-carbon technologies.

Both scenarios are calculated based on the same model setting of POLES-JRC. The only difference between both scenarios is the applied single global carbon value trajectory.

The *2°C base case scenario* of this study is identical with the "*Global CETO 2°C scenario 2024*" used in the CETO technology reports of the series "*Clean Energy Technology Status, Value Chains and Markets*" published within the CETO 2024 exercise.

Methodology

In POLES-JRC, global technology progress is modelled by endogenous learning. According to this approach the evolution of costs and efficiencies is driven by cumulative technology capacities (i.e., a measure of experience) and a *learning rate* describing the progress per cumulative capacity. For each of its technologies POLES-JRC applies a default learning rate that corresponds to the observed dynamics of the respective technology.
Enhanced technology progress is modelled by increasing learning rates above their default levels. Increasing learning rates aims to simulate the enhanced technology progress induced by additional research and innovation (R&I) expenditures. This study considers two levels of augmenting the learning rates above their default levels: a *moderately enhanced* level (+25%) and a *highly enhanced* level (+50%).

Enhancing the technology progress within this study is limited to the period 2025 to 2050, which aims to simulate additional R&D expenditures during this period. Nevertheless, the impacts of boosting technology progress are analysed until 2100.

Thematic technology groups

The POLES-JRC model considers a comprehensive range of technologies in its energy scenarios [1], but only a subset of these are examined in detail in this analysis. To this end, this study takes into account *eight thematic technology groups* of clean energy technologies. These thematic groups cover a wide spectrum of clean technologies for energy supply, energy demand and carbon capture. Each thematic group consists of several technologies:

- ***W***: Wind power (on- and off-shore);
- ***S***: Solar power (utility-scale, residential photovoltaics (PV) and concentrated solar power (CSP);
- ***BA***: (i) Stationary batteries for energy storage. (ii) Batteries for various transport modes;
- ***H2FC***: Hydrogen production (13 technologies) and fuel cell technologies (electrical power and transport);
- ***CC***: Carbon capture from electricity generation (3 technologies) and hydrogen production (3 technologies);
- ***DACSY***: Direct air capture and synfuels (gaseous and liquids) from hydrogen and captured CO_2;
- ***BE***: Biofuels (1st and 2nd generation, biomethane), biomass power (3 technologies) and biomass hydrogen production (3 technologies);
- ***HP***: Heat pump technologies for heating and cooling.

Technology adoption patterns in the base case scenarios

Although clean energy technologies exhibit significantly more growth under the *2°C scenario* than the *Reference scenario*, both base case scenarios share common patterns in the development of several technologies, as highlighted in *Chapter 2*:

- Wind and solar technologies dominate power generation in the second half of the century.
- PV technologies are the dominating solar technologies throughout the century.
- On-shore wind capacities outpace off-shore wind capacities more than 10-fold throughout the entire century.
- Electric vehicles are by far the prevailing technology in transport, slightly challenged by fuel cells in the second half of the century.
- Biofuel technologies substantially increase deployment throughout the century.
- It is not until the second half of the century that a meaningful role becomes apparent for (i) carbon capture technologies in electricity generation and hydrogen production, as well as (ii) DAC and synfuels.
- Heat pumps are used for two purposes: heating and cooling. The heat pumps used for heating increase primarily in the first half of the century as fossil boilers are substituted. Whereas the heat pumps used for cooling are increasingly deployed throughout the entire century.

Main differences in technology adoption between both scenarios are the following:

- Electrolysis becomes the prevailing hydrogen production technology under both scenarios. However, under the *Reference scenario* hydrogen production still relies heavily on fossil fuels throughout the whole century, while under the *2°C scenario* hydrogen production is virtually decarbonised by 2050.
- Carbon capture technologies for electricity generation and hydrogen production require significant climate policies support to develop. Consequently, carbon capture technologies are deployed substantially less in the *Reference scenario* compared to the *2°C scenario*.
- Similarly, DAC and synfuels require stringent climate policies for their development.

The electrification rate is projected to increase substantially from today's 21% in the *2°C scenario* to about 58% in 2050 and 68% in 2100. In contrast, under the *Reference scenario*, the electrification rate increases at a slightly slower pace, reaching 51% by 2050 and 62% by 2100.

Impacts of enhanced learning rates

Enhanced learning within the limits of the technology groups (Chapter 2 and Section 3.2) results in:

- significantly decreasing costs for all technologies;
- substantial expansion of capacities and production for several relevant technologies (e.g., PV, wind, electrolysers, heat pump technologies, DAC and synfuels);

Certain highly dynamic technologies are projected to reach their minimum cost (or "floor cost") as early as 2055-2080 under base case scenarios, assuming default learning rates. However, with highly enhanced learning, floor cost levels can be reached about 20 to 35 years earlier. As a result, the beneficial impacts of these technologies occur about two decades earlier. For instance, with highly enhanced learning the floor cost level of batteries for electric vehicles (42$/kWh) is reached in 2035 instead of 2055 under the default learning rate. For PV modules, the minimum investment cost (40$/kW) is already reached by 2045 for highly enhanced learning instead of by 2080 for the default learning rate.

Learning synergies of enhanced learning

In the next step of this study, impacts are analysed by combining enhanced learning across multiple technology groups (Section 3.3). The aim is to identify favourable combinations that can create learning synergies across technology groups, whereby learning in each individual technology benefits the learning and cost reductions experienced by the other technologies.

In this context, *renewable electrification* stands out as a learning strategy for reducing emissions and costs for the economy by creating synergies from accelerating progress in wind and solar power generation (**W** and **S** groups) as well as in heat pump technologies (**HP** group) and batteries in transport (**BA** group).

Another successful learning strategy is related to carbon capture. Such a strategy is very effective in reducing CO_2 emissions, but less effective in reducing the costs for the economy. A carbon-capture-related learning strategy combines enhanced learning from several capture-related technology groups, such as carbon capture for electricity and hydrogen production (**CC** group), direct air capture and synfuels (**DACSY** group), bioenergy technologies (**BE** group), and hydrogen and fuel cell group (**H2FC** group).

A third and more comprehensive strategy builds synergies across fuel-related technologies, combining learning from clean fuel-related technologies such as biofuels (**BE** group), hydrogen-based fuels (**H2FC** group) and synfuels (**DACSY** group). Synergies with these fuel-related technologies increase further when enhanced learning for wind (**W** group) and solar (**S** group) is added as they further reduce hydrogen production costs by electrolysis.

Sensitivity analysis

The analysis of learning impacts culminates in a sensitivity analysis (Section 3), taking into account all possible learning combinations from the *eight* thematic technology groups. A total of *1020* scenario variants are analysed, comprising *four* complete ensembles of combinations. These ensembles are based on the *two* base case scenarios (*2°C scenario*, *Reference scenario*) and the *two* learning levels (*+* and *++*). Each ensemble consists of combinations that uniformly apply either moderately enhanced learning (*+*) or highly enhanced learning (*++*). The systematic analysis of learning combinations allows the identification of favourable technology combinations and the assessment of the overall impacts.

Technology composition

Reducing CO_2 emissions

The most effective learning strategies for reducing energy-related CO_2 emissions aim to boost learning across a broad range of clean energy technologies. This approach leverages additive effects from progress in multiple technologies and creates synergies between them, leading to significantly greater overall impact.
Under the *2°C scenario*, the top-performing combinations for reducing CO_2 emissions by 2100 require highly enhanced learning in at *least five* technologies.
However, in a scenario without stringent climate policies (*Reference scenario*), concentrating additional learning efforts on merely *three* or *four* technologies can be a very effective strategy for reducing CO_2 emissions by 2100. Focusing highly enhanced learning efforts on wind, solar, and hydrogen and fuel cells brings superior results under the *Reference scenario*.

Lower investment needs and energy supply costs

In order to mitigate the higher investment needs of stringent climate policies (*2°C scenario*), concentrating additional learning efforts on three to four technologies is a very effective strategy. In this context, boosting learning efforts for technologies such as wind, solar, batteries, and hydrogen and fuel cells is a very promising strategy.
With a view to mitigate energy supply costs, a slightly broader set of technologies is required to achieve best-results. Boosting learning efforts for batteries, wind, and solar has a profound impact on reducing energy supply costs throughout the century. Furthermore, under the *2°C scenario*, particularly in the first half of the century, boosting learning for heat pumps, and hydrogen and fuel cells substantially impacts energy supply costs.

Overall impacts based on the energy scenario analysis (POLES-JRC)

CO_2 emissions

Under the *2°C base case scenario*, cumulative net CO_2 emissions for 2020-2100 (i.e. global carbon budget) amount to 1170 $GtCO_2$. By applying enhanced learning to the technologies featured in this study, cumulative emissions can be reduced by up to 6% within this scenario. However, for mitigation pathways that limit global warming to 1.5°C, the carbon budget is significantly lower, about 200-400 $GtCO_2$ [2], [3]. While enhanced learning can substantially reduce CO_2 emissions, the resulting reductions are insufficient to bridge the gap to the carbon budget required for 1.5°C pathways.

Under, the *Reference scenario*, which assumes no stringent climate policies, cumulative CO_2 emissions at the end of the century amount to approximately 2700 $GtCO_2$ in the base case. Enhanced learning within the scope of this study can reduce these cumulative CO_2 emissions by up to 7%, which falls short of the carbon budget required to meet the 2°C target.
These results suggest that enhanced learning can reinforce the impacts of carbon policies. However, boosting the progress of clean energy technologies is by no means a substitute for stringent climate policies.

Energy-related investment needs
Notably, boosting learning for clean energy technologies is a very viable strategy to overcome the economic disadvantage of higher energy-related investment needs under the *2°C scenario* compared to the Reference scenario. This study suggests that with the best-performing highly enhanced learning combinations, investments required under the *2°C scenario* could be reduced by up to 3% below the investment needs of the base case *Reference scenario*.

This finding has significant implications for the green transition. By combining highly enhanced learning in key technologies such as wind, solar, batteries, and hydrogen and fuel cells, it is possible to reduce the substantial investment associated with this transition.

Energy supply costs
Energy supply cost - as defined in this study - measures the overall costs of energy supply including the costs of the carbon value. Energy supply costs under the *2°C scenario* are higher than in *Reference scenario*, mainly due to the carbon value. The difference in energy supply costs between both scenarios ranges between 7-20% over the projection period.

A significant benefit of boosting learning for clean energy technologies is its potential to mitigate higher energy supply costs associated with a scenario containing stringent carbon policies (*2°C scenario*). This study finds that the best-performing combinations of enhanced learning, more than halve the cost difference between the *2°C scenario* and the *Reference scenario*.

Socio-economic impacts based on the macroeconomic analysis (JRC-GEM-E3)
The global socio-economic impacts of the energy scenarios provided by the POLES-JRC model are analysed with the JRC-GEM-E3 model. For this purpose, the JRC-GEM-E3 is well suited as it is a multi-regional, multi-sectoral, recursive dynamic computable general equilibrium (CGE) model.
The socio-economic implications of three energy scenarios were examined: the two base cases of the *Reference scenario* and *2°C scenario*, and an enhanced learning variant of the *2°C scenario*, which applies highly enhanced learning for wind and solar (*W++_S++*).

Macroeconomic impacts
The results of the macroeconomic analysis reveal that, by 2050, the base case *2°C scenario* is associated with a 0.9% lower global GDP compared to the *Reference scenario*. However, the enhanced learning variant of the *2°C scenario* (*W++_S++*) reduces this loss to 0.7%. This more favourable development of GDP can be attributed to a lower loss in private consumption under the enhanced learning *2°C scenario* variant. The underlying drivers of this development are significantly lower electricity generation costs and household energy consumption prices which result in increased disposable income and eventually more consumption of durable goods (i.e., household appliances and vehicles).

Employment impacts
Regarding employment, the overall impact of the three scenarios is relatively neutral in the coming decades. However, the *2°C scenarios* are characterised by job losses in the fossil energy industry, which are compensated by job opportunities in non-fossil power generation and the general electricity sector. This aligns well with the transition towards electrification of demand and renewable power supply. Notably, the enhanced learning variant of the *2°C scenario* results in slightly fewer job opportunities in these sectors, as the enhanced learning implies improvements in labour efficiency. This effect is more pronounced for employment in wind power due to beneficial economies of scale and less noticeable for solar power.

Takeaway for policymakers

Key findings of this study for an effective climate policy are:

- Boosting the progress of clean energy technologies is by no means a substitute for stringent climate policies. This analysis suggests that technology progress can reinforce the impacts of carbon policies as enhancing the progress of clean energy technologies significantly reduces emissions.
- However, boosting technology progress of clean energy technologies is a very effective strategy to improve the economic outcomes of decarbonisation policies.
- In particular, boosting technology progress results in substantially lower investment needs and energy supply costs, reducing both the financing burden of the transition and the impact on energy users. Moreover, accelerating technology progress pays off from a macroeconomic perspective as it results in more favourable outcomes in terms of GDP, economy-wide investments, consumption and energy prices.
  Therefore, boosting technology progress presents for policymakers an opportunity to balance environmental goals with economic concerns and to mitigate the economic risks of the green transition.
- The most effective learning strategies for reducing energy-related CO_2 emissions by the end of the century is to boost progress for a very broad range of relevant clean energy technologies.
- Focusing on a few key technologies with high *synergies* (batteries, wind, solar, and hydrogen and fuel cells) is an effective strategy to decrease investment needs associated to the green transition.

Introduction

This study examines the long-term impacts of enhancing clean energy technology progress on the global energy system and economy.
The analysis follows a two-step approach. First, the long-term development and adoption patterns of clean energy technologies are projected to 2100 for two scenarios with distinct policy settings: a *2°C scenario* and a *Reference scenario*. Furthermore, the impacts of both scenarios on the global energy system (until 2100) and the economy (until 2050) are assessed.
In the second step, the impacts of accelerated technology progress for clean energy technologies are analysed. This includes two complementary perspectives: (i) an in-depth analysis of the effects of accelerating progress for a specific group of technologies, and (ii) an examination of the impacts and synergies that arise when accelerating progress across a broad range of technologies.

This study uses well-established models for its analysis: the POLES-JRC long-term energy scenario model [1] for energy-related projections and analysis, and the JRC-GEM E3 model [4] for socio-economic evaluation.
All figures and numbers in this study refer to global data; regional data is explicitly not shown. However, all scenarios are calculated with the full detailed regional resolution of the POLES-JRC model (Annex 1) and the JRC-GEM E3 model (Annex 2). Moreover, all monetary numbers refer to constant US dollars ($) of 2022.

Analytical framework and methodology

<u>Scenarios</u>
The framework of this study comprises two *base cases*, consisting of two long-term energy scenarios with distinct policy settings:

- In the *Reference scenario* today's legislated policies are considered, and no future climate policy pledges and targets are considered. The energy and emissions projections in the *Reference scenario* are driven by market forces and technology learning. The global mean temperature at the end of the century in the *Reference scenario* limits temperature rise to 3°C.
- The *2°C scenario* aims to limit global temperature increase to 2°C at the end of the century. To this end, a single global carbon value trajectory for all regions is used in this scenario. Introducing a global carbon value leads to decarbonisation and the deployment of low-carbon technologies.

Both base case scenarios are long-term scenarios (until 2100) produced with the POLES-JRC model. Both scenarios' settings are similar to those of the Global Energy and Climate Outlook 2023 [5].

<u>Eight thematic clean energy technology groups</u>
A comprehensive range of technologies form part of the POLES-JRC model [1], but this study focuses only on a subset. Within the scope of this study, e*ight thematic technology groups* of clean energy technologies are examined. These thematic groups cover a wide spectrum of clean technologies for energy supply, energy demand and carbon capture. Each thematic group consists of several technologies:

- ***W***: Wind power (on- and off-shore);
- ***S***: Solar power (utility-scale, residential and concentrated solar power (CSP);
- ***BA***: (i) Batteries for energy storage. (ii) Batteries for various transport modes;
- ***H2FC***: Hydrogen production (13 technologies) and fuel cell technologies (power and transport);
- ***CC***: Carbon capture for electricity generation (3 technologies) and hydrogen production (3 technologies);
- ***DACSY***: Direct air capture and synfuels (gaseous and liquids) from hydrogen and captured CO_2;
- ***BE***: Biofuels (1st and 2nd generation, biomethane), biomass power (3 technologies) and biomass hydrogen production (3 technologies);
- ***HP***: Heat pump technologies for heating and cooling.

Boosting technology progress

The technology progress in POLES-JRC is modelled by endogenous learning. This approach considers that the evolution of costs and efficiencies is driven by cumulative technology capacities (i.e., a measure of experience) and a learning rate describing the progress per cumulative capacity. For each of its technologies POLES-JRC applies a default learning rate that corresponds to the observed dynamics of the respective technology.

Boosting the technology progress is modelled by increasing learning rates above the default levels. Increasing the learning rates aims to simulate the enhanced technology progress induced by additional research and innovation (R&I) expenditures. This study considers two levels of enhanced technology progress: a moderately enhanced level ('+') and a highly enhanced level ('++'), increasing the default learning rates by 25% and 50%, respectively. Accelerating the technology progress within this study is limited to the period 2025 and 2050, which aims to simulate additional R&D expenditures during this period. Nevertheless, the impacts of boosting technology progress within this limited period are analysed until 2100.

The enhanced learning is applied to the clean energy technologies within the aforedescribed *eight thematic technology groups*. The study first analyses the impacts of enhanced learning rates limited to individual *thematic technology groups*. After that, the impacts and synergies of combining enhanced learning across the *eight thematic technology groups* are examined. All technologies not subject to enhanced learning are modelled with their default learning rates.

Structure of the report

Chapter 1 'Scenarios and Methodology' introduces both base case scenarios and presents results at the global level. The evolution of greenhouse gas emissions, primary energy supply and final energy demand are presented. The evolution of investments by technology provides a view of technology adoption patterns and their importance in monetary terms. Moreover, the endogenous learning approach used in POLES-JRC is described. Finally, a methodology is presented to estimate the prospective R&I expenditures corresponding to the enhanced learning.

Chapter 2 'Analysis by technology group' investigates the *eight thematic technology groups* in separate sections. For each thematic group, the technology modelling approach used in POLES-JRC is described. Subsequently, the technology adoption patterns of the base case scenarios (*2°C scenario*, *Reference scenario*) are discussed. Finally, the impacts of enhanced learning rates within the respective technology group are analysed. Additionally, for wind and solar technologies, the R&I expenditures associated with enhanced learning are estimated.

Chapter 3 'Overall impacts of enhanced technology learning' analyses the impacts of enhanced learning rates along three main dimensions: (i) CO_2 emissions, (ii) energy-related investment needs and (iii) energy supply costs (*Section 3.1*). The subsequent *Section 3.2* analyses the overall impacts of unpaired technology learning, which considers enhanced learning within each of the *eight thematic technology groups* in isolation. *Section 3.3* examines the overall impacts and synergies of combining enhanced learning across the various technology groups. The aim of this section is to identify favourable learning strategies that allow the creation of synergies across various technology groups. *Section 3.4* presents a comprehensive sensitivity analysis, examining the overall impacts of all possible combinations of enhanced learning across the *eight thematic technology groups*.

The systematic analysis enables the assessment of the maximum overall impacts that can be achieved through enhanced learning within the scope of this study. The findings provide valuable insights into the role of technology learning to support effective climate policy. The findings are presented and discussed for two distinct scenarios, the *2°C scenario* with stringent carbon policies and the *Reference scenario* driven primarily by market forces.

Finally, *Chapter 4 'Socio-economic analysis'* provides results of the analysis with the global economy model JRC-GEM-E3. The socio-economic analysis examines the impacts on GDP, economy-wide investment and consumption, consumer prices, and employment. The macroeconomic outcomes are analysed for the base case of the *2°C scenario* and the *Reference scenario*, and a variant of the *2°C scenario* that applies highly enhanced learning for wind and solar technologies.

Relation to the CETO project

Role within the CETO project

This study was conducted as part of the task '*Energy System Modelling for Clean Energy Technology Scenarios*' within the *Clean Energy Technology Observatory* (CETO) project. A comprehensive overview of the CETO project is given in the Foreword. Within the aforementioned CETO task, a complementary report, 'The POTEnCIA CETO 2024 Scenario' presents a deep decarbonisation scenario with a focus on the European Union [6].

Connection to the CETO 2024 technology reports

CETO publishes an annual series of reports on specific clean energy technologies, titled '*Clean Energy Technology Status, Value Chains and Markets'*. The 2024 series of *CETO technology reports* utilise global technology projections (e.g., capacity, production, costs) that are drawn from this study. Notably, the '*Global CETO 2°C scenario 2024'* used in the CETO technology reports is identical to the *2°C base case scenario* presented in this study.

1 Scenarios and Methodology

1.1 POLES-JRC model

The global energy and emission scenarios presented in this study are produced using the POLES-JRC model (Prospective Outlook for the Long-term Energy System). POLES-JRC is a world energy-economy partial equilibrium simulation model of the energy sector, with complete modelling from primary supply (fossil fuels, renewables, etc.) to transformation (power, biofuels, hydrogen) and final user demand. The model provides full energy and emission balances for 66 countries or regions worldwide (including an explicit representation of OECD and G20 countries). Moreover, international energy markets and prices of energy fuels are simulated endogenously. Its high level of regional detail and sectoral description allows for assessing a wide range of energy and climate policies in all regions within a consistent global frame. POLES-JRC follows year-by-year recursive modelling, with endogenous international energy prices and lagged supply and demand adjustments by region, which allows for describing full development pathways to 2100.

A short description of the POLES-JRC model used in this report can be found in Annex 1; more comprehensive documentation of POLES-JRC is provided in [1]. POLES-JRC scenario results are published within the series of yearly 'Global Climate and Energy Outlook' (GECO) publications. Previous GECO reports, along with detailed regional energy and greenhouse gas (GHG) balances and an online visualisation interface, can be found at [7], [8].

1.2 Base Case Scenarios

The framework of this study consists of two base case (BC) scenarios, referred to as *Reference scenario* and *2°C Scenario*, with fundamentally different policies. Within this study, these base cases serve two purposes. Firstly, they are used to illustrate technology adoption patterns of clean energy technologies in the coming decades. Secondly, the base cases serve as benchmarks in the sensitivity analysis of enhanced learning.

Reference scenario: corresponds to a world where no new policies are implemented. These existing and enacted policies include energy supply and demand policies and targets, as well as legislated GHG policies and targets that are backed by concrete supporting energy-sector policies. For a list of policies considered in the *Reference scenario* see **Table 9 and 10** in the Annex 4 of the GECO 2023 report of [5]. Some of these policies are simulated by low carbon value trajectories for some countries. Climate policy pledges and targets, such as countries' Nationally Determined Contributions (NDCs) and long-term strategies, are not considered.

Notably, the *Reference scenario* does not aim for a deep decarbonisation. Energy and emissions projections in the *Reference scenario* are mainly driven by market forces and technology learning and, to a minor extent, by the aforementioned already legislated GHG policies and targets. The *Reference scenario* results in an end-of-century temperature rise of below 3.0°C with a more than 66% probability.

2°C scenario: this scenario is designed to limit global temperature increase to 2°C at the end of the century. In this scenario, the cumulative net CO_2 emissions from 2020 until 2100 reach approximately 1170 Gt_{CO2}, which is below the carbon budget levels required for a *2°C scenario* provided by [2]. To verify temperature projections liveMAGICC [9] was applied using the net CO_2 emissions complemented with emission projections of non-CO_2 and air pollutants. This scenario results in a likely below 2°C temperature increase with a more than 66% probability in 2100.

In the *2°C scenario* a single *global* carbon value for all regions is used on top of the aforementioned already legislated GHG policies and targets of the *Reference scenario*. The carbon value under the *2°C scenario* increases immediately, starting in 2024, with a steep rise until 2030, followed by a gradual and modest increase until 2100. The *2°C scenario* is, therefore, a stylised representation of an economically efficient pathway to the temperature targets, as the uniform global carbon value ensures that emissions are reduced where abatement costs are lowest. This scenario does not consider financial transfers between countries to implement mitigation measures. This scenario is a simplified representation of an ideal case where strong international cooperation results in a concerted effort to reduce emissions globally; it is not meant to replicate the result of announced targets and pledges, which differ greatly in ambition across countries.

The *2°C scenario* base case is identical to the "*Global CETO 2°C scenario 2024"* used in the [2024 series of CETO technology reports] "*Clean Energy Technology Status, Value Chains and Market*"'.

1.2.1 Specifications and limitations

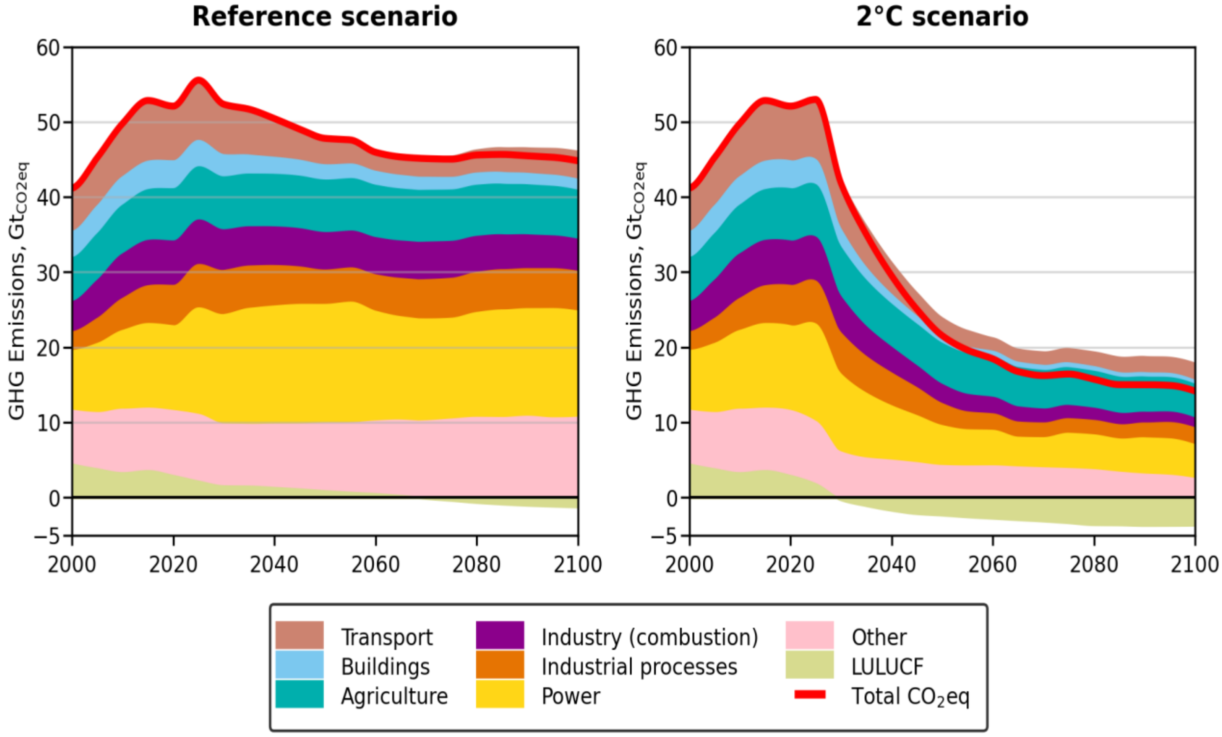
The POLES-JRC model version used for this study is based on the version employed for the GECO 2023 report [5]. The used POLES-JRC version has been modified and enhanced to address the specific issues relevant to this task of the CETO project. Mayor changes since the publication of the GECO 2023 report refer to the modelling of direct air capture (DAC) and the transport sector. Moreover, the techno-economic parameters (overnight investment cost, operation and maintenance cost, efficiencies, learning rates) for all technologies have been revised thoroughly. Techno-economic parameters used in the POLES-JRC version of this report are detailed in Annex 5.

The POLES-JRC model is developed and enhanced continuously. Consequently, POLES-JRC scenarios published in other reports may differ from the scenarios presented in this report. The scenarios of this report may vary from energy and emissions projections from official national sources or international organisations.

The *Reference scenario* and *2°C scenario* of this study use an identical configuration of the POLES-JRC model, except that the *2°C scenario* applies a global carbon value trajectory. Both scenario cases use the same exogenous macroeconomic projections (GDP and population) as a basis, with endogenously calculated energy prices and technological development specific to the POLES-JRC model.

All data shown in this report refer to global figures - unless stated otherwise. This report does not intend to show regional data related to energy supply and demand, energy prices or investment. Nonetheless, the global projections shown are the result of modelling the entire energy system of each of the 66 countries and regions in POLES-JRC, which includes the regional modelling of energy prices. The cost figures for energy technologies are global unitary figures reflecting a representative average.

Figure 1. Global GHG emissions by sector under the *Reference* and *2°C scenario* base cases.



Source: POLES-JRC model

1.2.2 Global Emissions

In both scenarios, emissions are projected to peak in the middle of this decade (**Figure 1**). In the *Reference scenario*, emissions fall subsequently, mainly driven by the continued deployment of renewables, electric vehicles (EVs), and other low-emission technologies. By the middle of the century a plateau of about 47 Gt_{CO2eq} is reached, as continued fossil fuel use and non-CO_2 emissions growth offset growth in renewables.

Decarbonisation in the *2°C Scenario*

The *2°C Scenario* sees substantial further emission reductions, reaching about 14 Gt_{CO2eq} in 2100 for all greenhouse gases (i.e., "*Total CO2eq*" in **Figure 1**). Drastic emission reductions occur in power generation, transport, buildings, and industry until 2050. In the second half of the century, emissions continue to decrease, but at a lower speed. Although power generation expands substantially in the second half of the century, emissions of power generation decrease from today's 11 Gt_{CO2} to about 5 Gt_{CO2} by 2050 and stagnate at this level in the second half of the century.

Negative emissions technologies and options, such as bioenergy with carbon capture and storage (BECCS), direct air capture (DAC) and LULUCF (Land use, land-use change, and forestry), are crucial components for the decarbonisation of the *2°C Scenario*. As an entire sector, LULUCF turns from a source to a substantial emission sink from 2030 onwards. Reducing deforestation, increasing afforestation, and improving land management practices are key to converting the LULUCF sector into a global carbon sink. Moreover, bioenergy with carbon capture and storage (BECCS) is an important technology for achieving negative emissions in the power sector (Sections 2.5.1 and 0) as well as for producing hydrogen (Section 2.5.2). Finally, direct air capture (DAC) is a crucial negative emission technology in the second half of the century (Section 2.6.1).

As a result, in 2100, the actual 14 Gt_{CO2eq} of net emissions in the *2°C Scenario* consist of 22 Gt_{CO2eq} of gross emissions, which are offset by about 8 Gt_{CO2} of negative emissions. Of these roughly 5 Gt_{CO2} refer to LULUCF (**Figure 1**), and approximately 3 Gt_{CO2} originate from BECCS and DAC (comprised in 'Other' in **Figure 1**).

On the *demand side* (*2°C Scenario*), energy efficiency combined with electrification (see **Figure 4**) offsets fossil fuel consumption at different speeds depending on the technology substitution mechanisms and the characteristics of the energy-using processes within each sector:

- The *transport sector* sees rapid decarbonisation from 2025 to 2050 as electric vehicles (EVs), and to a lesser extent fuel cell vehicles, reduce fossil fuel demand.
- The *building sector* switches from fossil fuels (mainly fossil gas) to electricity and decarbonises based on relatively mature technologies like heat pumps and thermal insulation.
- *The industrial sector* sees a significant fuel switch in the *2°C Scenario* towards electrification which, combined with modest deployment of CCS, results in reducing its emissions from 11 Gt_{CO2eq} today to about 4 Gt_{CO2eq} in 2100.

In the *2°C Scenario*, substantial residual emissions remain in the latter half of the century, particularly in the agriculture, industry and transportation sectors.

Comparison to pathways compatible with 1.5°C target

The global carbon budget for 2020-2100 (cumulative net CO_2 emissions) in the *2°C Scenario* amounts to 1170 $GtCO_2$. In contrast, mitigation pathways that limit global warming to 1.5°C have a significantly lower carbon budget of approximately 200-400 $GtCO_2$ and require reaching net-zero CO_2 emissions by the second half of the century [2], [3]. This highlights that achieving the 1.5°C target would necessitate substantially more aggressive emission reductions than the 2°C Scenario presented in this study.

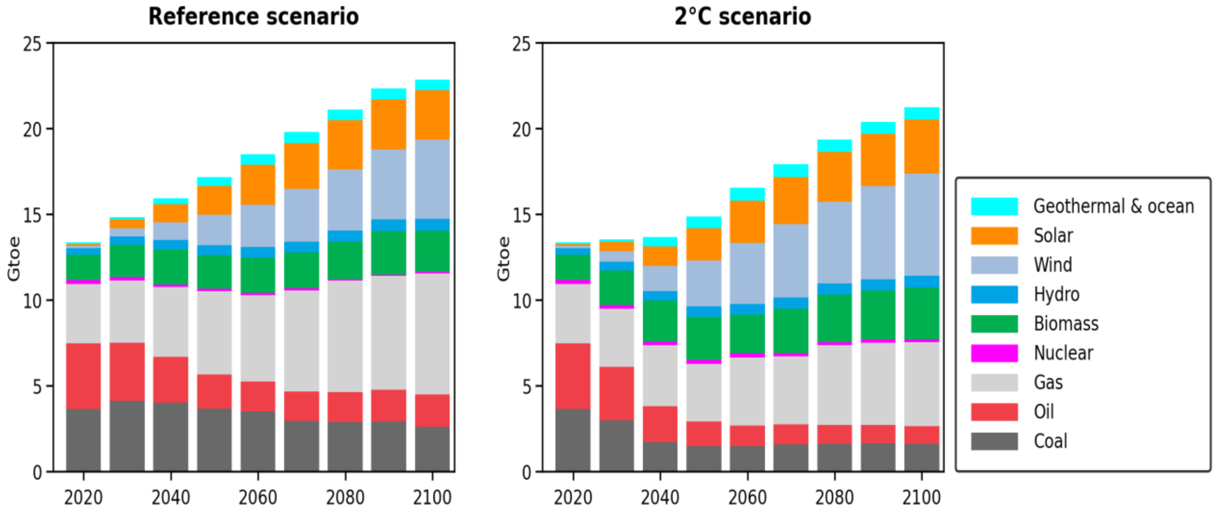
1.2.3 Energy supply and demand

1.2.3.1 Primary energy supply

The decarbonisation in the *2°C scenario* compared to the *Reference scenario* is characterised by a significant transition of the primary energy supply towards renewables and the combination of several factors as presented in **Figure 2**:

- Stagnation of primary energy supply until 2050, which is a result of decreasing final energy demand in the buildings and transport sector mainly from electrification and the use of more efficient technologies.
- In both scenarios, surging renewables play an important role. However, substantially more wind is deployed in the *2°C scenario*.
- Fossil energy supply in 2100 declines for coal to half of its current level, and oil declines to even a quarter of its current supply.
- Gas supply grows steadily throughout the century in both scenarios, but less in the *2°C scenario*. This development occurs largely as gas power plants are required to balance the intermittency of surging solar and wind power.

Figure 2. Primary energy supply under the *Reference* and *2°C scenario* base cases.



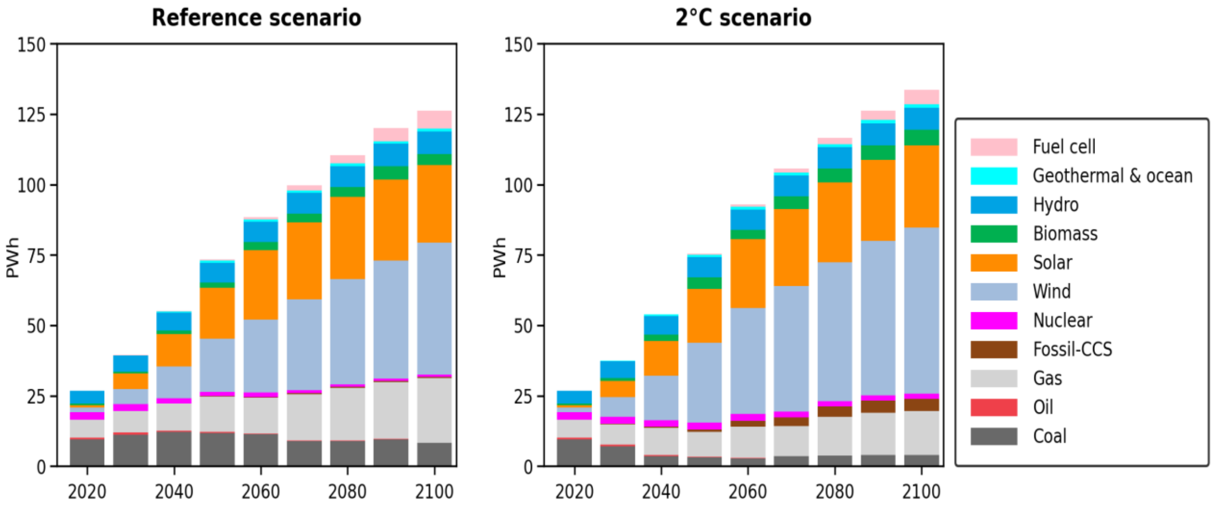
Source: POLES-JRC model

1.2.3.2 Power generation

In 2100, power generation is projected to increase almost five times to about 134 PWh compared to the current demand of roughly 27 PWh, as can be seen in **Figure 3**. Both scenarios show an impressive surge in wind and solar generation driven by ever-cheaper renewable power. Solar and wind generation increases drastically from approximately 2.4 PWh in 2020 to about 47 PWh by 2050 and grow further to about 88 PWh by 2100 (*2°C scenario*). In 2050, solar and wind account for 63% of total generation in the *2°C scenario* and 50% in the Reference scenario. All renewables combined (including biomass, ocean and geothermal) grow to about 80% of total power generation in 2050 and remain at this level for the latter half of the century.
Intermittent renewables require short-term and seasonal balancing power capacities. For balancing the power system POLES-JRC considers large-scale storage (pumped-hydro storage, batteries) and fast ramping gas power plants. With surging intermittent renewables, the need to balance power capacities increases. Therefore, gas-based power increases drastically in the power mix from approximately 6.5 PWh (2020) to 16 PWh (2100) in the *2°C scenario*. Whereas pumped-hydro storage and batteries do not appear in the power mix as they are charged by other sources of energy.

In the *2°C scenario*, coal-based power (without CCS) declines from 2030 to about half of today's level. The resultant lack in providing baseload is, to some extent, substituted by increasing fossil CCS power generation from coal and gas. Moreover, nuclear power plays a more prominent role compared to the *Reference scenario*. Concurrently, biomass plays a limited role in both scenarios due to its relatively high cost (Section 2.7).

Figure 3. Power generation under the *Reference* and *2°C scenario* base cases.



Source: POLES-JRC model

Power system modelling in POLES-JRC

For producing electricity, POLES-JRC comprises a comprehensive set of more than *thirty* power-generating technologies. The model considers *nine* fossil power technologies without CCS and *three* fossil power technologies with CCS. Moreover, *three* biomass technologies with and without CCS, and hydrogen and gas fuel cells are considered.

Furthermore, *two* nuclear technologies are considered. Renewable technologies encompass *three* solar technologies, *two* wind technologies, *three* hydro power technologies as well as ocean and geothermal power. Finally, a range of storage technologies are considered: battery energy storage (BES), compressed air energy storage (CAE), and pumped hydro storage (PHS). Moreover, the model considers vehicle-to-grid (V2G) and demand side management. The latter technologies and the storage technologies play a crucial role in balancing the increasing intermittent renewable power sources.

Each technology is characterised by its cost parameters (overnight investment cost, variable & fixed operation and maintenance cost), efficiencies in case of thermal power and various other techno-economic parameters. Endogenous learning is taken into account for cost parameters and efficiencies (see 1.3.1). The main techno-economic parameters for all POLES-JRC power technologies are documented in Annex 5 (see Section AN 5.1).

For renewable technologies, maximum resource potentials are taken into account. Similarly, the deployment of carbon capture and storage (CCS) technologies is linked to region-specific geological storage potential. In addition to these technical and economic characteristics, non-cost factors are applied to capture the historical relative attractiveness of each technology, in terms of investments and of operational dispatch.

For modelling hourly temporal variations, POLES-JRC uses a set six representative days with an hourly time-step. This allows to capture electricity load variations as well as to take into account the intermittency of solar and wind generation. The usage of representative days also allows to capture hourly profiles by sector and end-uses.

Electricity demand in POLES-JRC is computed by summing electricity demand for end-uses (e.g., heating, steel making, etc.) over all sectors (e.g., residential & service sector, industry). Time variations of end uses are taken into account by hourly profiles of representative days. The annual evolution of end-use electricity demand is driven by the activity of each sector and price competition between electricity and fuels.

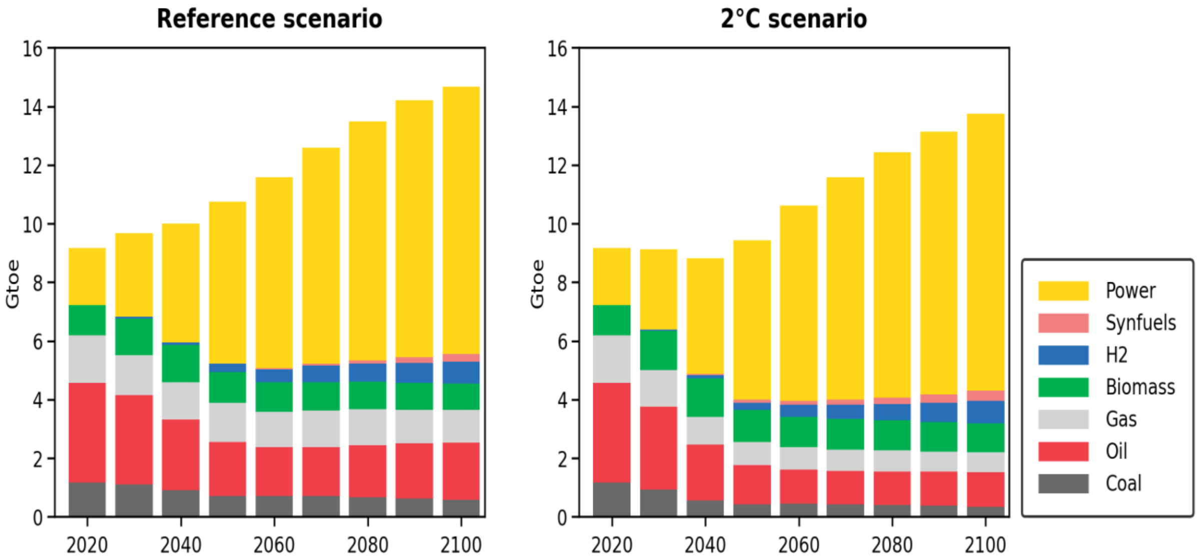
The modelling of the power system in POLES-JRC comprises operation and capacity planning. The operation of the power system models how the existing capacities of power generating and storage technologies are employed in order to meet the overall demand, including grid imports and exports from adjacent regions. While capacity planning models the deployment of new power capacities. It considers the existing structure of the power mix (vintage technology), the expected evolution of the electricity demand, load and flexibility characteristics of the technologies and the production cost of technologies.

1.2.3.3 Final energy demand

In both scenarios, electricity rapidly evolves into the largest final energy demand component (**Figure 4**). The increasing dominance of electricity results from declining technological costs and changes in end-use equipment. Additionally, the increasing global carbon value in the *2°C scenario* further promotes electrification. Electricity accounted for 21% of final global energy demand in 2020 and is projected to increase steeply to reach 58% in 2050 and 68% in 2100 in the *2°C scenario*. While the *Reference scenario* also exhibits substantial electrification but at a slightly slower pace, reaching 51% by 2050 and 62% by 2100. Moreover, hydrogen and synfuels increasingly play a role in the energy mix. Each of them will contribute to about 5% of the energy mix of 2100 in the *2°C scenario*.

With a view to the clean energy demand technologies treated in this report, the remainder of this section looks into the demand of the (i) transport sector and the (ii) residential and service sector.

Figure 4. Final energy demand under the *Reference* and *2°C scenario* base cases.



Source: POLES-JRC model

1.2.3.3.1 Transport sector

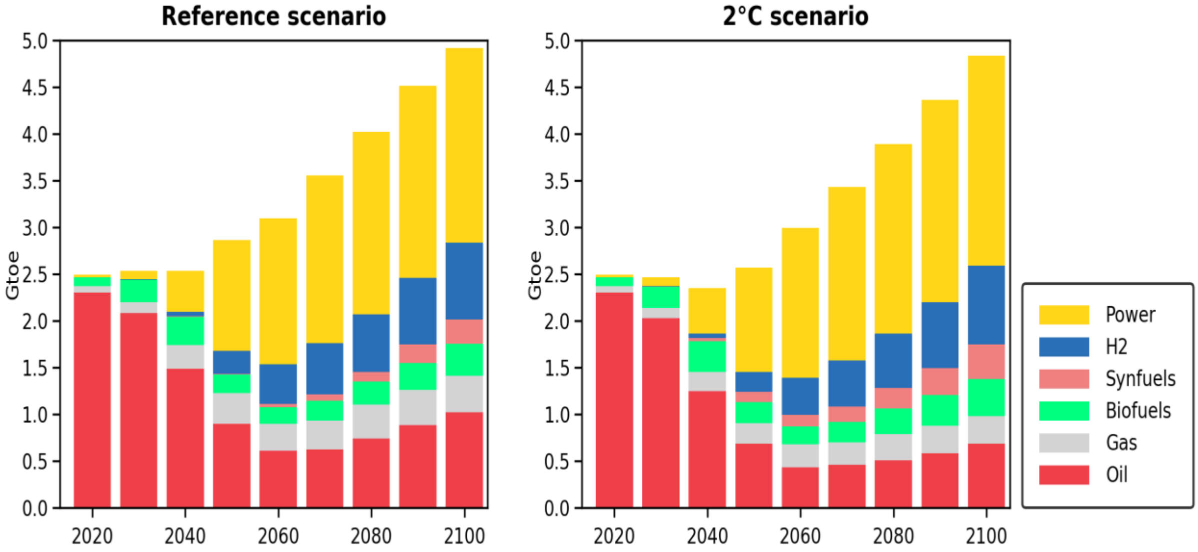
The transport sector in POLES-JRC comprises various transportation modes such as road transport (passenger cars, light commercial vehicles (LCV) and heavy-duty trucks (HDV)), international maritime transport and domestic navigation, and international and domestic air transportation of passengers and freight.

In the *transport sector*, global final energy demand is expected to remain relatively stable in the coming decades (**Figure 5**). This stability is attributed to two offsetting trends: increasing demand for transport services and improved efficiencies of electric vehicles compared to those with internal combustion engines. From 2040 onwards, the efficiency gains are surpassed by the general demand increase in all transport modes. In 2100, total energy demand reaches about 4 Gtoe, which is about 85% higher than today.

Although the global energy demand grows, the energy mix changes by progressive electrification and decarbonisation of transport modes. This is reflected in increasing electricity consumption and increasing shares of synfuels and hydrogen. This profound transformation results in a drastic reduction of oil consumed at the end of the century.

Transport energy demand evolves similarly in both scenarios, showing that electric vehicles are also cost-competitive also in the *Reference scenario*. A slight difference is the higher demand for synfuels in the *2°C scenario*.

Figure 5. Transport sector's final energy demand under the *Reference* and *2°C scenario* base cases.

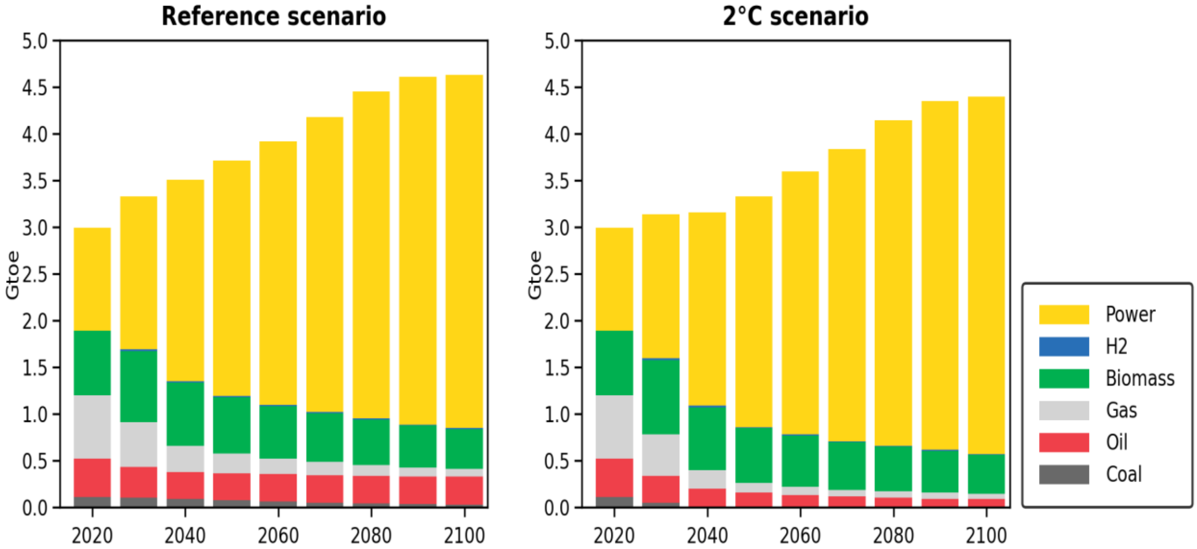


Source: POLES-JRC model

1.2.3.3.2 Residential and services sector

The energy demand in the residential and services sector encompasses heating and cooling of buildings, cooking, hot water demand, electric appliances and lighting. The sector's global energy demand is projected to increase steadily from currently about 3 Gtoe (2020) to 4.4 Gtoe by 2100 under the *2°C scenario* (**Figure 6**). *Heating and cooling* of buildings account for a significant proportion (37% in 2022) of the residential and service sector's energy demand.

Figure 6: Building sector's final energy demand under the *Reference* and *2°C scenario* base cases.



Source: POLES-JRC model

The energy mix in the residential and services sector is expected to undergo a transition driven by two primary trends: electrification and improving energy efficiency.

Heating of buildings experiences a series of transitions. First, heat pumps are increasingly replacing oil and gas boilers due to the rising global carbon value and lower acquisition costs, along with lower acquisition cost and improving efficiencies induced by technology learning (Section 2.8). Second, better thermal insulation of buildings leads to increased efficiency, resulting in lower useful energy needs despite economic growth.

Cooling needs are expected to surge in the coming decades. First, growing prosperity will lead to a higher installation rate of air conditioning equipment, particularly in countries with warmer climates. Second, rising global temperatures will increase the need for cooling. Consequently, electricity demand for cooling buildings grows, although this trend is somewhat mitigated by improving the efficiencies of cooling appliances (Section 2.8).

Moreover, electrical heating technologies and electrical cooking is projected to replace traditional biomass and liquefied petroleum gas (LPG) in developing countries. These electrification processes also contribute to overall energy efficiency gains in the global building sector.

1.2.4 Investments in clean energy technologies

The energy transition described in the *Reference* and *2°C scenarios* requires significant investments in energy technologies. **Figure 7** provides an overview of the corresponding *annual* investments by its main elements. The investments contain fossil-related and clean-energy investments. Fossil-related investments comprise:

- Coal-, oil- and gas-related investments (upstream, downstream, transformation);
- Fossil power;
- Fossil hydrogen.

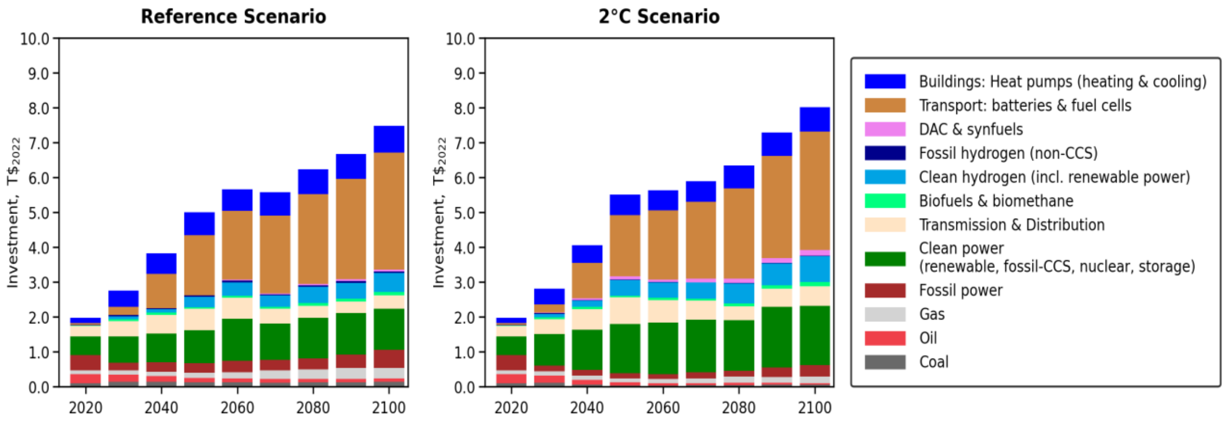
The investment needs for clean energy technologies are illustrated in more detail in this section. To this end, clean energy technologies investment needs are categorised into three groups:

- Clean power generation (for details, see **Figure 8**);
- Supply of clean fuels and direct air capture (DAC): (a) Clean hydrogen, (b biofuels and biomethane, and (c) DAC & synfuels (for details, see **Figure 9**);
- Demand side investments in (a) transport for batteries and fuel cells used in vehicles and (b) buildings for heat pumps used for heating and cooling (for details, see **Figure 10**).

Moreover, investments in the power transmission and distribution (T&D) infrastructure are shown in **Figure 7**. T&D investments increase with the substantial expansion of solar and wind capacities driven by the need for new or upgraded grid infrastructure to (i) connect these energy sources, (ii) transport electricity, and (iii) manage their intermittent output. Under the 2°C scenario, T&D investments are projected to roughly double from current levels to approximately $0.8 trillion by 2050. In contrast, the Reference scenario shows a similar investment pattern until 2050 but with a notable deviation in the second half of the century, where T&D investments are around 20% lower than in the 2°C scenario, reflecting the slower expansion of wind and solar capacities.

Other energy infrastructure costs like pipelines, new fuel infrastructure in harbours, or infrastructure to liquefy hydrogen are reflected by factors related to the cost of fuels but are not considered in the overall investment figures. Investments required for other energy-related technologies, such as for renovation of buildings or for energy efficiency measures, are considered in POLES-JRC but are not depicted in the figures of this section as they are not the focus of this report.

Figure 7. Overall annual investments by its main elements under the *Reference* and *2°C scenario* base cases.



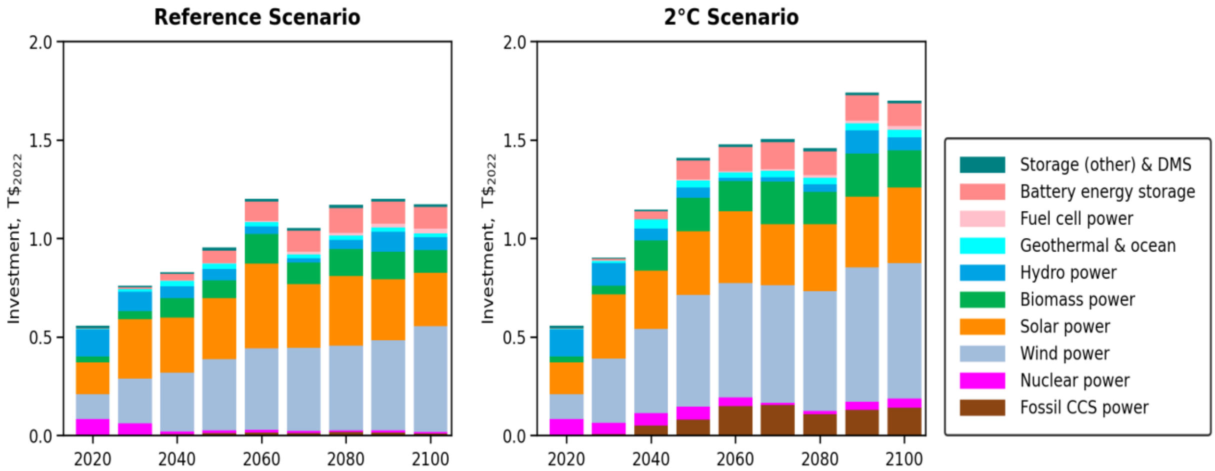
1.2.4.1 Clean power generation

In the power sector, total annual investments in clean power technologies increase from nearly 0.5 T$ (2020) to 1.4 T$ in 2050 under the *2°C scenario* **Figure 8**. In comparison, the *Reference scenario* involves significantly less investment in clean power technologies.

The technology evolution of clean technologies in the power mix (**Figure 3**) is reflected in the annual investments made:

- Solar and wind technologies dominate the investment landscape in clean power technologies in both scenarios. In the *2°C scenario*, the combined investments in solar and wind increase from around 0.35 T$ in 2020 to 0.9 T$ by 2050.
- Biomass power requires significantly more investments than its relatively small share in the power mix suggests (**Figure 3**).
- Investment needs in battery energy storage correlate with the growth of solar and wind investments, as battery storage is essential for balancing the power system. A minor role plays investments in other storage technologies (i.e., pumped hydro storage, compressed air energy storage) and demand side management (DMS).

Figure 8. Annual clean energy investments in clean power generation and battery storage under the *Reference* and *2°C scenario* base cases.



Source: POLES-JRC model

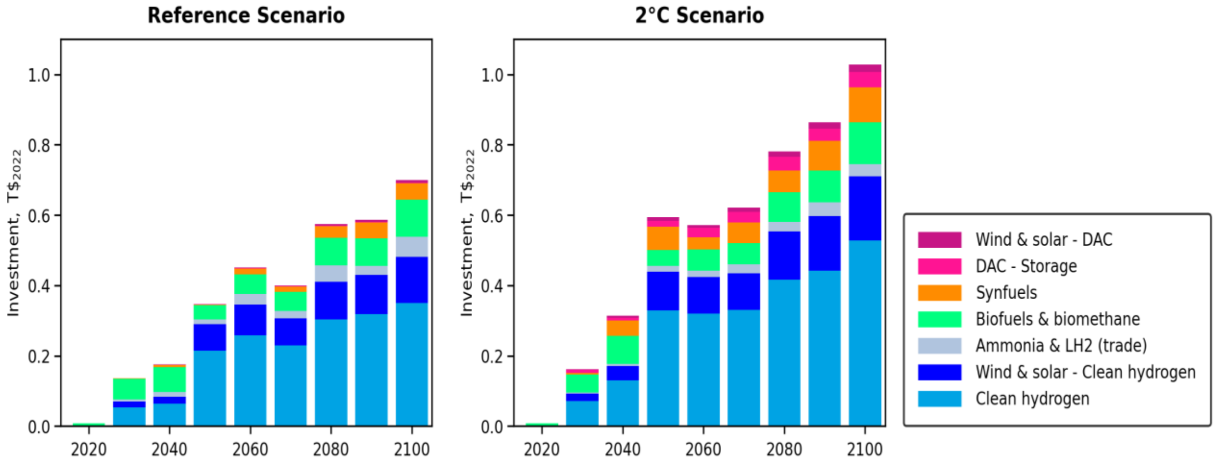
1.2.4.2 Clean fuels and direct air capture (DAC)

Annual investments in various clean energy fuels production technologies and direct air capture (DAC) are shown in **Figure 9**:

- The *Clean Hydrogen* category comprises several production technologies (see Section 2.4.2), with solar and wind-powered electrolysis and methane stream reforming with carbon capture and storage (CCS) being the most significant. The investments in clean hydrogen also include investments in dedicated solar and wind capacities, which are not accounted as part of the power system. The dip in hydrogen investments by 2070 results from investment cycles induced by equipment lifetime.
- Related to the hydrogen economy are A*mmonia & LH2* (i.e., liquid hydrogen), which serve as energy carriers for hydrogen trade. The investments for ammonia and liquid hydrogen refer to facilities of (re)conversion of hydrogen.
- *Biofuel & Biomethane* category encompass investments for the production of first and second generation biofuels, as well as biomethane installations.
- The *Synfuels* category involves investments in facilities that produce gaseous and liquid synfuels from hydrogen and captured CO_2. The shown investment figures also encompass the cost for DAC installations capturing the required CO_2.
- The *DAC storage* category covers investments for DAC installations and CO_2 storage.
- The *Wind & Solar – DAC* category accounts for the renewable investments required to power the DAC installations as are necessary for synfuel production and DAC storage.

Overall, clean fuel investments are dominated by the emerging hydrogen economy. Total clean fuel investments are substantial, amounting to about a third of the investments in power generation for the *2°C scenario* (**Figure 8**). Differences between the scenarios highlight significantly higher hydrogen investments in the *2°C scenario*, particularly in synfuels and DAC-related technologies from 2040 onwards.

Figure 9. Annual investments in clean energy hydrogen-based fuels (H_2, NH_3, LH2, synfuels), biofuels & biomethane and DAC under the *Reference* and *2°C scenario* base cases.



Source: POLES-JRC model

1.2.4.3 Transport and buildings

On the demand side, this study encompasses clean energy technologies in transport and buildings.

In the *transport sector*, clean energy technologies refer to batteries and fuel cells that power vehicles, trucks, ships and even aircrafts.

- Batteries and fuel cells are regarded as emerging technologies and play a crucial role in decarbonising the transport sector (**Figure 5**). Consequently, annual investments in batteries and fuel cells are projected to surge in the coming decades (**Figure 10**).

– Investments in batteries and fuel cells in transport are significant compared to all other clean energy technologies. For instance, in 2050, batteries and fuel cells investment amount to about 170% of the investments in power generation under the *2°C scenario* (**Figure 8**).

– The shown investments refer to the battery and fuel cell cost part of total transport equipment purchases, not the cost of the entirety of the transport equipment. The technology adoption pattern of batteries and fuel cells within the different transportation modes is analysed in the Sections 2.3.1 and 2.4.3.1.

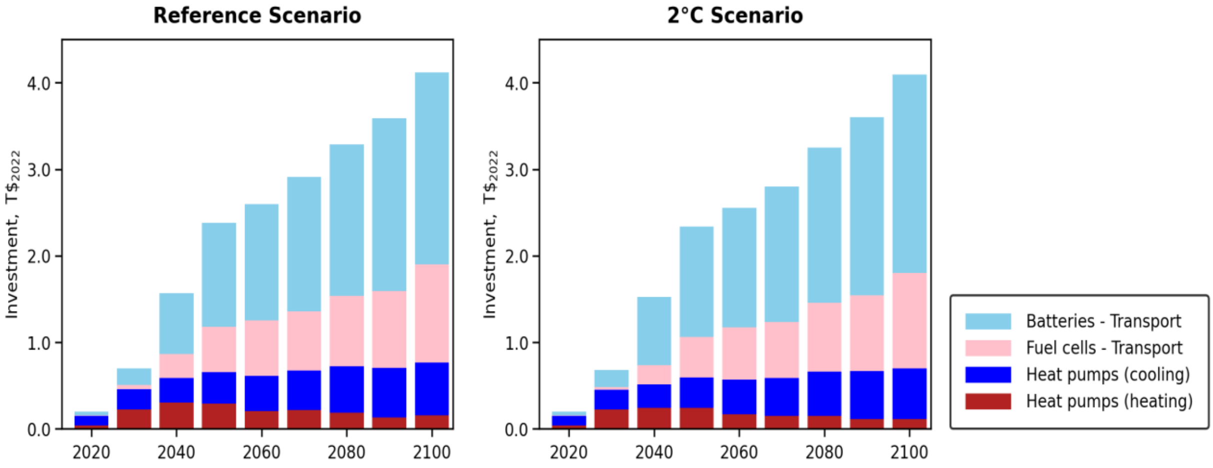
In the context of *buildings*, this report concentrates on heat pumps for heating and cooling as clean energy technology (see Section 2.8). Heat pump technologies are regarded as a key technology for the electrification of the energy demand of buildings for space heating and cooling, which accounts for a major share of the energy demand in the residential and service sector (see Section 1.2.3.3.2).

– While heat pumps for cooling (i.e., air conditioning) are well-established today, heat pumps for heating are less widespread today but hold tremendous potential.

– Annual investments in heat pumps for heating are projected to surge in the coming decades. However, from 2060 onwards, less investment in heat pumps for heating is required as the energy consumption of buildings decreases due to better insulation.

– Investments in heat pumps for cooling (i.e., A/C) grow steadily until the end of the century, reflecting the increasing global cooling needs.

Figure 10. Annual investments in clean energy technologies in transport and the residential and service sector under the *Reference* and *2°C scenario* base cases.



Source: POLES-JRC model

1.3 Methodological approach

1.3.1 Endogenous technology learning

Component-based learning-by-doing
The POLES-JRC model uses a one-factor learning-by-doing (LBD) approach to endogenise the evolution of technology costs [1]. The LBD approach posits that doubling cumulative installed capacities leads to a reduction in investment costs by the learning rate (*LR*) [10]–[13]. In its most commonly used approach, the LBD describes the evolution of investment costs of a technology as a function of its cumulative capacities [11]–[13].

In the POLES-JRC model, total investment cost is broken down into various cost components, which are associated to functional units of the technology. Consequently, POLES-JRC applies the LBD approach to the components of a technology:

(Eq. 1) $$\log(C_i) = a_i + b_i \log(X_i)$$

(Eq. 2) $$LR_i^{LBD} = 1 - 2^{b_i} \quad ,$$

where C_i is the cost of component *i*, X_i the cumulative capacity of component *i*, a_i and b_i are the LBD parameters (axis intercept and slope on a log–log scale) and LR_i^{LBD} is the actual LBD learning rate of component *i*.

For the energy technology, its actual investment cost C is the sum of all its individual components C_i :

(Eq. 3) $$\mathrm{C} = \sum_{i=1}^{n} C_i$$

This approach allows for the modelling of spillover effects, as functional components are shared by several technologies [11], [14], [15]. For instance, a gasifier unit is a component used for several power generation technologies (e.g., integrated gasification combined cycle, IGCC) as well as for several hydrogen production technologies (e.g., gasification of coal and biomass, see 2.4.2.1). Therefore, the component-based LBD approach allows the modelling of spillover effects not only across technologies but also across sectors. Also, it allows to estimate the cost for emerging technologies for which historical experience does not yet exist [11]. Furthermore, while certain components may rapidly improve through technological advancements, others may already be highly developed. The component approach addresses this by assigning specific learning rates to each component, reflecting their individual maturity and dynamics. The interaction between components with different maturity is illustrated in Section 2.5.1.2 for a power technology with and without carbon capture.

Floor cost
Moreover, for each component exists a floor cost, which marks the minimum for the component's investment cost and serves as a limitation for the cost reduction by endogenous learning. Moreover, POLES-JRC considers that cost reductions by learning to slow down once investment costs fall below a certain threshold (i.e., 133% of floor cost level). Below this threshold, learning rates converge to zero when approaching the floor cost level. The floor costs used by each technology are listed in the tables of Annex 5. These floor cost values are estimates based on long-term projections of investment costs (e.g., until 2050) [23] to which an additional 40% cost reduction is applied to account for potential technological advancements. Estimating minimum cost limitations by the end of the century poses a fundamental challenge. The approach used aims to strike a balance, on the one side, between informed estimates of achievable minimum costs and on the other side allows for substantial room for cost decreases driven by endogenous learning.

Operation and maintenance costs
Operation and maintenance (OM) costs also go down as technologies improve. In the model, OM costs diminish in proportion to the decrease of total investment cost of the technology. According to this approach, the cost evolution of fixed OM and variable non-energy-related OM is modelled based on their default values in 2022 (see Annex 5).

Efficiencies

Efficiencies play a crucial role in energy system modelling. POLES-JRC accounts for endogenous efficiency learning in a range of technologies. These technologies encompass 11 power technologies (thermal technologies and fuel cells), fuel production and transformation processes (including biofuels, biogas, synfuels, NH3 and liquid hydrogen), residential heat pumps and direct air capture.

Endogenous efficiency learning models the evolution of technology efficiency (η) by a modified one-factor LBD approach applying the efficiency learning rate LR_{η}^{LBD} for modelling decreasing technology losses L:

(Eq. 4) $$\eta = (1 - L)$$

(Eq. 5) $$\log(L) = a_{\eta} + b_{\eta} \log(X \quad) \qquad and \qquad LR_{\eta}^{LBD} = 1 - 2^{(b_{\eta})},$$

where X refers to cumulative capacities of the technology, and a_{η} and b_{η} LBD parameters. This approach uses as a starting point current efficiencies and applies learning rates, which are listed in the tables of Annex 5 (see column 'Efficiency, %' and for the learning rates column 'LReff, %'). Moreover, the efficiency improvements are limited by a maximum achievable efficiency.

In contrast, efficiencies for certain technologies are determined exogenously. These technologies include batteries (power and transport), fuel cells in transport, and industrial processes.
Moreover, conversion efficiencies for non-thermal renewable power generation technologies are not explicitly modelled. However, their efficiency improvements are implicitly captured through the investment cost decrease by endogenous learning and increases in capacity factors.

Techno-economic parameters of POLES-JRC

For all technologies implemented in POLES-JRC, the aforementioned technology parameters (investment cost by component, OM costs, efficiencies and learning rates) are documented in Annex 5.

***Two-factor learning* approach**

The above-described endogenous LBD approach could be expanded by considering the effect of cumulative research and innovation (R&I) expenditures on learning. This "two-factor learning" could be schematically described as [11]–[13] for the total overnight investment cost of a technology:

(Eq. 5) $$\log(C \quad) = a_i + b_{LBD_{2F}} \log(X \quad) + +b_{LBR_{2F}} \log(R) ,$$

where $b_{LBD_{2F}}$ is the learning-by-doing (LBD) parameter and $b_{LBR_{2F}}$ is the *learning-by-research* (LBR) for "two-factor" approach. Moreover, R refers to cumulative R&I expenditures, and C is the overnight investment cost.

In principle, the "two-factor learning" approach appears suitable for analysing the impacts of R&I expenditures on the energy system. However, there are major drawbacks to applying the "two-factor learning" to an energy system scenario model:

- Firstly, parameter sets (b_{LBD}, b_{LBR}) for the "two-factor learning" approach are only available for a few technologies [11].
- Moreover, from a methodological point, a major limitation is the interdependence of LBD and LBR, which does not allow for clearly separating cause-effect relations [11], [16].
- Furthermore, statistics on R&I expenditures are available by an entire technology class (e.g., batteries) but may lack detail on sub-technologies within the technology class (batteries for

transport or energy storage). The latter is a major difficulty in applying the "two-factor learning" approach to the multitude of technologies used in POLES-JRC.
Also, the availability of detailed statistics on R&I expenditures is often fragmented. A specific challenge is that public and private R&I data may not be aligned in scope or time. In the absence of actual statistics, R&I expenditures can be estimated using suitable proxies [17], [18].

Enhanced learning simulating R&I expenditures
Due to the reasons above, the *two-factor learning approach*, which would allow the modelling of the impacts of R&I expenditures, is not considered in the POLES-JRC model. Instead, in this study, the impact of additional R&I expenditures is simulated by enhancing technology learning within the one-factor learning-by-doing approach. To this end, *enhanced technology learning* is modelled as augmenting component learning rates above its default levels of the base case scenarios.

1.3.1 Estimating R&I expenditures

This study attempts to estimate R&I expenditures, which correspond to enhanced learning of augmenting learning rates. Although R&I expenditures are not modelled with POLES-JRC, the amount of R&I expenditures could be estimated based on the results of the enhanced learning scenarios. To this end, a *one-factor* learning-by-research (LBR) approach attributes technology progress to cumulative R&I expenditures. Analogously to LBD, the learning-by-research approach postulates a logarithmic relation between the cumulative R&I expenditures R and the total investment cost C by applying an LBR learning rate LR^{LBR}:

(Eq. 6) $$\log(C \quad) = a_i \ + b_{LBR}\log(R) \qquad and \qquad LR^{LBR} = 1 - 2^{b_{LBR}}$$

This approach allows to estimate the required R&I expenditures for a certain LBD learning rate as investment cost over time vary according to the applied LBD learning rate. Therefore, this approach is suitable to estimate future R&I expenditures associated to the enhanced learning variations of this study.

However, the application of the LBR approach is in practise limited as it requires an adequate time series of historic R&I expenditures. In practise, the available R&I data only allowed to estimate future R&I expenditures for photovoltaics and wind technologies (Sections 2.1.4 and 2.2.4).

1.3.2 Enhanced learning variations

Thematic learning groups
This study explores enhanced learning for eight thematic groups, each focused on a learning theme related to clean energies (see **Table 1**). The thematic groups are abbreviated using capital letter acronyms throughout the study (e.g., *W* for *wind power*).

Enhanced group learning
Enhanced learning within each thematic group is applied only to components related to the group's learning theme. The components addressed by enhanced learning within each thematic group are listed in the Tables in Annex 5 (see column 'Thematic group').

Enhanced technology learning is modelled as augmenting component learning rates above its default levels of the base case scenarios. This study considers two levels of enhanced technology learning:

1. *Moderately* enhanced level ('*+*'), which increases default learning rates by 25%
2. *Highly* enhanced level ('*++*'), which increases default learning rates by 50%

The *moderately* and *highly* enhanced level of the components corresponding to the thematic learning groups are shown in Tables in Annex 5 in the columns 'LR +, %' and 'LR ++, %'). The thematic learning variations are referred to as the name of the thematic group combined with the enhanced learning level. For instance, '*H2FC++*' refers to *highly* enhanced learning for clean energy components of *hydrogen and fuel cell* technologies.

Table 1. Thematic learning groups.

Acronym	Thematic group	Technologies	Clean energy components	Spillover components	Learning variation
W	Wind power	On-shore and off-shore wind	All wind power components	none	*W+*, *W++*
S	Solar Power	Utility-scale PV, rooftop PV, CSP	All solar power components	none	*S+*, *S++*
BA	Battery technologies	a) Power generation; b) <u>Demand:</u> batteries in transport (vehicles, aeroplanes).	All battery components	none	*BA+*, *BA++*
H2FC	Hydrogen and fuel cell technologies	a) <u>Supply:</u> 13 hydrogen production technologies b) <u>Demand:</u> fuel cells in vehicles and power generation	a) *Clean* hydrogen components; b) Fuel cell components	Gasifier components of a) biomass power generation; b) Biomass hydrogen production	*H2FC+*, *H2FC++*
CC	Carbon capture	a) 3 Carbon capture power generation technologies; b) 3 Carbon capture hydrogen production technologies.	Carbon capture components	Carbon capture components of a) power generation; b) hydrogen production; c) DAC.	*CC+*, *CC++*
DACSY	Direct air capture (DAC) and synfuels	a) Direct air capture (DAC). b) Liquid and gaseous synfuels.	DAC and synfuel components	'CO_2 compression' component of a) power generation; b) hydrogen production; c) DAC.	*DACSY+*, *DACSY++*
BE	Bioenergy technologies	a) 1st and 2nd generation of biofuels (4 technologies); b) 3 Biomass power generation technologies; c) 3 Biomass hydrogen production technologies.	Bioenergy components	a) Gasifier components of - biomass power generation; - Biomass hydrogen production; b) Hydrogen components of biomass hydrogen production.	*BE+*, *BE++*
HP	Heat pump technologies	<u>Demand:</u> heat pumps for heating and cooling in residential and service sector	All heat pump components	none	*HP+*, *HP++*

The base case learning rates of the components aims to reflect the expected technology progress based on a broad literature review (see column 'References learning' in Tables in in Annex 5). The chosen variation of learning rates ('*+*': +25% and '*++*': +50%) aim to strike a balance between covering a wide range of permissible values of learning rates and a systematic variation for all technologies. As the literature on learning rates shows that observed learning rates of a certain technology can vary over large ranges[11], [15], the *highly* enhanced learning level ('*++*') aims to represent an extreme but justifiable learning rate.

Spillover across technologies

Some components are shared across several technologies, allowing for the modelling of spillover effects spreading across technologies through two effects: (i) the enhanced component learning rate applies to all technologies using the same component and (ii) by relating technology progress to the cumulative capacities of a certain component used by different technologies (see Eq. 1 and Eq. 2). For example, the component '*CO_2 compression*' is shared by carbon capture technologies for (i) power generation, (ii) hydrogen production, and (iii) direct air capture (DAC), as revealed in the Tables in in Annex 5. This enables the spillover of technology progress among clean energy technologies. Furthermore, this approach allows for technology spillover between clean energy technologies and fossil technologies. For example, the "Gasifier" component is shared by several gasification technologies with and without carbon capture.

Four of the thematic technology groups address components (see column '*Spillover components*' of **Table 1**) that are also subject to technologies within other groups. However, for four thematic learning groups, the component learning is effectively limited to the technologies encompassed in this group as the components are not used in other groups (marked as 'none' in column '*Spillover components*' of **Table 1**.

Impact analysis of enhanced learning

Enhancing technology learning within this study is limited to the period 2025 and 2050, which aims to simulate additional R&D expenditures during this period. Nevertheless, the impacts of boosting technology progress within this limited period are analysed until 2100.

Chapter 2 is dedicated to an analysis by technology groups, illustrating the technology adoption patterns of the technologies in the respective technology groups within the base cases of the *2°C* and *Reference scenarios*. Additionally, the impacts of enhanced learning rates variations within the limits of thematic groups are analysed in terms of capacities, production, and investments. Additionally, the impacts of enhanced learning rates variations within the limits of thematic groups are analysed in terms of capacities, production, and investments.

Chapter 3 analyses the overall impacts of enhanced learning rates variations in terms of (i) CO2 emissions, (ii) investment needs and (iii) energy supply costs. Section 3.2 examines the overall impacts of enhanced learning rates limited to learning within the thematic groups. Synergies across the thematic learning groups are analysed in Section 3.3 by examining the overall impacts of combinations of enhanced learning (i.e., learning strategies). The analysis culminates in a sensitivity analysis considering all possible learning combinations from the eight thematic groups (Section 3.4).

2 Analysis by technology group

2.1 Wind power technologies

2.1.1 Wind power generation

The wind power technology group encompasses on-shore and off-shore wind power generation technologies. In POLES-JRC, the deployment of wind technologies is determined by costs and resource potentials. The main cost factor for wind power generation is investment cost, whereas operation and maintenance costs are of minor importance.

Resource potentials for on-shore and off-shore wind power are derived from a detailed technological assessment, which include meteorological potential, exclusion factors (representing geographical, social and environmental considerations) and technology characteristics. This assessment distinguishes three wind classes for each wind technology (i.e., on-shore and off-shore wind). For on-shore wind, these classes are only based on the average wind speed, whereas for off-shore wind, the distance to the coast is additionally considered [19], [20].

The amount of new wind capacities to be deployed is calculated by the model's capacity planning and distributed across the three wind classes according to resource use efficiency. Wind power generation in POLES-JRC is determined by hourly production profiles of six representative days. These profiles are calculated based on wind speed data from satellite measurements [21], [22] assuming a typical wind generator production curve and a mix of current and future expected locations of plants (impacted by today's population density and the areas with high resource availability) [23].

Furthermore, wind overproduction can occur when electricity storage capacities (Sections 1.2.3.2 and 2.3.2.1) are insufficient to absorb high levels of wind power generation. In POLES-JRC, excess wind energy can be either curtailed or utilised as a feedstock for hydrogen production (Section 2.4.2).

2.1.2 Technology adoption pattern

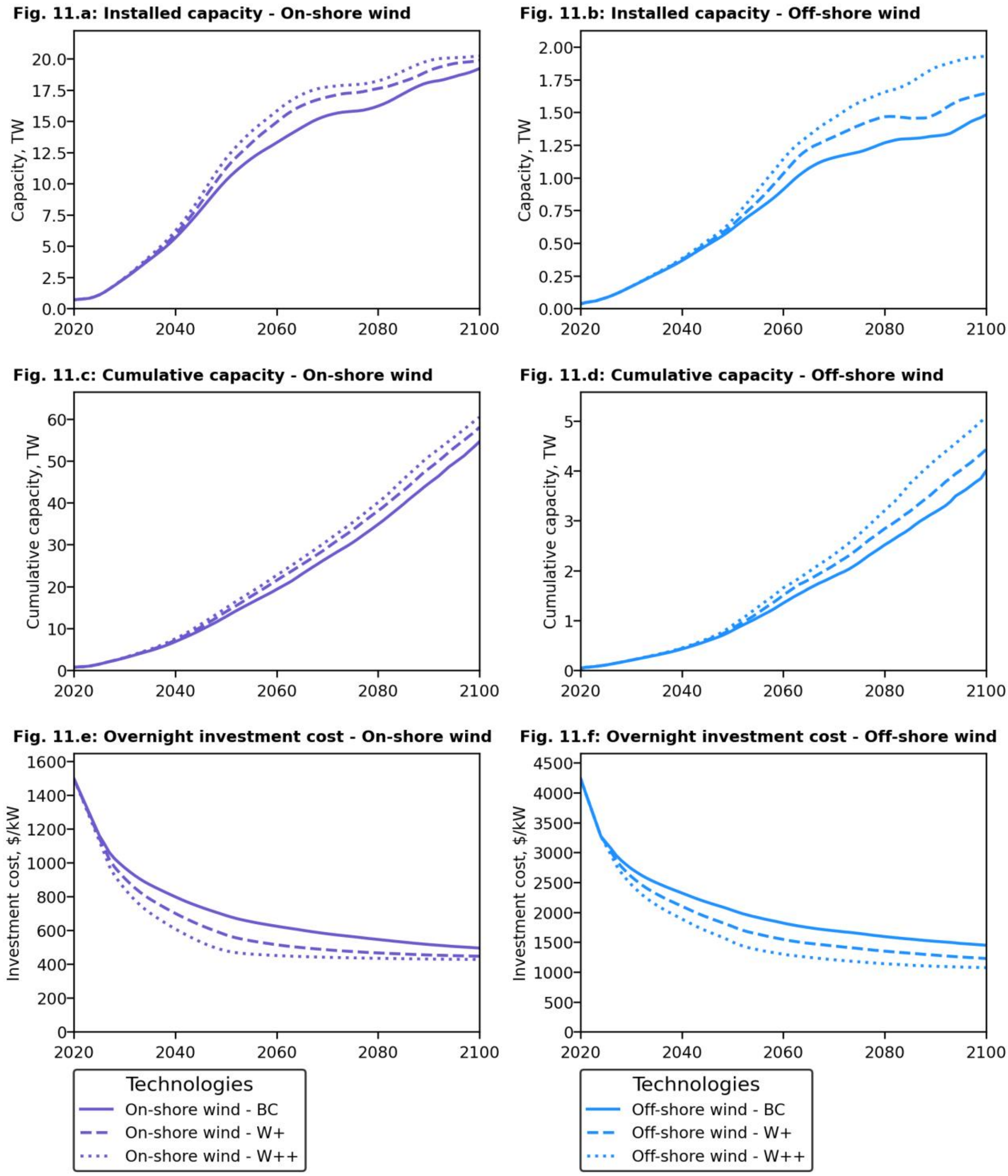
Wind power expands massively in the coming decades in the *2°C base case (BC)* and Reference BC scenario. In both scenarios, on-shore wind is the dominating technology. Its installed capacities increase rapidly in the coming decades from 0.8 TW in 2022 to about 11 TW in 2050 for the 2°C BC scenario (**Figure 11.a**). In the second half of the century, capacities grow slightly slower to reach 20 TW in 2100. Meanwhile, off-shore capacities increase substantially, meeting 0.7 TW in 2050 and 2 TW in 2100, but remain about a factor ten smaller compared to on-shore wind capacities (**Figure 11.b**).

Cumulated capacity (**Figure 11.c and d**) is the driver for the cost decline in the learning-by-doing approach (see 1.3.1). Cumulative capacities for on-shore and off-shore wind increase from 2020 to 2050 18-fold and 23-fold, respectively. As a result, overnight investment cost decreases for on-shore wind by 54% to about 690 $/kW (2050) and for off-shore wind by 52% to about 2020 $/kW (2050), as can be seen in **Figure 11.e and f**.

In the second half of the century, cost decline slows down and decreases merely by an additional 28% for both technologies (2050 compared to 2100) as cumulative capacities for on-shore and off-shore wind increase from 2050 to 2100 merely about 4-fold and 5-fold, respectively. These results refer to a learning rate of 14% for on-shore wind components and 13% for off-shore wind components. For both wind technologies, the investment cost is split into a turbine component and a balance of system (BOS) component (including e.g., foundation, transmission, cable). The techno-economic parameters including cost data (overnight investment costs, operation and maintenance costs) and learning rates used for the wind technologies are available in the Annex (see **Table 10** in AN 5.1).

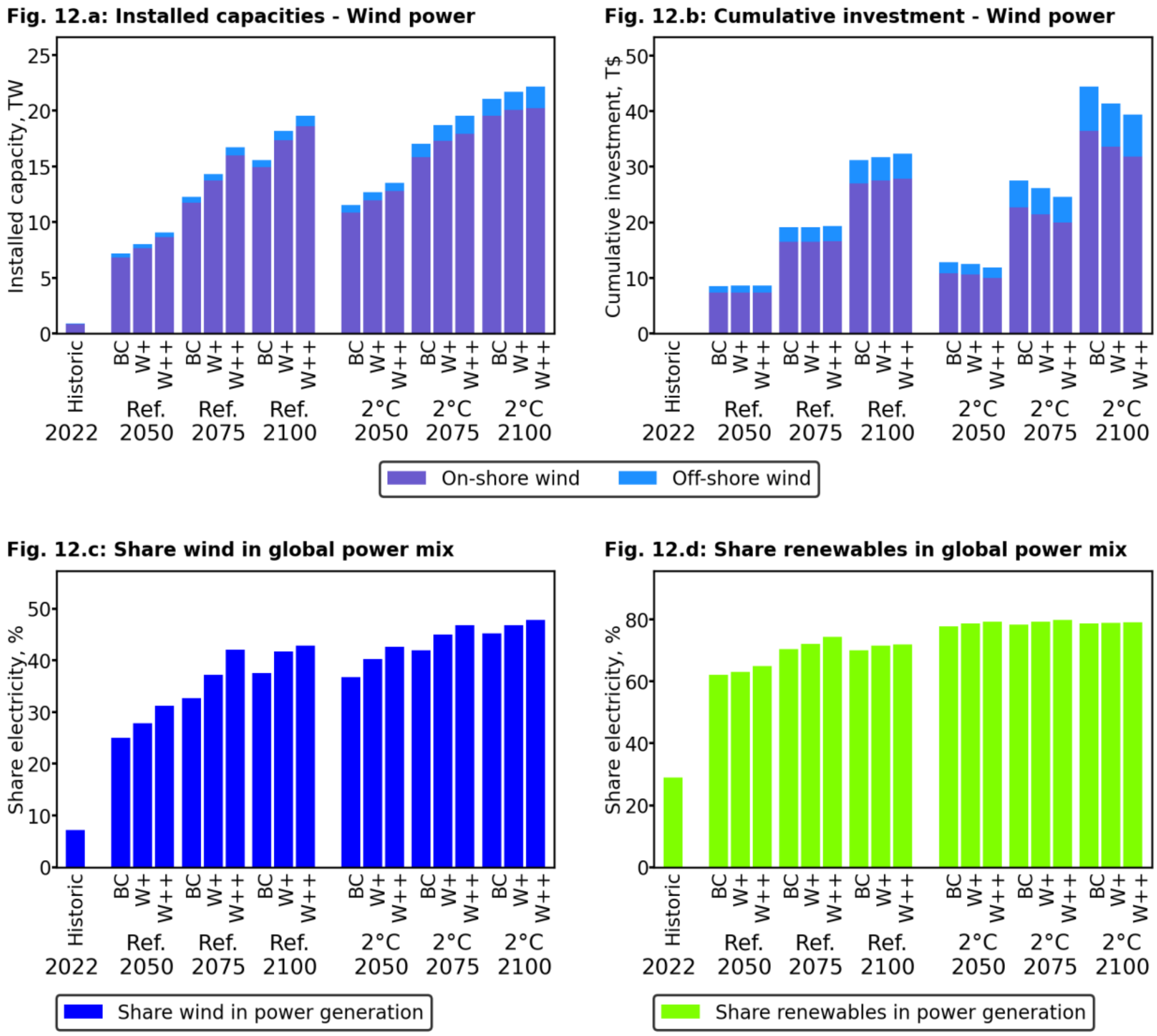
In the *Reference BC scenario*, wind power also expands, but at lower levels. On-shore installed capacities reach merely 7 TW in 2050 and 15 TW in 2100 (**Figure 12.a**). Meanwhile, off-shore wind in the *Reference BC scenario* meets merely half of the levels in the 2°C BC scenario. The share of wind power in the global power mix increases steeply from 7% in 2022 to 37% in 2050 and 45% in 2100 (**Figure 12.*c***) in the *2°C BC scenario*. In the *Reference BC scenario*, the share of wind power reaches merely 25% in 2050 and 37% in 2100.

Figure 11. Evolution of on-shore and off-shore (a & b) wind capacity, (c & d) cumulative capacity and (e & f) overnight investment cost for learning variations (*BC*, *W+*, *W++*) under the *2°C scenario*.



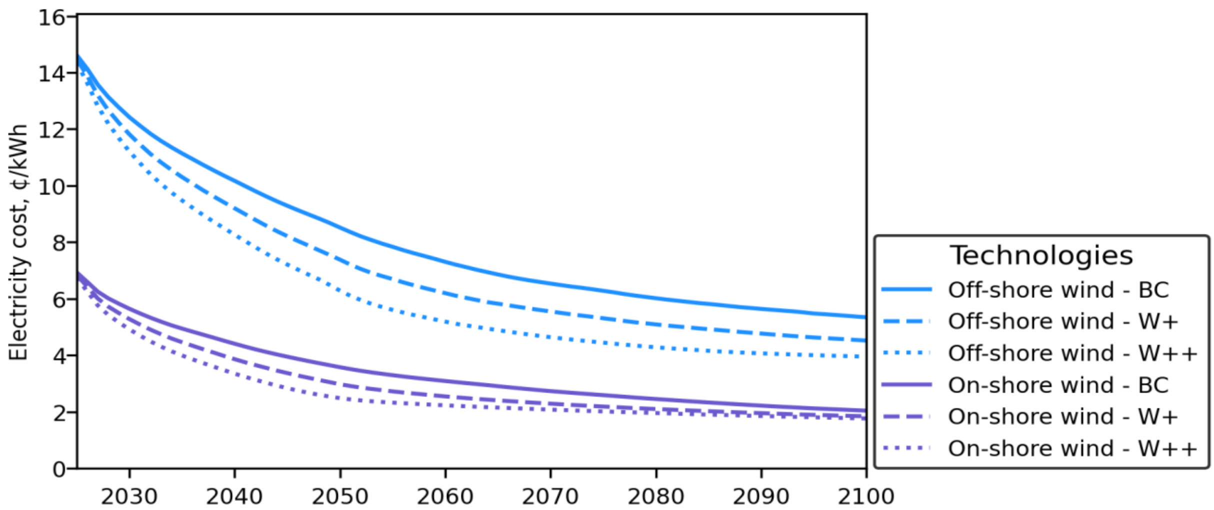
Source: POLES-JRC model

Figure 12. Impacts of learning variations (*BC*, *W+*, *W++*) under the *Reference* and *2°C scenario* for wind power technologies.



Source: POLES-JRC model

Figure 13. Power generation cost for wind on-shore wind and off-shore compared to global average electricity cost for learning variations (*BC*, *W+*, *W++*) of the *2°C scenario*.



Source: POLES-JRC model

The substantial growth in wind power is reflected in a growing share of all renewables in the power mix (**Figure 12.d**). The share of renewables increases from 29% in 2022 to about 77% in 2050 in 2°C BC scenario and remains at this level in the second half of the century (**Figure 12.d**).

In POLES-JRC, wind power is also used for hydrogen production by electrolysis (section 2.4.2) and direct air capture (DAC, section 2.6.1). These capacities come on top of the wind capacities of the actual power system, as reported in **Figure 11** and **Figure 12**. Their deployment is an additional factor driving down investment costs. Under the *2°C BC scenario*, wind capacities dedicated to electrolysis are projected to reach about 1 TW by 2050 and 3.5 TW by 2100 (**Figure 31.d** in section 2.4.2.4). Whereas substantially lower wind capacities are used for DAC, amounting to 0.1 TW by 2050 and almost 0.4 TW by 2100 (**Figure 43.d** in section 2.6.1.1) in the *2°C BC scenario*. Notably, the *Reference BC scenario* projects significantly lower wind capacities, which are roughly a half lower for electrolysis and several times lower for DAC than those in the *2°C BC scenario*.

Power generation costs for wind decline substantially due to technology learning (**Figure 13**). In the 2°C BC scenario, on-shore wind power generation costs decrease from about 8 ¢/kWh in 2022 to about 3.6 ¢/kWh in 2050, while off-shore wind power generation costs decrease from about 16 ¢/kWh in 2020 to about 8.5 ¢/kWh in 2050.

2.1.3 Impacts of enhanced learning rates

Enhanced learning leads to faster decreases in overnight investment costs, as illustrated in **Figures 10.e and 10.f**. In the *2°C scenario* by 2050, enhanced learning (*W+*) results in a 17% cost reduction for onshore wind and a 13% reduction for offshore wind compared to the *2°C BC scenario*. Highly enhanced learning (*W++*) yields a 30% cost decrease for onshore wind and a 26% reduction for offshore wind. Notably, the floor cost level for onshore wind is reached by 2055 with highly enhanced learning. As a result of enhanced learning, substantially more wind capacities are installed (**Figure 12.a and b**). In the *2°C scenario* by 2050, on-shore wind capacities increase with enhanced (*W+*) and highly enhanced learning (*W++*) by 9% and 17%, respectively.

The wind share in the power mix in 2050 increases by 8 and 15 percentage points compared to the 2°C BC scenario for enhanced (*W+*) and highly enhanced learning (*W++*), respectively (**Figure 12.c**). While the overall share of renewables in the power mix increases merely by two percentage points even for highly enhanced learning (*W++*) as other renewables (e.g., PV) are crowded out due to the additional cost decrease of wind power (**Figure 12.d**).

In the *Reference scenario*, enhanced learning has even more impact in relative terms on installed capacities and wind share in the power mix (**Figure 12.a and c**).

Notably, in the enhanced learning cases, the amount of funding required for expanding capacities in the *2°C scenario* is lower than in the base case due to enhanced learning (**Figure 12.b**). For highly enhanced learning (*W++*), by 2050, about 7% less cumulative investments are required, and by 2100, 13% less compared to the *2°C base case scenario*. This outcome stems from investment costs decreasing more rapidly as capacities grow. On the other hand, in the *Reference scenario*, the impact of enhanced learning on total investment appears to be less significant, as the increase in capacity does not fully offset the reduction in investment costs.

The effects of enhanced learning on the power generation costs of new installations are considerable (**Figure 13**). By 2050, the highly enhanced learning case (*W++*) leads to cost reductions of about 30% for onshore wind and 21% for offshore wind compared to the *2°C BC scenario*. In the second half of the century, on-shore wind power generation costs converge towards their minimum, while off-shore generation costs continue to fall.

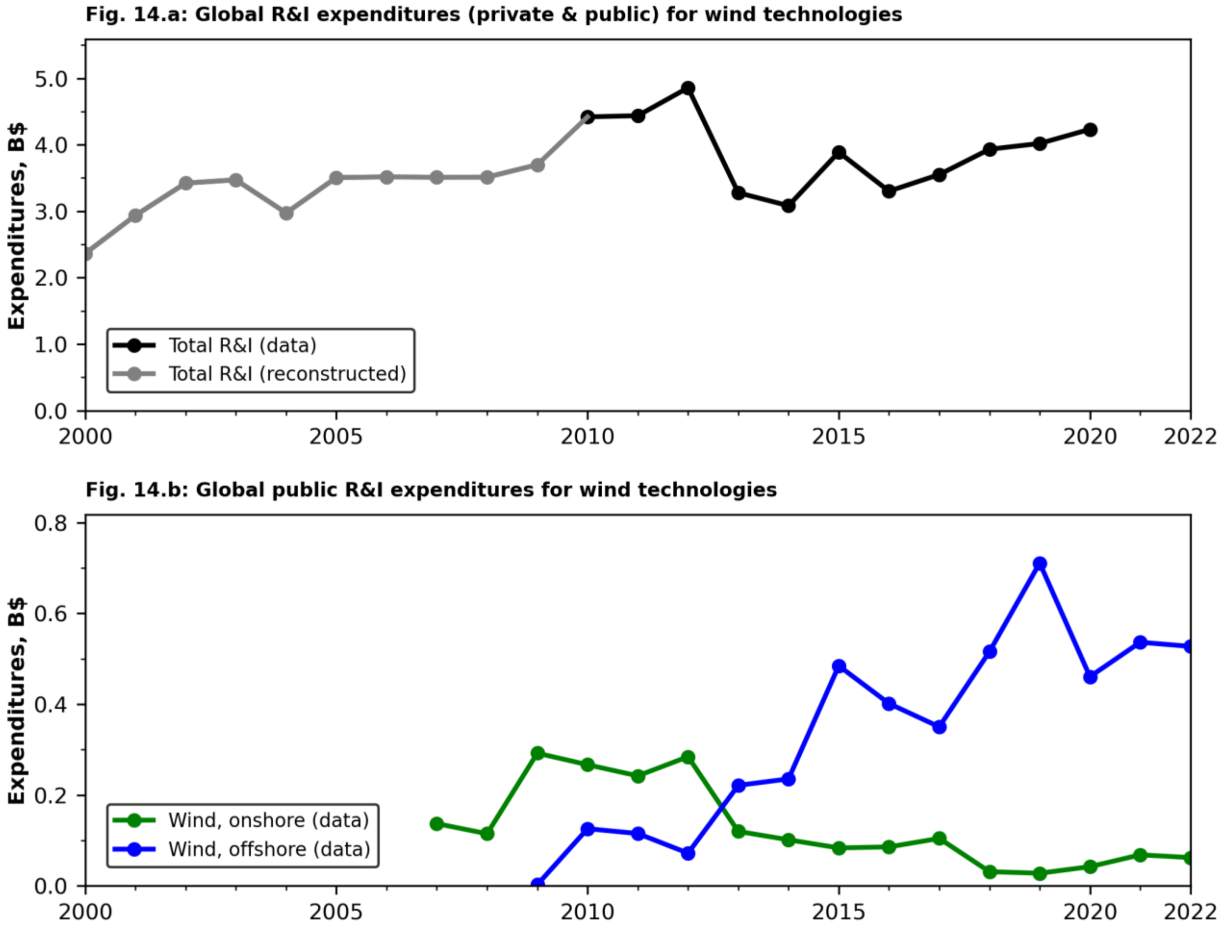
2.1.4 Research and innovation expenditures

Research and innovation (R&I) expenditure data

Between 2010 and 2020, global R&I expenditures for wind technologies, both private and public investments, oscillated around 4 billion USD. Since 2013, R&I expenditures show a strong upward trend (**Figure 14.a**). The vast majority of these expenditures originate from private sources, with public R&I investments accounting for a minor part ranging between 9% and 18% over the years (**Figure 14.b**).

Notably, there has been a shift in public R&I investments towards off-shore wind, which has experienced continuous and significant growth in recent years. In contrast, public R&I investments for on-shore wind (**Figure 14.b**) have continuously decreased since 2009, reflecting the increasing competitiveness of on-shore wind electricity generation (**Figure 13**).

Figure 14. R&I expenditures for wind power: Total private & public expenditures (top) and public expenditures (bottom).



Source: JRC analysis. The public R&I data is based on IEA [24], and private R&I data is based on estimates using patents as a proxy [25].

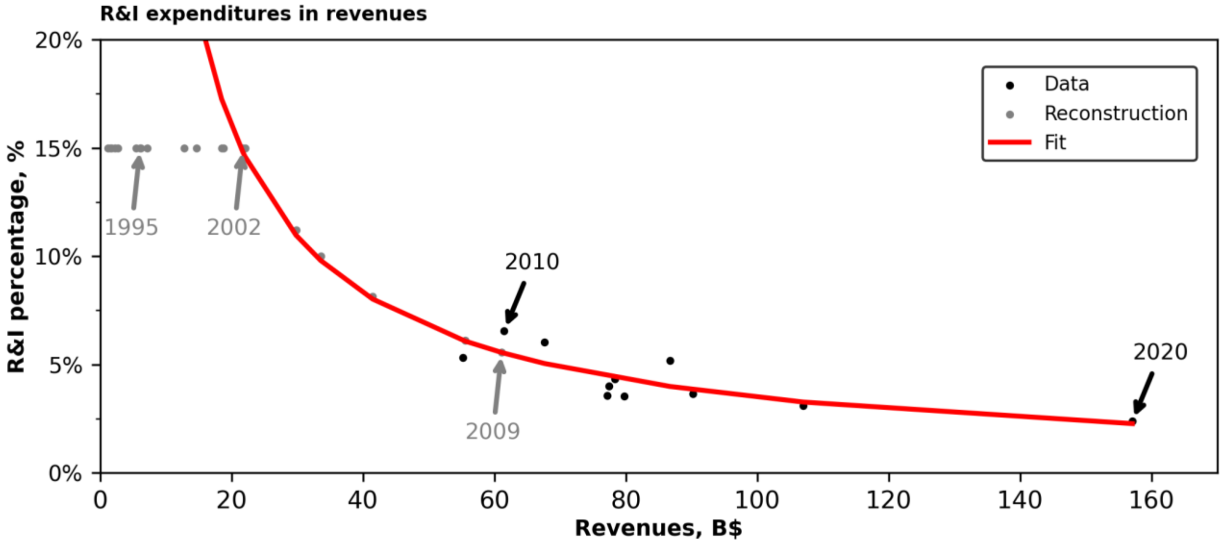
Estimating R&I expenditures

In the scenarios, the decrease in cost due to endogenous learning is attributed to the increasing deployment of capacities (**Figure 11**). Based on the projected cost decrease from the scenario results, the associated R&I expenditures are recalculated using the one-factor learning-by-research (LBR) approach described in Section 1.3.1. The applied LBR approach relates cost progress to the sum of private and public R&I expenditures.

Reconstruction of historic R&I expenditures

To properly apply the LBR approach, R&I expenditure time series are required, which extend back into the past, at least for periods when significant capacities of the technologies were installed. Consequently, reconstructing historic R&I data is necessary.

Figure 15. R&I expenditures as a percentage of revenues.



Source: JRC

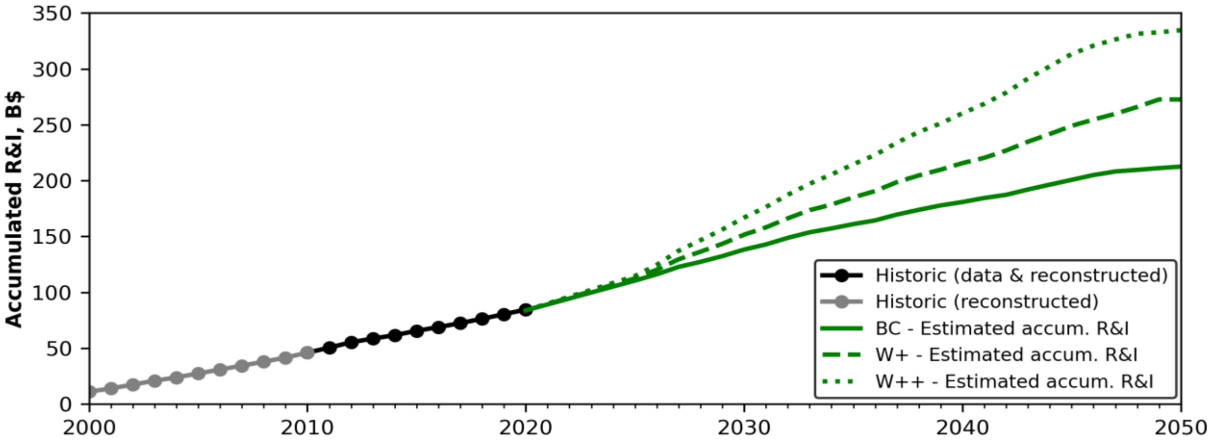
Empirical evidence shows that the share of R&I in revenues decreases with increasing volumes of manufactured equipment for the respective technology. **Figure 15** depicts data on private R&I shares and wind installation revenues (i.e., investment cost multiplied by new annual capacities) between 2010 and 2020. **Figure 15** reveals that the R&I share in revenues fell from about 5% in 2010 to less than 2% in 2020, as R&I expenditures stagnated (**Figure 14.a**), while capacities grew substantially during this period.

Fitting the historical relationship allows to extrapolate this trend for lower revenues and, thus, to the past. Based on this fitted curve (capped by a maximum of 15%), historic R&I expenditures are reconstructed. In the next step, cumulative R&I expenditures (private and public) are calculated (**Figure 16**) by using the reconstructed R&I expenditures in the period 1990 to 2010 (grey dots) and actual data for R&I expenditures after 2010 (black dots).

Estimating of future R&I expenditures

Cumulative R&I expenditures for wind technologies (private and public) amount to approximately 85 billion USD in 2020 (**Figure 16**). Applying the LBR approach to the *2°C BC scenario* projects a steady increase in cumulative R&I expenditures to about 213 billion USD by 2050. This increase in R&I investments is associated with the progress in expanding wind power in the *2°C BC scenario*.

Figure 16. Cumulative R&I expenditures for wind power technologies – Estimations for *2°C BC scenario*.



Source: JRC

For the additional progress made under the enhanced (*W+*) and highly enhanced learning (*W++*) variants of the *2°C scenario*, cumulative R&I expenditures are projected to increase by 2050 to 273 billion USD and to 335 billion USD, respectively. Consequently, according to the applied methodology, an additional 122 billion USD in R&I expenditures are required to achieve the additional progress in the highly enhanced learning variant (*W++* compared to the *BC* scenario). In annual terms, these additional R&I expenditures amount to roughly 4 billion per year, which is equivalent to approximately doubling the current global R&I expenditures (**Figure 14.a**).

From a monetary perspective, these additional 122 billion USD in R&I expenditures are required to reduce cumulative investments until 2050 by approximately 1 trillion USD (**Figure 12.b**, difference between *2°C scenario* base case and W++ for 2050). Until 2100, these R&I expenditures presumably result in savings of 4 trillion USD. Furthermore, with highly enhanced learning (*W++*), electricity generation costs are projected to decrease by an additional 1.2 ¢/kWh compared to the *2°C BC scenario*, which compares to expenditures of 0.065 ¢/kWh when relating the additional R&I expenditures (i.e., difference *W++* to BC) to the amount of electricity generated in this period.

In conclusion, additional R&I expenditures in wind technologies to trigger enhanced learning is a beneficial strategy to boost the green transition and to gain significant global economic advantages.

2.2 Solar power technologies

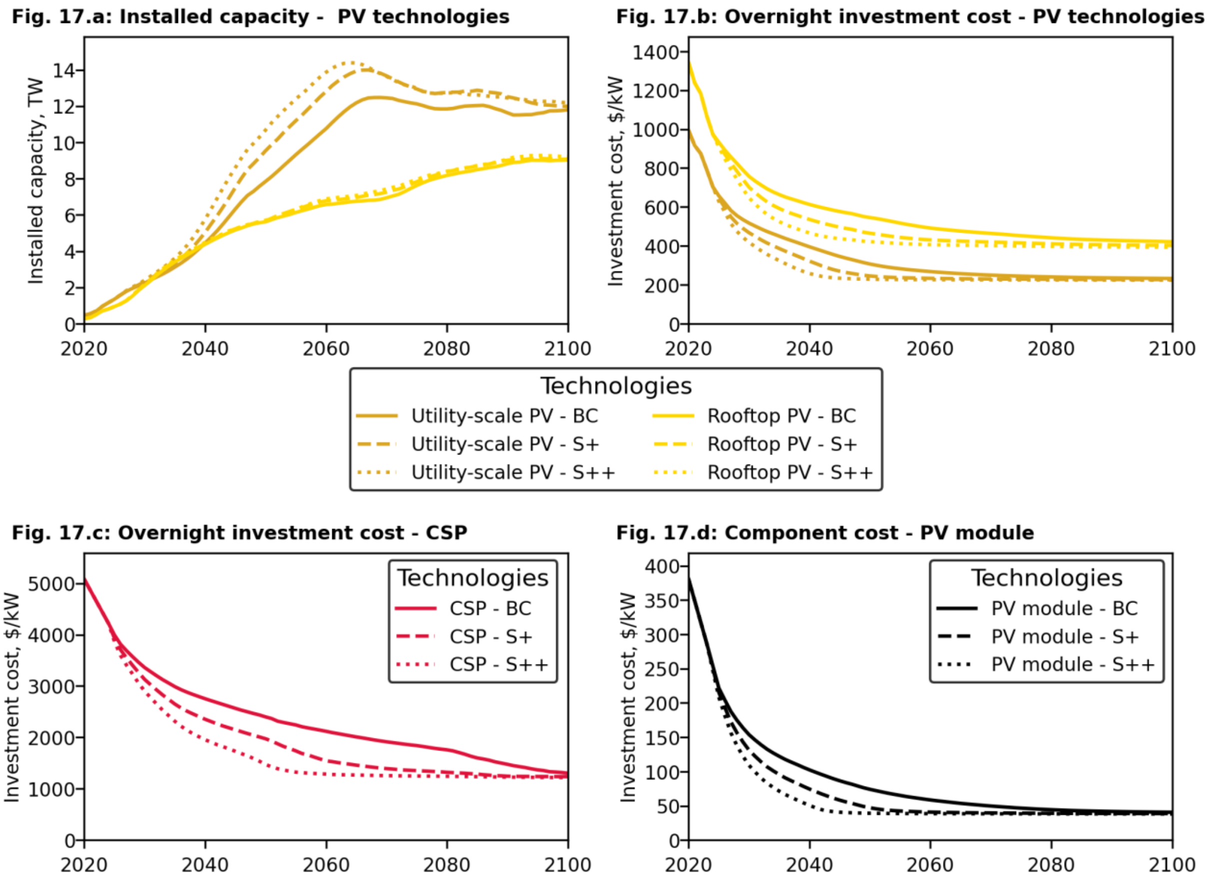
2.2.1 Solar power generation

The solar power technology group encompasses utility-scale photovoltaics (PV), rooftop PV and concentrated solar power (CSP). In solar power technologies, the primary cost driver is the investment cost, with operational and maintenance expenses playing a relatively more minor role. Solar power generation in POLES-JRC is determined by hourly production profiles of six representative days. These profiles are calculated based on irradiance data from satellite measurements [22], [26]. Moreover, resource potentials for solar power technologies are taken into account in POLES-JRC. Resource potentials are implemented as a functional relation of (i) available surfaces for deploying solar power and (ii) solar irradiation. Both factors consider geographical and environmental factors as well as competition between different surface uses. The deployment of utility-scale PV and CSP is dedicated to the availability of large surface areas (i.e., grasslands, deserts). In contrast, the availability of roof surfaces is exclusively relevant for installing rooftop PV.

2.2.2 Technology adoption pattern

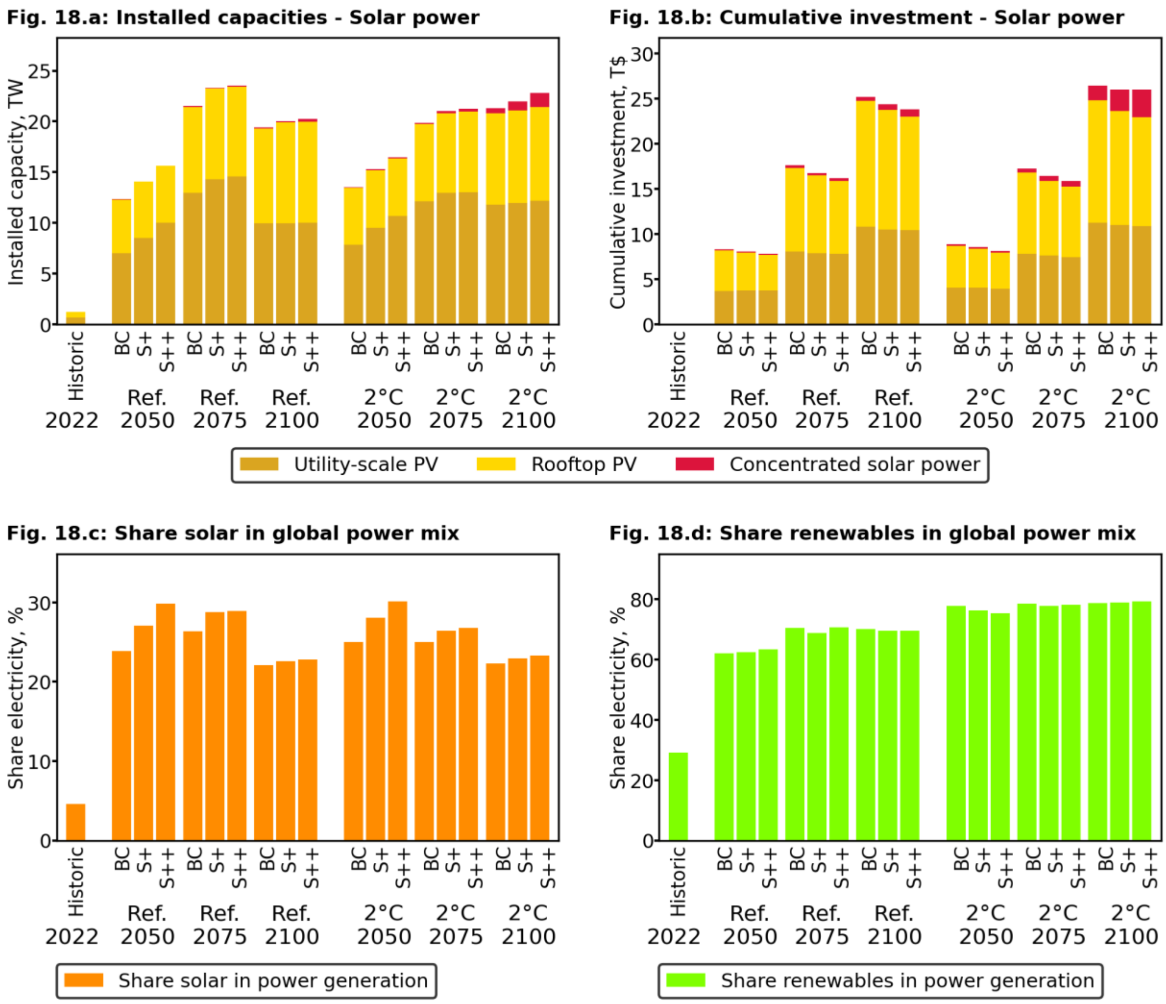
In the *2°C base case (BC) scenario,* installed capacities of utility-scale PV surge in the coming decades to a maximum of about 12 TW in 2070, but slightly decrease in the last decades of the century (**Figure 17.a**). The slight decrease in utility-scale PV is in part a result of increasing concentrated solar power (CSP) capacities (**Figure 18.a**) as this alternative solar technology becomes more competitive in the latter half of the century (**Figure 17.c**). Moreover, investment costs of utility-scale PV reach floor cost in the second half of the century (**Figure 17.b**), while rooftop PV and also wind technologies (**Figure 11.e and Figure 11.f**) still reduce their investment cost in the second half of the century. Hence, new installations in renewables experience a shift towards CSP, rooftop PV and wind technologies in the latter half of the century.

Figure 17. Evolution of (a) installed capacity, (b & c) overnight investment cost for solar power technologies and (d) overnight investment cost for PV modules for learning variations (*BC, S+, S++*) under the *2°C scenario*.



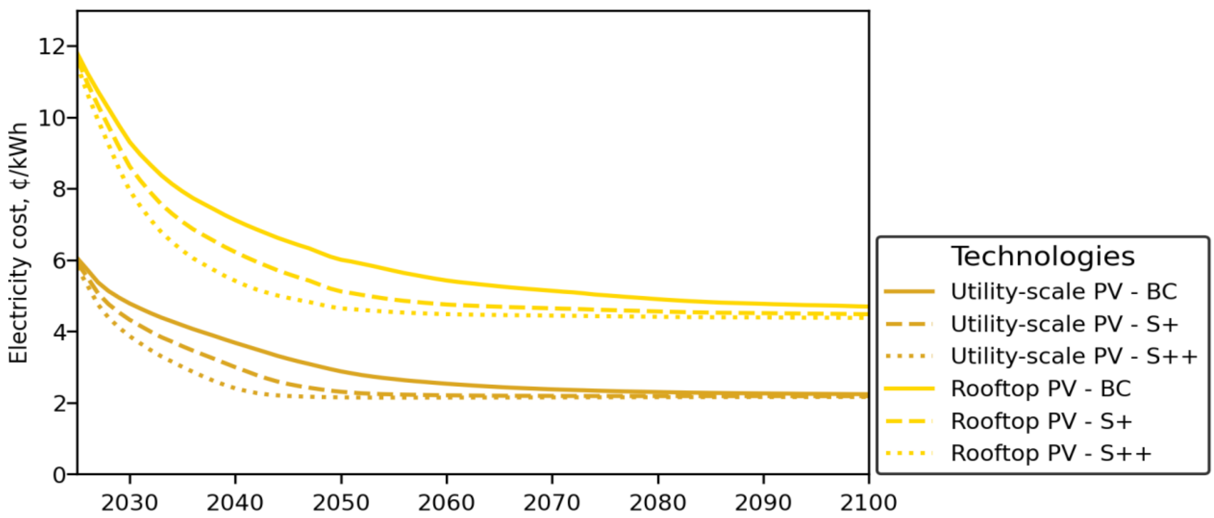
Source: POLES-JRC model

Figure 18. Impacts of learning variations (*BC*, *S+*, *S++*) under the *Reference* and *2°C scenario* for solar power technologies.



Source: POLES-JRC model

Figure 19. Evolution of global average electricity generation cost for new PV installations (utility-scale PV, rooftop PV) for learning variations (*BC*, *S+*, *S++*) of the *2°C scenario*.



Source: POLES-JRC model

Moreover, utility-scale PV is one of the technologies generating electricity dedicated for electrolysers (section 2.4.2) and direct air capture (DAC, Section 2.6.1). Although these capacities are not reported in the power system (i.e., not appearing in **Figure 17** and **Figure 18**), their deployment is an additional factor driving down investment costs. Under the *2°C BC scenario*, utility-scale PV capacities dedicated to electrolysis are projected to reach 1.5 TW by 2050 and 5 TW by 2100 (Figure 31.d in section 2.4.2.4). Whereas utility-scale PV capacities used for DAC are substantially lower, amounting to almost 0.2 TW by 2050 and 0.6 TW by 2100 (Figure 43.d in Section 2.6.1.1) in the *2°C BC scenario*. Notably, the *Reference BC scenario* projects significantly less PV capacities used for electrolysis (roughly 50% lower) and used for DAC (several times lower) than those in the *2°C BC scenario*.

The investment cost of PV technologies is broken down in a PV module component and a balance of system (BOS) component (see **Table 11** in **AN 5.1**). The BOS component encompasses all other cost factors such as hardware (e.g., inverters, mounting, cabling), installation and soft cost (except financing) [27], [28]. For the CSP technology, the investment cost consists of merely one component.

For the PV module a high learning rate of 30% is applied reflecting the fast technology improvements of the core PV component. For the BOS components lower learning rates are used (LR of 18% for utility-scale PV and 12% for rooftop PV) as the BOS is characterised by slower cost decrease [27], [29], [30]. As a result, investment costs of utility-scale PV reach floor cost earlier than rooftop PV. In the *2°C BC scenario*, the solar share in the power mix reaches 25% in 2050 and a maximum of 30% by around 2075 (**Figure 18.c**). However, over the same period, the share of all renewables in the power mix stagnates (**Figure 18.d**) as the share of wind power increases substantially in the second half of the century in the *2°C BC scenario* (**Figure 12.c**).

In the *Reference BC scenario*, the expansion of solar power technologies is comparable to the *2°C BC scenario* up until 2050 but reaches slightly lower levels. However, by around 2075, solar power in the *Reference BC scenario* slightly surpasses the *2°C BC scenario* in terms of capacities and solar share in the power mix, as depicted in **Figure 18.a and c**. This phenomenon can be attributed to the global carbon value in the *2°C BC scenario*, which promotes the expansion of various other renewable energy sources (e.g., wind power **Figure 12.c**), whereas in the *Reference BC scenario*, solar power dominates due to its high learning rates.

2.2.3 Impacts of enhanced learning rates

For utility-scale PV, investment cost reaches a level close to the floor cost in 2090 in the *2° BC scenario* (**Figure 17**.b). Similarly, the global average power generation cost of utility-scale PV would converge to a limit of about 2 cents/kWh at the end of the century (**Figure 19**). With enhanced learning (*S+*), these cost limits are reached by 2080 and even earlier by 2050 with highly enhanced learning (*S++*).

The additional cost decline due to enhanced learning results in substantially faster growing utility-scale PV capacities between 2040 and 2070 compared to the *2° BC scenario* (**Figure 17.a**). For the last decades of the century, enhanced learning results in higher capacities compared to the base case.

For rooftop PV, costs also decrease faster in the coming decades with enhanced learning, but less pronounced compared to utility-scale PV. The floor cost level can only be reached before the end of the century with highly enhanced learning. However, the effect on capacities is mainly limited as the deployment of rooftop PV is limited to the demand in the building sector (**Figure 17.a**).

The cost for PV modules (**Figure 17.d**) decreases with enhanced learning even more rapidly and reach the floor cost level already by 2045 for highly enhanced learning instead of about 2080 in the *2° BC scenario*.

Overall, total solar capacities increase with enhanced learning in both scenarios until the end of the century. Remarkably, less money needs to be spent to install the higher capacities with enhanced learning **Figure 18.b**). This effect is because investment cost decreases faster than capacity increases. Solar shares in the global power mix increase with enhanced learning in both scenarios until about 2075 (**Figure 18.c**), while in the last quarter of the century, the effect is much less pronounced.

To conclude, the impacts of accelerating learning in solar technologies are considerable in the coming decades, but rather limited in the second half of the century as cost approaches floor cost levels.

2.2.4 Research and innovation expenditures

Research and innovation (R&I) expenditure data

Global R&I expenditures for photovoltaic technologies (private & public) accounted for roughly 7 billion USD in 2020 (**Figure 20.a**). Global R&I expenditures have declined from their peak in 2011 and were relatively stagnant in recent years, according to available data. Private R&I expenditures dominate the global R&I expenditures. Public R&I expenditures (**Figure 20.b**) also show a declining trend since 2013. The share of public R&I of global expenditures (private & public) was merely 5% in 2020.

Estimating future R&I expenditures

For periods without available R&I expenditure data, these expenditures have been reconstructed using the same methodology as described in Section 2.1.4 for wind technologies, based on the relationship between the share of R&I in revenues, following a fitted curve (**Figure 15**). The reconstructed data for global R&I expenditures (private & public) is shown in **Figure 20.a**; the reconstructed evolution of cumulative R&I expenditures (private and public) is depicted in **Figure 21**.

In 2020, cumulative R&I expenditures for PV technologies (private and public) amounted to approximately $164 billion USD.

Estimating future R&I expenditures

Cumulative R&I expenditures until 2050 are calculated based on the trajectories of investment costs by applying the one-factor learning-by-research (LBR) approach described in Section 1.3.1. Under the *2°C BC scenario*, cumulative R&I expenditures continue to increase in the coming decades but with a smaller growth rate from 2025 onwards as PV becomes increasingly mature. In 2050, cumulative R&I expenditures are projected to reach 270 billion USD under the *2°C BC scenario*.

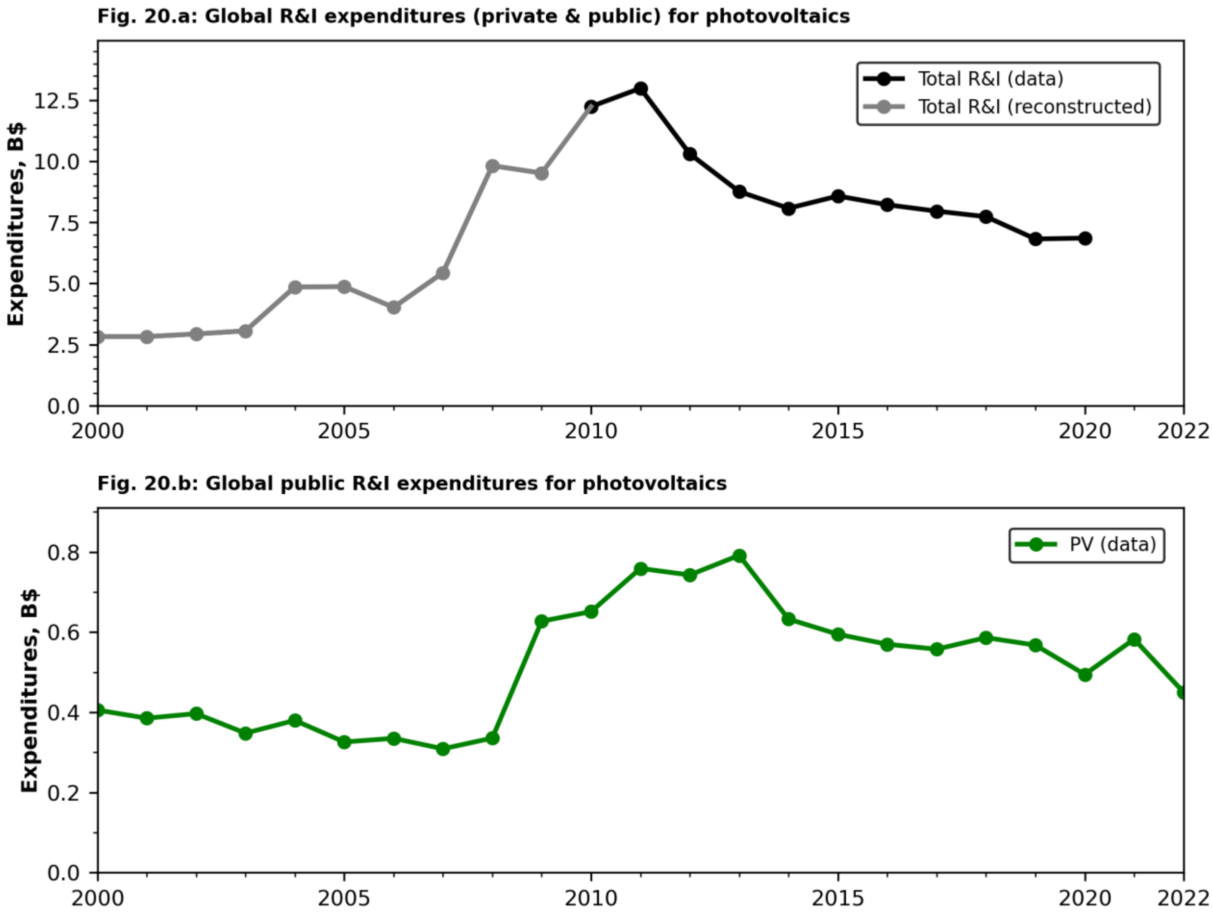
For the additional progress made in the variants of enhanced (*S+*) and highly enhanced learning (*S++*), the LBR approach shows that cumulative R&I expenditures are required to increase to $296 billion USD and $305 billion USD, respectively, by 2050. In the highly enhanced learning scenario, R&I expenditures stagnate from 2040 onwards, reflecting that overnight costs reach floor cost levels from 2040 onwards (**Figure 16.b and c**).

The *S++* variation requires an additional $92 billion USD in R&I expenditures compared to the *BC scenario* to achieve the additional progress. This additional learning effort is expected to increase the solar share in power generation from 25% to 30% by 2050 (**Figure 17.c**).

From a monetary perspective, these additional R&I expenditures are required to reduce cumulative investments until 2050 by approximately $0.7 trillion USD (**Figure 17.b**) difference between BC and *S++* in the *2°C scenario)*. Moreover, with highly enhanced learning (*S++*), electricity generation costs are projected to decrease by an additional 0.4 ¢/kWh compared to the *BC scenario*, which compares to additional expenditures of 0.06 ¢/kWh when relating the additional R&I expenditures (i.e., difference *S++* to BC) to the amount of electricity generated in this period.

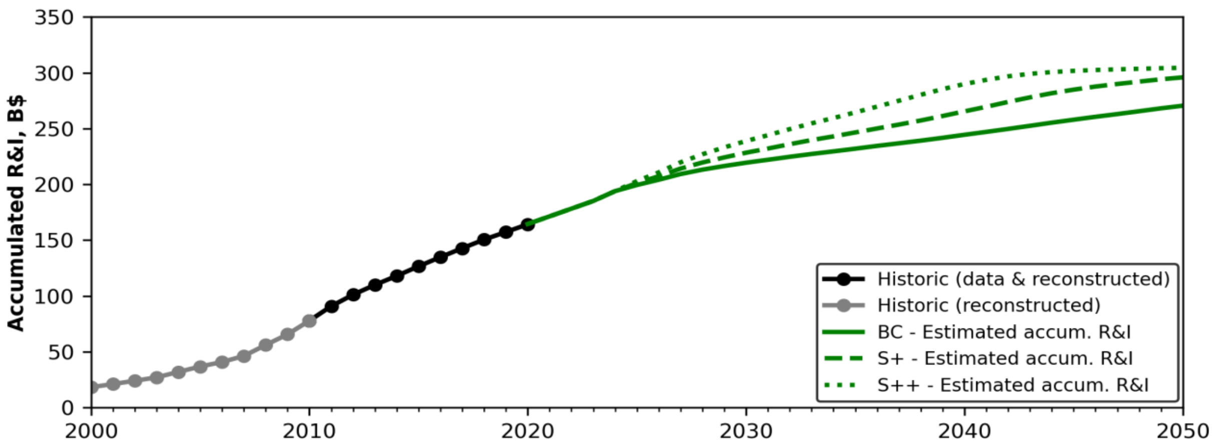
To conclude, spending additional R&I expenditures in PV technologies in order to promote additional learning, results in significant beneficial economic impacts, but also boost the green transition.

Figure 20. R&I expenditures for PV technologies: Total private & public expenditures (top) and public expenditures (bottom).



Source: JRC analysis. The public R&I data is based on IEA [24], and private R&I data is based on estimates using patents as a proxy [25].

Figure 21. Cumulative R&I expenditures for photovoltaic technologies – Estimations for *2°C BC scenario*.



Source: JRC

2.3 Battery technologies

Electrification is an important way of decarbonising the economy as it allows the substitution of fossil fuels with electricity produced from low-emitting sources. Batteries play a crucial role in electrification due to their dual role in enabling the electrification of the transport sectors and revolutionising energy storage in the power sector, allowing for a better integration of variable renewables and changing patterns in the load curve.

Battery characteristics

In recent years, research and innovation have emphasised the search for cheaper and more powerful operational characteristics. Principally, a battery is a pack of one or more cells, each of which has a positive electrode, a negative electrode, a separator and an electrolyte. The properties of a battery are affected by the chemicals and materials used within the battery. Research and innovation focussed very much on these chemicals and materials as they are highly relevant to the costs and properties of the batteries. Apart from the costs, the energy density, battery degradation, recyclability, the security of supply, charging speed and the number of loading cycles are also important parameters for a battery [31].

Battery types

Early applications in transport entered the market with lead-acid, followed by nickel-based batteries. Currently, the lithium-ion battery is the most used battery type in electric vehicles (EV). The lithium-ion battery type is a very advanced technology which allows for a high energy density and has advantages related to high numbers of charging and discharging cycles. Lithium-ion batteries are produced in several different chemical formulations, defining their properties and applications. Lithium-sulphur batteries use sulphur as the positive electrode and lithium as the negative electrode. They enable a much higher theoretical energy density. This characteristic would make them more apt to be used in the aviation sector, in which energy density is a key factor. However they are not yet widely commercialised.

Further battery types, which might play a role for the transport sector, are sodium batteries – having substantially higher life-cycles -, metal air batteries – allowing for faster charges and higher recyclability – and flow batteries - helping to reduce substantially costs by replacing costly lithium with cheaper zinc [32].
Batteries not only differ regarding key materials, but also by the implemented technology e.g., liquid or solid electrolyte like in the solid-state battery. The latter battery technology might enhance substantially the lifetime of batteries. The list of battery chemistry types is not exhaustive, as ongoing research is exploring further alternatives that may lead to the development of new types in the future.

Battery technologies in POLES-JRC

Within the POLES-JRC model, the complexity of current and future battery technologies is reduced by treating batteries as a generic technology, as it is hardly foreseeable which ones will prevail in the long term. The model, however, accounts for batteries in various uses with differing costs based on their specific requirements (e.g., charging cycles, energy capacity, weight, etc.).

In POLES-JRC, batteries are used for *transportation* and for *battery energy storage* (BES). For both uses, generic battery technologies with specific characteristics are applied.

For *transportation* three generic battery technologies are considered:

- Battery for electric cars
- Battery for electric trucks
- Battery for electric aircrafts

The techno-economic parameters used for these generic transport battery technologies are provided in **Table 21** in Section AN 5.4.1.

Battery energy storage in POLES-JRC is considered in the (i) power system and (ii) for direct air capture (DAC) to balance its intermittent wind and solar power supply (Section 2.6.1.1). For *battery energy storage*, only a single generic battery technology is used. Its techno-economic parameters are provided in **Table 15** in Section AN 5.1.

Endogenous technology learning
In POLES-JRC, batteries are modelled as an emerging technology characterised by high learning rates, with 13% for batteries used in transportation and 12% for battery energy storage (BES). Moreover, battery learning in POLES-JRC is driven by the cumulative battery capacities of all battery uses in (i) transportation (electric cars, trucks, and aircrafts), (ii) BES in the power system, and (iii) BES for balancing intermittent wind and solar power in direct air capture (DAC) (Section 2.6.1.1). Consequently, the model's endogenous learning approach leads to a rapid decline in battery costs across all applications, driven by substantial demand growth and high learning rates. However, the model also considers a floor cost constraint, which ensures that battery costs cannot fall below a minimum long-term value.

Floor costs
Minimum battery costs are determined by the primary components of batteries, such as electrolytes, electrode materials, and packaging materials. The cost of these components depends on the quantity of material used and its market prices. Therefore, it is difficult to estimate the long-term minimum cost. However, what can be determined is the minimum required amount of material per kWh according to the laws of physics [33]. For lithium-based- batteries, the required amount of lithium is about 85 g/kWh [33]. Assuming a current lithium price of about \$10,000 per ton of lithium carbonate [34], the minimum cost for electrolyte material in lithium-type batteries is approximately 9.1 \$/kWh. However, lithium prices have been much higher in recent years, reaching over \$80,000 per ton of lithium carbonate [34]. Moreover, additional material costs need to be considered (e.g., electrode materials, packaging) to calculate the minimum cost for a battery.
In the POLES-JRC model, a floor cost of \$42/kWh is assumed for batteries used in electric cars. This implicitly presumes that material cost will not be a limiting factor in the long term due to the use of cheaper electrolyte materials (e.g., sodium instead of lithium), more resource-efficient battery materials, and the expansion of recycling and mining capacities.

2.3.1 Transport sector

The POLES-JRC model encompasses various modes of transport in the road sector, including:

- Passenger cars;
- 2-wheelers;
- Light commercial vehicles (LCV,);
- Heavy-duty vehicles (HDVs), including buses.

For simplification purposes, this report presents battery-related results for two aggregates: (i) *electric cars* (encompassing electric 2-wheelers) and (ii) *electric trucks* (comprising LCVs and HDVs).

For all road vehicles, battery applications are separated into pure battery-electric vehicles (BEVs) and plug-in hybrid vehicles (PHEVs). They compete with the internal combustion engine (ICE) using liquid fuels (gasoline, diesel) or gas (LPG, CNG) and fuel cell vehicles (FCVs).

Regarding the aviation sector, POLES-JRC considers various technologies for its aircraft fleet. Electric aircrafts compete with conventional aircrafts using kerosene or jet fuel, and with hydrogen-based aircrafts.
Under the *2°C scenario*, electric aircrafts emerge from 2030 onwards, eventually reaching a fleet share of 8% by the second half of the century. However, the volume of batteries used in aircraft is negligible compared to those used in electric vehicles. Consequently, the remainder of this section will focus exclusively on batteries used for electric vehicles.

2.3.1.1 Technology adoption patterns

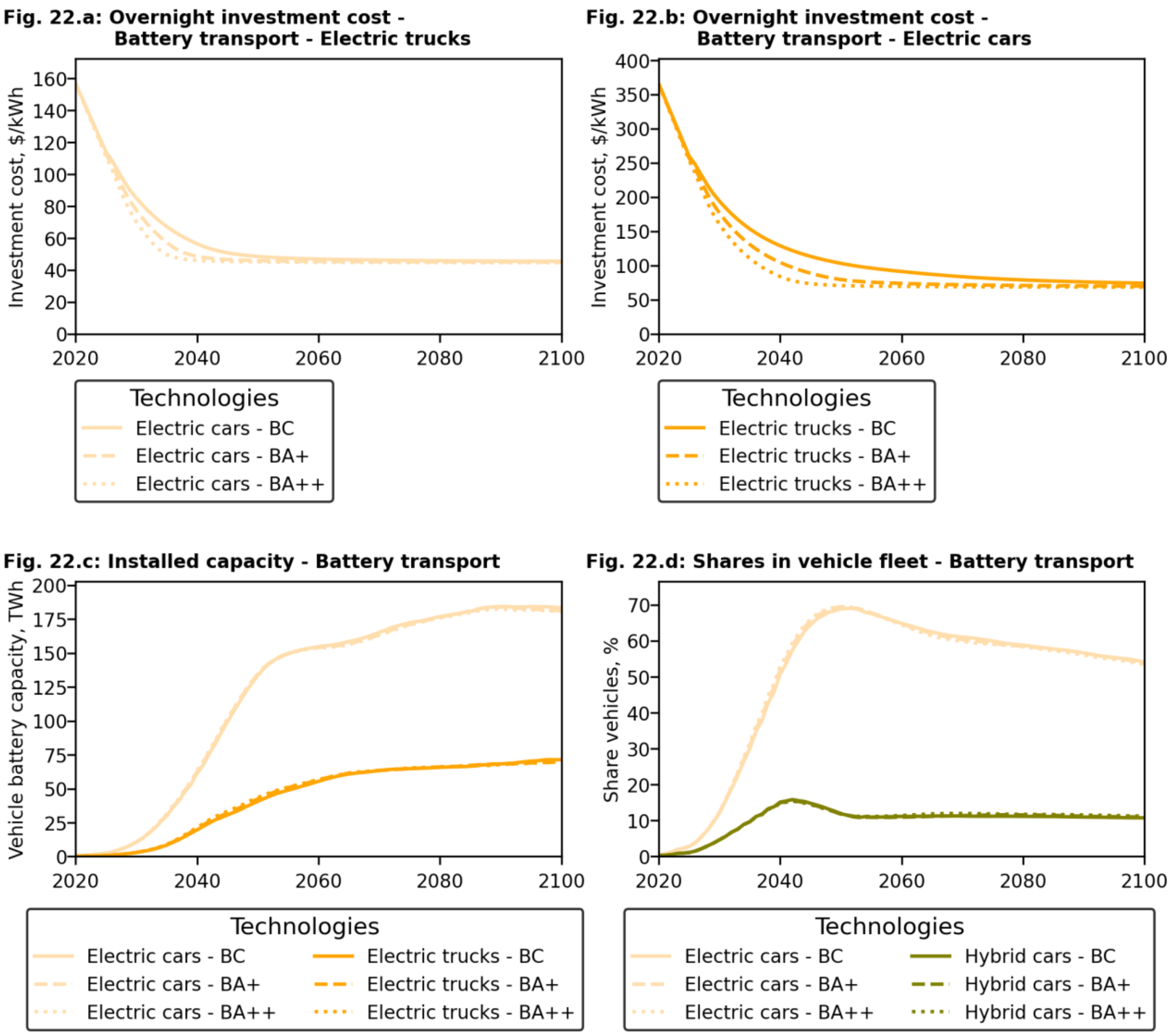
Investment costs
The projected evolution of overnight investment costs of batteries for *electric cars* reveals a fast and significant decrease driven by tremendously increasing battery capacities. The floor cost level of batteries used in cars (42 \$/kWh) is already reached around 2055 in the *2°C scenario* base case (BC) (**Figure 22.a**).

Batteries for *electric trucks* are more costly per kWh due to the higher complexity of the battery management system. For *electric trucks* the overnight investment costs of batteries decrease also fast in the coming decades but continue to decrease until reaching floor cost level at the end of the century.

Technology diffusion

A steep increase in the share of *electric cars* in the fleet occurs until 2050 (**Figure 22.d**). After reaching a peak by about 2050, the share of *electric cars* decreases in the second half of the century due to changing competitiveness compared to other technologies (**Figure 23.a**). For *electric trucks*, the diffusion occurs even earlier and reaches its peak almost a decade earlier (**Figure 22.d**). In contrast to electric cars, the share of *electric trucks* remains at a plateau level until the end of the century.

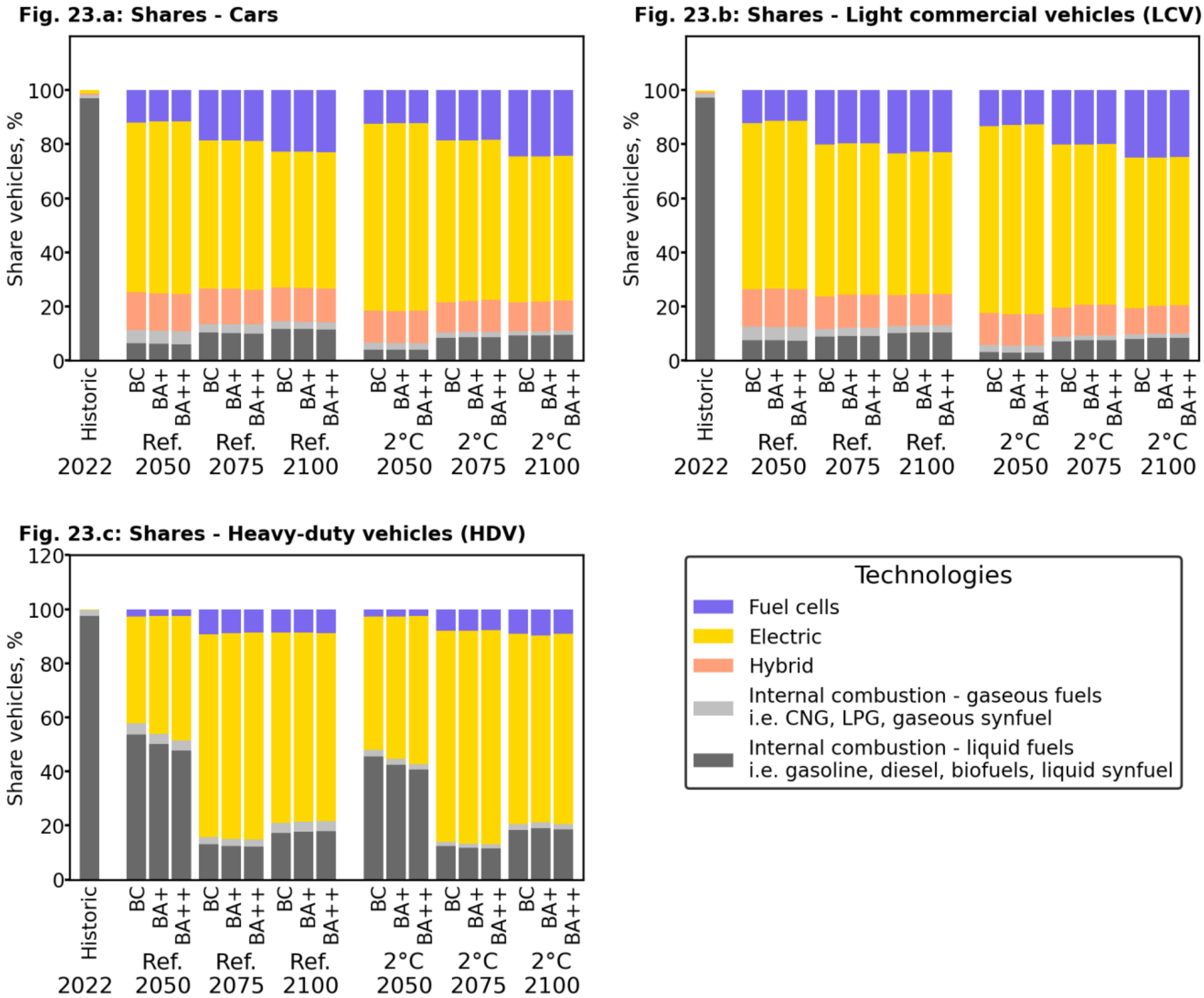
Figure 22. Evolution of (a & b) overnight investment cost, (c) installed capacities and (d) shares in vehicle fleet for battery uses in transport (cars, trucks) for learning variations (*BC*, *BA+*, *BA++*) under the *2°C scenario*.



Source: POLES-JRC model

Different timing patterns of the diffusion can also be observed currently. Electric car sales neared 14 million in 2023, equal to 18% of all cars sold in 2023, while electric truck sales reached 54,000, 70% of which were sold in China (market share less than 3%). Despite decreasing purchase prices for EVs in recent years, supportive policies heavily influence their sales.. For instance, the phasing out of purchase subsidies has slowed EV sales growth in countries such as Germany, highlighting the ongoing impact of government incentives on the market. Overall, electric cars and plug-in hybrid cars reach about 80% in 2050 for the base cases of the *Reference* and *2°C scenario*, followed by 10% of fuel cell vehicles (**Figure 23**.a). In the second half of the century, the share of fuel cell vehicles increases further. Moreover, after 2050, the share of cars with internal combustion engines (ICE) increases slightly, while their fuel use shifts from fossil to non-fossil fuels. For LCVs, the technological trajectory evolves remarkably similarly to cars. However, for HDV, the technological trajectory is significantly different. By 2050, the shares for ICE HDV remain for the *Reference* and the *2°C scenario* at 60% and 50%, respectively. After 2050, battery and fuel cell HDV increase their market share. However, a substantial market share remains for ICE HDV fuelled by synfuels.

Figure 23. Shares of traction type by transport modes: a. cars, b. light commercial vehicles (LCV) and c. heavy-duty vehicles (HDV) for learning variants (*BC*, *BA+*, *BA++*) of the *Reference scenario* and *2°C scenario*.



Source: POLES-JRC model

Battery capacity

The battery capacities in transportation increase tremendously in the coming decades as illustrated in **Figure 22**.c. The battery capacities reflect the evolution of the fleets of electric cars and trucks (**Figure 22**.d) and are calculated based on assuming an average battery size for electric cars of 71 kWh, and for LCV and HDV battery sizes of 105 kWh and 350 kWh, respectively. The average battery size remains constant over time.

The battery capacities (**Figure 22**.c.) increase steeply until about 2050 which corresponds to the peak of electric cars in the vehicle fleet (**Figure 22**.c.). In the second half of the century, the battery capacities keep increasing at a slower pace, although the share of electric cars and vehicles remains below its peak values.

The tremendous increase in battery capacity in transportation requires an enormous production of new battery capacity each year: About 3 TWh/y by 2030, 10.6 TWh/y by 2040 and still 7.9 TWh/y by 2050 (*2°C scenario* base case). By 2050 in the *2°C scenario* base case, the overall battery capacity of the vehicle fleet amounts to 174 TWh (**Figure 24.a**). Electric cars are the dominating use for batteries in transportation. The battery capacity of trucks reaches about 40 TWh in 2050, which is about one third of the battery capacity of cars.

The regional split in battery demand shows strong dominance of China, while their global market share decreases from more than 50% to 31% in 2030. At the same time the EU and the USA follow similar paths and are expected to reach 24% and 12% in 2030, respectively.

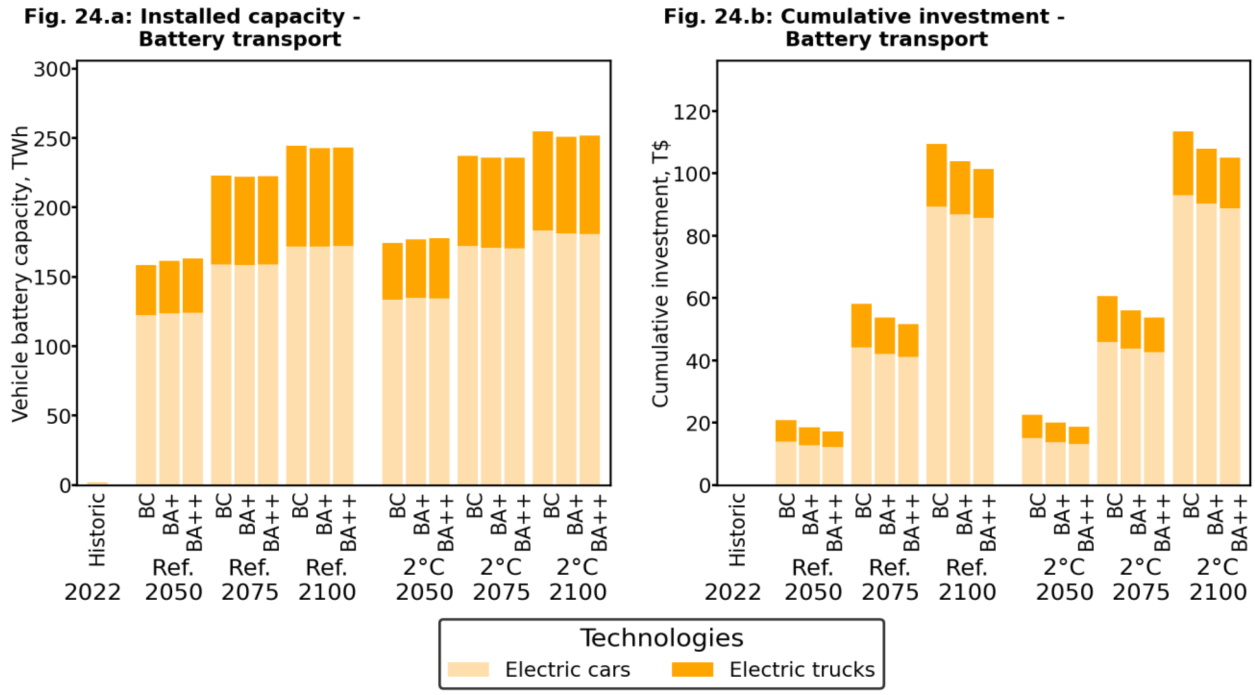
2.3.1.2 Impacts of enhanced learning rates

Highly enhanced learning (*BA++*) for batteries used in electric cars leads to a faster cost reduction, with the floor cost level of $42/kWh being reached a decade earlier (2045) compared to the *2°C scenario* base case (2055) as illustrated in **Figure 22.a**. For batteries used in electric trucks, highly enhanced learning (*BA++*) could lead to floor cost levels being reached almost half a century earlier (2050) compared to 2100 under the *2°C scenario* base case(**Figure 22.b**).

However, the impact of enhanced learning on battery capacities for electric vehicles (EVs) is limited (**Figure 22.c**) as the battery cost component of the total price of a car is already projected to decrease dramatically in the coming decades. As a result, additional cost decreases have a minimal effect on the total price of a car, which is a key factor in the decision to purchase an electric vehicle.

A comparison of the *2°C scenario* and the *Reference scenario* base cases shows that the development towards electrification in transport proceeds similarly (**Figure 5** in Section 1.2.3.3)., with only minor differences in overall battery capacities (**Figure 24.a**). This is due to the rapid cost advantages electric cars offer, including decreasing costs and lower energy costs (electricity vs. gasoline/diesel). Moreover, enhanced learning (*BA+* and *BA++*) minimally impacts overall battery capacities (**Figure 24.a**), as the cost advantages of electric cars are already driving electrification in transport.

Figure 24. Impacts of learning variations (*BC*, *BA+*, *BA++*) under the *Reference* and *2°C scenario* for battery uses in transport (cars, trucks).



Source: POLES-JRC model

The cumulative battery investments for transportation uses are illustrated in **Figure 24.b**. By 2050, the cumulative battery investments amount to approximately $20 trillion and are projected to increase five-fold over the following five decades until 2100 under both scenarios. While enhanced learning has almost no impact on the total amount of battery capacity and the speed of diffusion, it has significant impacts on costs. Consequently, enhanced learning (*BA+* and *BA++*) substantially reduces investment needs, particularly in the first half of the century. With highly enhanced learning (*BA++*), cumulative investment needs decrease by 17% by 2050 and still by 7% under both scenarios.

2.3.2 Power storage

Investment in energy storage enables the capture and storage of electricity when it is generated, allowing for its delivery when demand arises. With more volatile and fluctuating power production technologies in the energy system, the need for energy storage options increases. Several technologies compete to store energy and balance the energy system.

2.3.2.1 Technology adoption patterns

Within the POLES-JRC model, the primary energy storage options are *battery energy storage* (BES), *compressed air energy storage* (CAE), and *pumped hydro storage* (PHS). These options are supplemented by measures to balance energy supply and demand, including *vehicle-to-grid* (V2G) and *demand side management*. V2G and demand side management help alleviate the need for energy system balancing by storing electricity in vehicle batteries and shifting energy needs from periods of scarcity to times of more abundant or cheaper supply. However, in the scenarios, these measures remain low and appear to be less favourable than the main energy storage options. As a result, the following analysis focuses on BES, CAE, and PHS.

The overnight cost for BES is projected to decrease rapidly in the coming decades, from approximately 330 $/kWh in 2023 to around 130 $/kWh by 2050 (**Figure 25.a**). This rapid cost decline is driven by the interplay of high learning rates and increasing battery capacities for transportation and power system applications (see '*Endogenous technology learning*' in this Section).

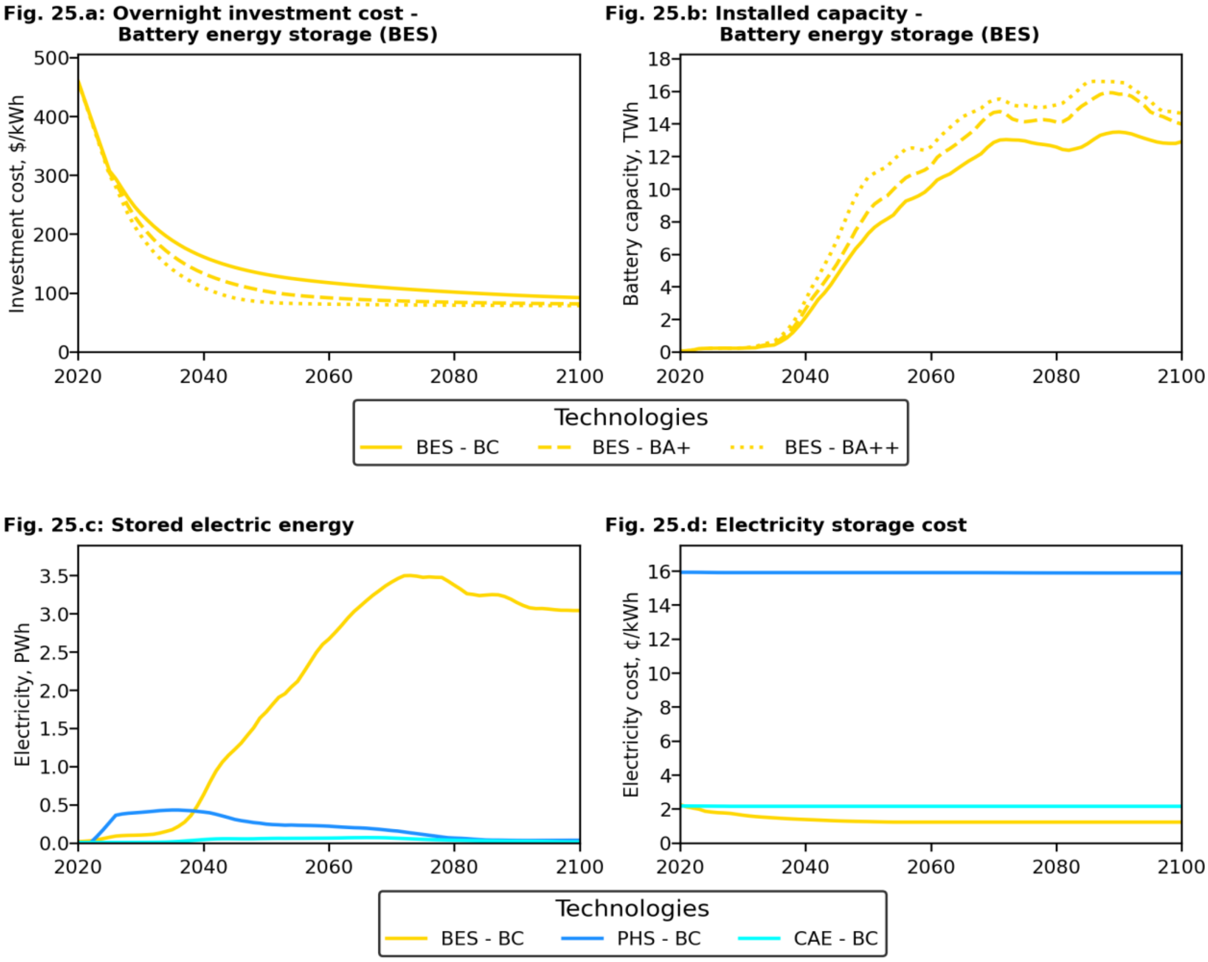
As the share of volatile and fluctuating energy technologies, such as wind and solar, grows, the need for energy storage increases. Under the *2°C scenario*, the share of wind and solar in global power generation is expected to rise from around 11% today to more than 60% by 2050, and slightly increase thereafter (**Figure 3** in Section 1.2.3.2).

Currently, PHS is the dominant energy storage option (**Figure 25.c**). However, the use of BES as a storage option is experiencing a steep increase, driven by its growing competitiveness, which is expected to enable it to overtake PHS before 2040. The electricity costs in **Figure 25.d** show that the costs for PHS (16 cents/kWh, 2023) are substantially higher than BES and CAE (ca. 2 cents/kWh, 2023). Despite the high electricity costs for PHS, POLES-JRC projects relatively small deployment of BES in the coming decade, as existing PHS capacities appear sufficient to balance the increasing renewable power production. PHS is not only more expensive compared to BES, but site-specific constraints and limited scalability also hinder its deployment. Despite having a similar cost profile to BES, CAE faces even greater challenges, as suitable geological sites for gas storage are scarce and difficult to find.

In the second half of the century, BES is expected to become the dominant energy storage technology in the power system (**Figure 25.c**). This development is reflected in the surge of BES capacities, reaching under the *2°C scenario* approximately 7 TWh by 2050 and plateauing at around 137 TWh from 2070 onwards.

Figure 26.a illustrates that BES capacities are significantly elevated under the *2°C scenario* compared to the *Reference scenario* until about 2075. The reasons for higher BES capacities under the *2°C scenario* relate to the higher wind and solar power generation (**Figure 3** in Section 1.2.3.2) and the higher shares of electric vehicles (**Figure 23**).

Figure 25. Evolution of (a) overnight investment cost, (b) installed capacities, (c) stored electric energy and (d) electricity storage cost for battery energy storage (BES) for learning variations (*BC*, *BA+*, *BA++*) under the *2°C scenario*.



Source: POLES-JRC model

Additionally, to the capacities of battery energy storage (BES) in the power system (**Figure 25** and **Figure 26**), POLES-JRC considers BES for balancing intermittent renewables powering direct air capture (DAC, Section 2.6.1). Under the *2°C scenario*, the BES capacities used for DAC are projected to be approximately 0.6 TWh by 2050 and 2.1 TWh by 2100 (**Figure 43** in section 2.6.1). Whereas under the *Reference scenario*, BES capacities are significantly lower (0.04 TWh by 2050 and 0.6 TWh by 2100) as DAC plays a less prominent role compared to the *2°C scenario*.

Notably, the scale of BES capacities is significantly smaller than that of battery capacities in transportation, with a factor of around 20 by 2050 and 2100 (**Figure 24.a** compared to **Figure 26**.a). Furthermore, the declining cost of BES in the coming decade (**Figure 25.a**) is primarily a spillover effect of the rapid growth in battery capacities for EVs, as the surge in BES is expected to begin in the late 2030s.(**Figure 25.b**).

The cumulative investments in BES are illustrated in (**Figure 25.b**). Similar to the capacity trends, cumulative investments in BES represent only a fraction of the cumulative investments in batteries for transportation uses. Under the *2°C scenario*, by 2050, cumulative investments in BES total approximately 1.2 T$ (**Figure 26.b**), a significantly lower amount compared to the cumulative investments in batteries for transport, which reach around 20 T$ (**Figure 24.b**).

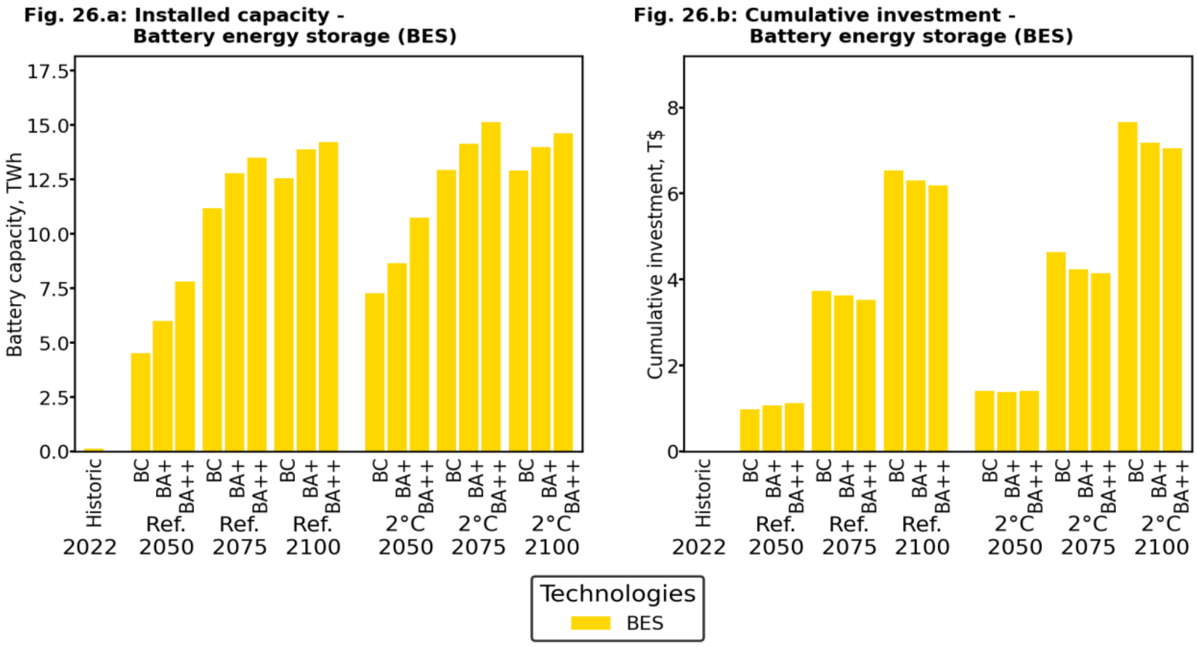
2.3.2.2 *Impacts of enhanced learning rates*

Enhanced battery learning (*BA+*, *BA++*) substantially impacts the overnight investment costs for battery BES as illustrated in **Figure 25.a**. With highly enhanced battery learning (*BA++*) floor costs are already reached by 2050, while in the base case floor costs are not reached until the end of the century (*2°C scenario*).

BES capacities increase substantially with enhanced battery learning (*BA+*, *BA++*) as illustrated for the *2°C scenario* in **Figure 25.b** and for both scenarios in **Figure 26.a**. Notably, under the *2°C scenario* enhanced learning (*BA+* and *BA++*) has reinforcing impacts on the deployment of BES capacities.

From a cumulative investment perspective (**Figure 26**.b), enhanced battery learning (BA+, BA++) has a twofold impact. On one hand, it drives a substantial increase in capacities (**Figure 26.a**), which is offset by a rapid decline in costs (**Figure 25.b**). As a result, the effect on cumulative investments (**Figure 26.b**), is substantially alleviated by 2050, and in the second half of the century, the cost savings outweigh the capacity increases, leading to a substantial reduction in cumulative investments.

Figure 26. Impacts of learning variations (*BC*, *BA+*, *BA++*) under the *Reference* and *2°C scenario* for battery uses for Battery energy storage (BES).



Source: POLES-JRC model

2.4 Hydrogen and fuel cell technologies

Hydrogen has the potential to play a key role in a clean, secure and cost-effective long-term energy strategy [35]. Analysing the role of hydrogen in the energy system of the 21st century is a complex and demanding task. POLES-JRC is particularly well-suited for this task due to its long-term perspective and its comprehensive representation of the entire hydrogen energy chain, encompassing supply and demand as well as transport and final delivery.

2.4.1 Modelling of hydrogen and fuel cell technologies

Supply of hydrogen
On the *supply side*, POLES-JRC considers various routes to produce hydrogen using thermo-chemical or electrolysis processes (see Section 2.4.2).

Demand for hydrogen
Hydrogen can be used as fuel in the transport sector, as feedstock in the steel sector, as an intermediate product (e.g., nitrogen-based fertilisers) in the chemical industry and refineries, and as an input for heat and power generation. In the present energy system, hydrogen demand stems almost exclusively from the chemical industry and refineries.

With the shift towards a green economy, hydrogen is poised to become a vital energy vector, leading to a significant increase in demand across all economic sectors. Consequently, demand for hydrogen is expected to rise sharply in various industries (e.g., steelmaking), including transportation, industrial processes, power generation by hydrogen fuel cells, and the production of synfuels. Moreover, with shifting to a green economy, hydrogen and its derivatives (i.e., synfuels or e-fuels) become increasingly *traded in global markets*. In the *transport* sector, POLES-JRC considers hydrogen-powered fuel cells as they offer a clean energy solution in multiple transportation modes (**Figure 23** in Section 2.3.1.1). For *power generation*, fuel cells provide an opportunity to generate electricity clean and very efficiently. In the power system module of POLES-JRC, hydrogen fuel cells directly compete with grid electricity and other forms of distributed power generation (Section 2.4.3.2). S*ynfuels* (gaseous or liquid) in POLES-JRC are produced from hydrogen and CO_2 captured by direct air capture (DAC) (see Section 2.6). The model considers liquid synfuels as substitute for oil products in transportation (i.e., road, aviation and maritime transport). Moreover, gaseous synfuels are taken into account as an alternative to natural gas in various sectors including the building sector, industry and transport.

Transport and distribution
International trade of hydrogen-based fuels in POLES-JRC is modelled for ammonia (NH_3), liquid hydrogen (LH2), and liquid synfuels (see techno-economic parameters of **Figure 19** in AN 5.3). These fuels are transported by maritime transport or pipelines. For trading of ammonia and liquid hydrogen, substantial losses occur in the converting hydrogen to NH_3 and LH2, and the reconversion to hydrogen.
Domestic hydrogen transport and delivery is modelled by several transport chains using pipelines and trucks. Pipelines (large or small) provide hydrogen to the sites of consumption in industry or buildings, or to refuelling stations for supplying transport demand; whereas trucks deliver hydrogen to small production sites or refuelling stations. Transportation and delivery costs vary according to the transport chain chosen. Factors such as population density and the distance between production and consumption sites are considered. A loss factor on transport and distribution is added for each demand sector. Transport costs are a significant cost element of the hydrogen value chain due to hydrogen's relatively low volumetric energy density.

Sensitivity analysis
Regarding the sensitivity analysis, enhanced learning within the *hydrogen and fuel cell* technology group (*H2FC+, H2FC++*) is considered for the following technologies:

- Clean hydrogen production routes (electrolysis and pyrolysis technologies)
- Fuel cells in transport and power generation
- Transport of ammonia as hydrogen carrier including conversion and reconversion.

Synfuels are analysed within the *DAC and synfuels* technology group (see Section 2.6).

2.4.2 Hydrogen production

2.4.2.1 Technologies

Hydrogen in POLES-JRC is produced by thermo-chemical or electrolysis routes with 13 distinctive technologies (see **Table 2**).

Thermo-chemical routes

- *Steam methane reforming* using natural gas is currently the prevalent hydrogen production process. Steam methane reforming involves the catalytic breakdown of light hydrocarbons when reacting with superheated steam, resulting in a hydrogen-rich gas mixture containing impurities. The hydrogen content is subsequently maximised through a water-gas shift reaction, followed by the final steps of separating and purifying the hydrogen.
- *Gasification*, utilising *coal* or *biomass* as feedstock is an alternative thermo-chemical route for hydrogen production. In this process, solid fuels react with steam, oxygen, or air to produce syngas, a mixture of carbon monoxide (CO) and hydrogen. Coal gasification is currently predominant in China.
- A third route is the *pyrolysis* process, which decomposes natural gas or biomass in the absence of oxygen, generating hydrogen and solid carbon as a by-product.

The carbon intensity for steam methane reforming is high, and for gasification of coal, it is even higher. However, low carbon variants of both technologies can be equipped with CO_2 capture, enabling the capture of up to 90% of implied CO_2 emissions. Pyrolysis using natural gas as feedstock is considered low carbon, as carbon is fixed as a solid by-product. Both gasification of biomass with CO_2 capture (CC) and storage and pyrolysis of biomass permanently removes CO_2 from the atmosphere and are considered as negative emission technologies.
More detail on the modelling of carbon capture technologies in POLES-JRC is provided in Section 2.5.2.

Table 2. Hydrogen production technologies in POLES-JRC.

	Technology	**Carbon Capture options**
	Steam methane reforming (SMR)	*with* and *without* CC
	Gasification of coal	*with* and *without* CC
Thermo-chemical routes	Gasification of biomass	*with* and *without* CC
	Pyrolysis of coal	fixed as solid carbon
	Pyrolysis of biomass	fixed as solid carbon
	Technology	**Electricity source**
		Wind[1] (on-shore and off-shore)
Electrolysis routes		PV[1] (utility-scale)
	Low temperature (LT) electrolysis	Nuclear[1] – Gen. III
		Grid electricity
	High temperature (HT) electrolysis	Nuclear[1] – Gen. IV (from 2060)

Source: POLES-JRC model

[1] Dedicated plants which are not part of the power system.

Electrolysis routes

- *Low temperature (LT) electrolysis* is very prominently presented in POLES-JRC. Power sources for the LT electrolysis are low-carbon: solar, wind and nuclear with dedicated power plants and grid electricity (at times of wind and solar over-supply). The techno-economic parametrisation of LT electrolysis in the model represents a generic mix of alkaline and PEM electrolysis.
- Moreover, *high temperature (HT) electrolysis* using power and heat provided by advanced nuclear plants (Gen IV) is considered from 2060 onwards.

Further combinations of electricity source and electrolysers do exist, e.g., grid electricity could be potentially used in combination with HT electrolysis. At the current stage of development of this sector in POLES-JRC, the number of combinations is limited to the ones listed above to reduce the complexity of the modelling.

2.4.2.2 Production cost and learning

In POLES-JRC, the production cost determines the deployment of new capacities and, eventually, the production of hydrogen. The production cost consists of investment cost, fixed and variable operation & maintenance cost (OM) and variable cost for fuel and the CO_2 price in the *2°C scenario*.

For most technologies, the total investment cost comprises several cost components (see AN 5.2). For the thermal-chemical technologies, several components are shared across these technologies (e.g., reformer, water shift unit). Some are also shared by power generating technologies (e.g., gasifier, CO2 compression unit, pollution control, cooling). For the electrolysis technologies, the investment cost of the actual electrolyser and the power supplying technology are considered, e.g., investment cost for solar and wind power (see Sections 2.1 and 2.2). Cost improvements by component learning led to a decreasing total investment cost. Moreover, learning drives down the fixed and variable non-energy OM costs. Furthermore, efficiency learning reduces energy consumption per unit of hydrogen produced.

For the sensitivity analysis within the hydrogen group (*H2FC+*, *H2FC++*) merely the clean hydrogen related components are varied (see assignment to *H2FC* technology group in AN 5.2 of **Figure 16**). The CC-related components (e.g., CO_2 compression unit) and the solar, wind and nuclear technologies are not subject to the enhanced learning of the hydrogen group. Therefore, its full potential of cost reduction with enhanced learning is achieved in combination with learning accelerations in other technology groups such as the *CC* group (*CC+* and *CC++* see 2.5.2), solar (*S+* and *S++* see 2.2) and wind (*W+* and *W++* see 2.1).

2.4.2.3 Technology adoption patterns

Capacities

Steam methane reforming (SMR) is the currently prevalent hydrogen production technology (see **Figure 27.a**). Steam methane reforming is mainly employed in the chemical industry and refineries. In the coming years, additional methane steam reforming capacities will be built to meet the expected hydrogen demand. However, the increasing global carbon value in the *2°C BC scenario* results in substitution by *steam methane reforming with CC* which becomes the prevailing technology among the thermo-chemical routes on a global level from 2050 onwards. Moreover, pyrolysis using natural gas plays also a significant role (**Figure 27.a**) due to its low carbon intensity and relatively low investment cost.

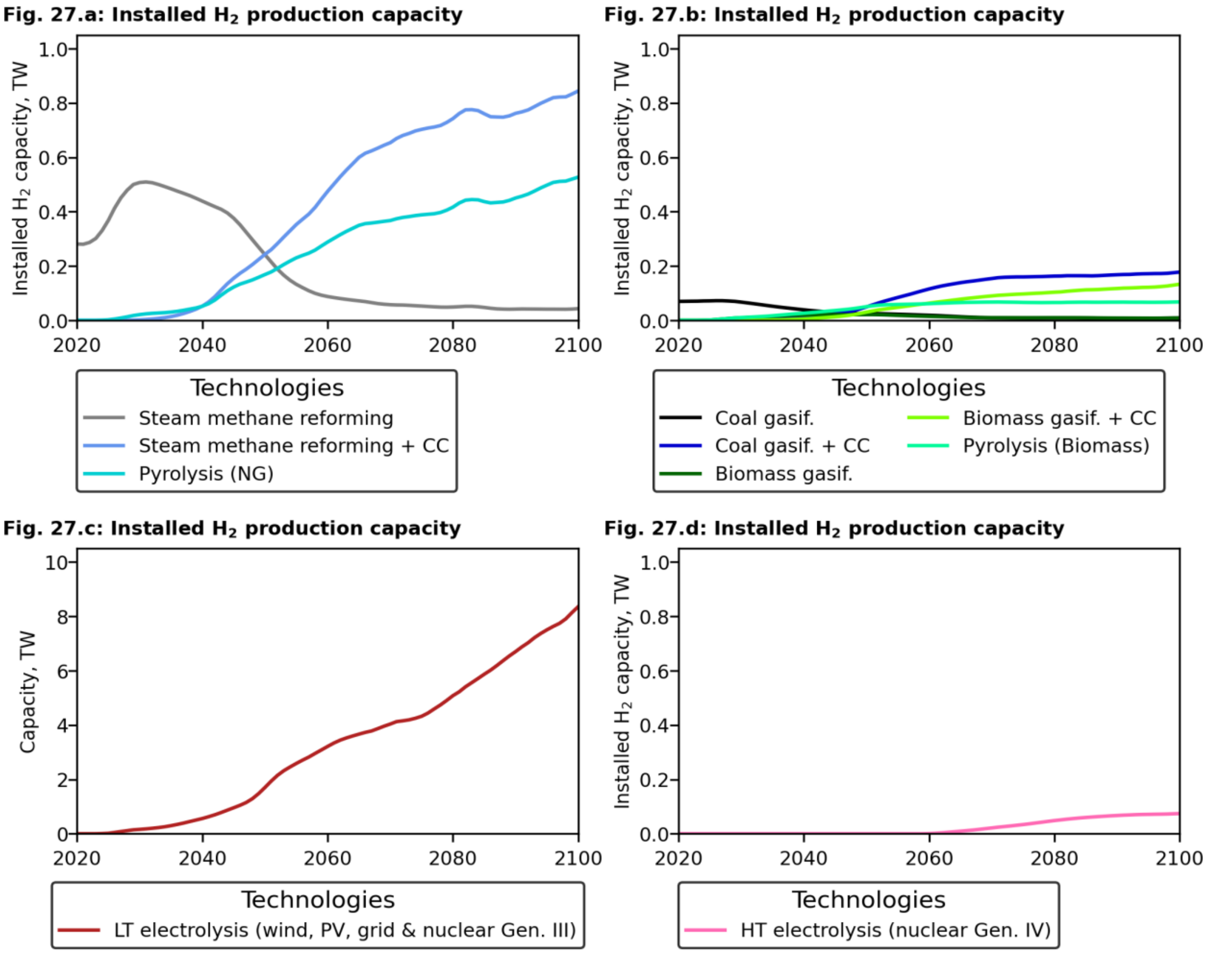
The other thermo-chemical hydrogen technologies play merely a minor role (**Figure 27.b**).: *Coal gasification* becomes soon too costly due to the CO_2 price within the *2°C BC scenario*. However, coal gasification capacities with CC are deployed from 2030 onwards, but reaching only about a fifth of the capacities of *steam reforming with* CC due to the substantial difference in overnight investment costs (see **Table 18** in Section AN 5.2). The deployment of biomass technologies is impeded by relatively high investment costs (compare **Figure 96** in Section AN 3.1) and increasing biomass costs.

Remarkably, the electrolysis routes and, among them the LT electrolysis become the dominating hydrogen production technology from 2035 onwards in terms of capacity in the *2°C BC scenario* (**Figure 27.c**) and outperforms the sum of all capacities of the thermo-chemical routes. The LT electrolysis capacities grow steadily in the coming decades and exceed even *steam reforming with CC* by about a factor of 10 in 2100.

Hydrogen production

In the *2°C BC scenario*, total hydrogen production more than quadruples by 2050 and reaches about 250 Mt of hydrogen (**Figure 28**). Until the end of the century, hydrogen production increases further to about 900 Mt of hydrogen. The production shares for electrolysis (LT and HT) and capture technologies increase substantially, reaching by 2050 about 45% and 35%, respectively.

Figure 27. Hydrogen production capacities by technology (*2°C scenario* base case).



Source: POLES-JRC model

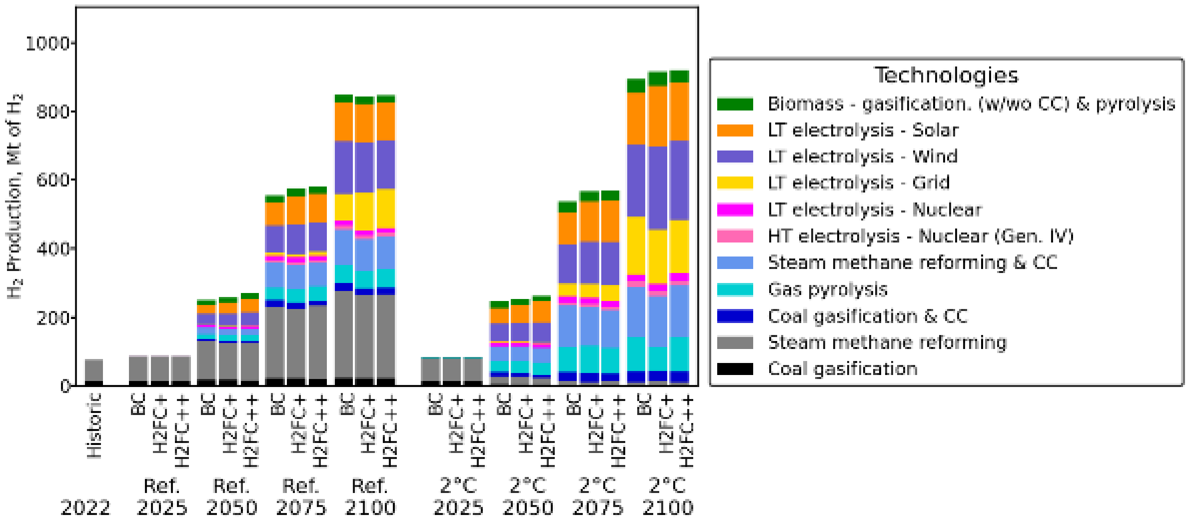
Competing technologies

For the competing thermo-chemical and nuclear hydrogen production routes, the evolution of investment costs and cumulative capacities are shown in **Figure 96** (Section AN 3.1). Compared to renewables-based electrolysis, these technologies exhibit higher investment costs and their costs decline substantially less. However, their advantage lies in substantially higher load factors, which compensate for the investment cost disadvantage.

The investment cost for the thermo-chemical routes with CC is substantially higher than the respective technologies without CC. In particular, this difference is pronounced for steam reforming. However, in the *2°C BC scenario* this cost advantage is overturned by the increasing global carbon value. As a result, more capacities with CC are deployed (**Figure 96** in Section AN 3.1). In particular, *steam reforming with CC* produces substantial hydrogen (**Figure 28**) due to a combination of low investment cost and high load factors.

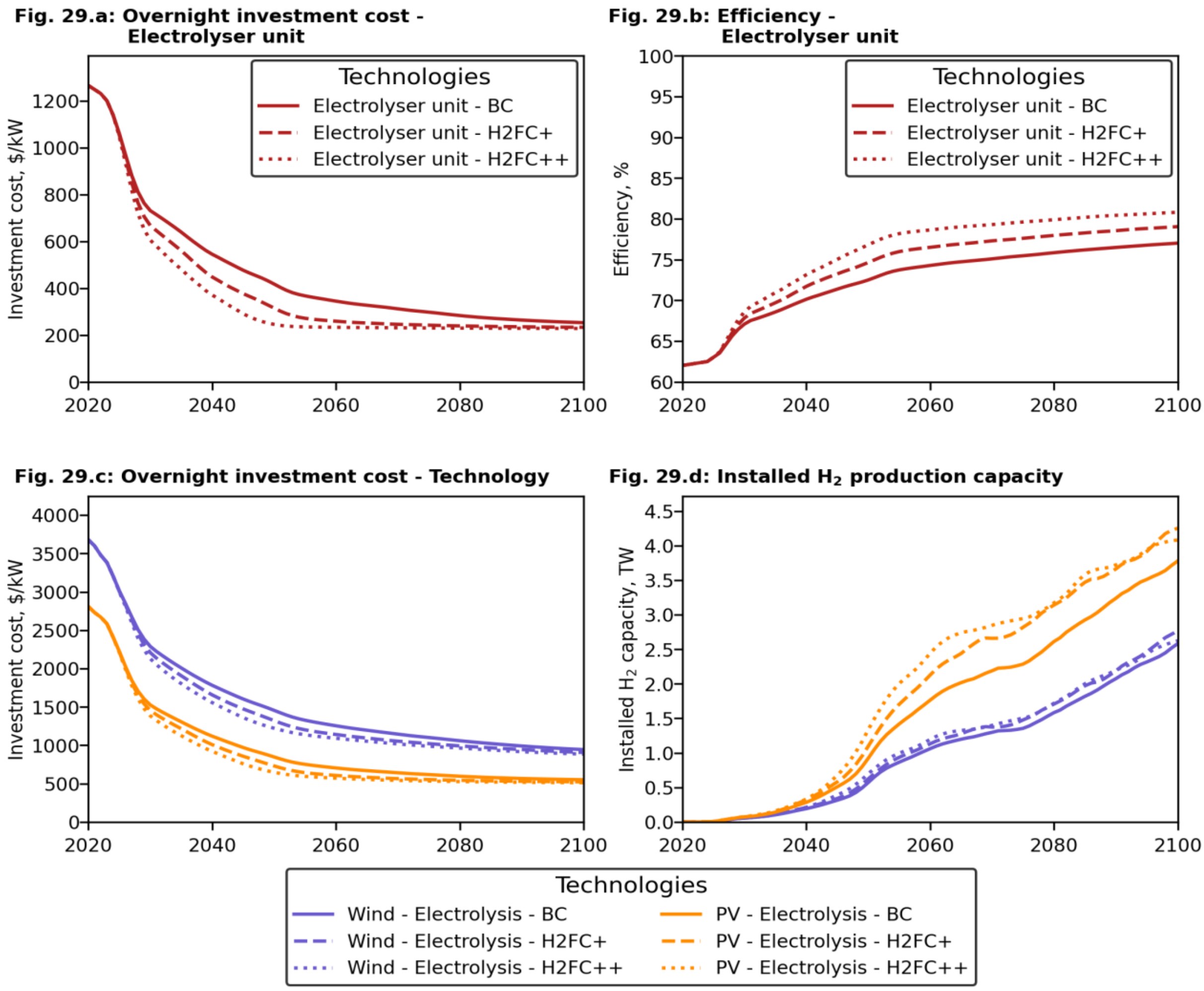
Nuclear-based hydrogen production plays a minor role in both scenarios. Although investment costs for nuclear technologies decrease (see **Figure 97** in AN 3.1) and the load factor for nuclear plants is substantially higher compared to solar and wind generation, nuclear-powered electrolysis cannot compete with renewable-powered electrolysis.

Figure 28. Hydrogen production by technology for learning variations (*BC*, *H2FC+*, *H2FC++*) under the *Reference* and *2°C scenario*.



Source: POLES-JRC model

Figure 29. Evolution of (a) overnight investment cost of electrolyser unit, (b) efficiency of electrolyser unit, (c) overnight investment cost of total technology and (c) hydrogen production capacity for learning variations (BC, H2FC+, H2FC++) under the *2°C scenario*.



Source: POLES-JRC model

Reference scenario

In the *Reference scenario* base case, total hydrogen production evolves very similarly to the *2°C BC scenario* during the century. However, in the *Reference BC scenario* the major share is still produced by conventional steam reforming. Capture technologies and electrolysis are employed at a substantially smaller scale than the *2°C scenario*. In particular, grid electrolysis becomes relevant much later in the *Reference scenario* as ample surpluses from renewables will become available decades later compared to the *2°C BC scenario*.

2.4.2.4 Impacts of enhanced learning rates

Electrolyser

The effects of learning are illustrated in **Figure 29** for renewable electricity-powered electrolysis (renewable hydrogen). Within these technologies, the electrolyser unit is a major cost component. The investment cost of the electrolyser unit decreases in the *2°C BC scenario* from an estimated value of about 1200 $/kW today to about 400 $/kW in 2050 (**Figure 29.a**). Until the end of the century, the investment cost become close to the floor cost for the electolyser unit (230 $/kW). Enhanced learning (*H2FC+*, *H2FC++*) results in even faster-declining cost for electrolyser; floor cost level are reached already by 2050 for the *H2FC++* variation.

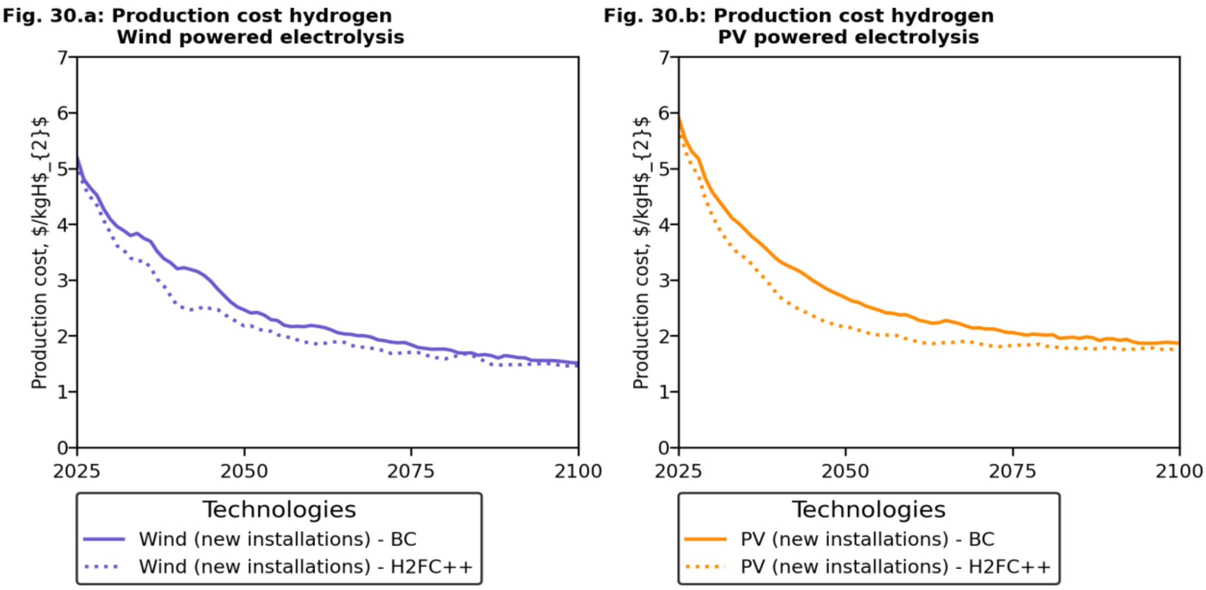
Learning rates

As electrolysis is an emerging technology, its associated learning rates are relatively high. The cost evolution in the BC refers to a learning rate for the electrolyser component of 15%, which is well in the range of 13% to 19% quoted in literature [36]–[41]. Also, the learning rate for the H2FC+ variation (18.8%) is still within the range of the literature. Moreover, even the learning rate of 22.5% for highly enhanced learning (H2FC++) seems still plausible, given that electrolysis is a fast-emerging technology.

For the competing thermo-chemical technologies, most of its components are technologically emerging, too. Therefore, relatively high learning rates in the range of 11% to 14% are used for these components. However, some components are considered mature (e.g., cooling, CO_2 compression) and therefore, low learning rates in the 3% to 5% range are applied. As a result, the thermo-chemical technologies exhibit substantially lower cost dynamics compared to electrolysis.

Also, the efficiencies of the hydrogen production technologies increase over time. For example, **Figure 29.b** shows the efficiency of the LT electrolyser unit. In the BC, efficiency increases from 65% today to about 75% in 2050. With highly enhanced learning (*H2FC++*) an efficiency of almost 80% could be achieved.

Figure 30. Evolution of hydrogen production cost for new installations for learning variations (*BC*, *H2FC++*) under the *2°C scenario*.



Source: POLES-JRC model

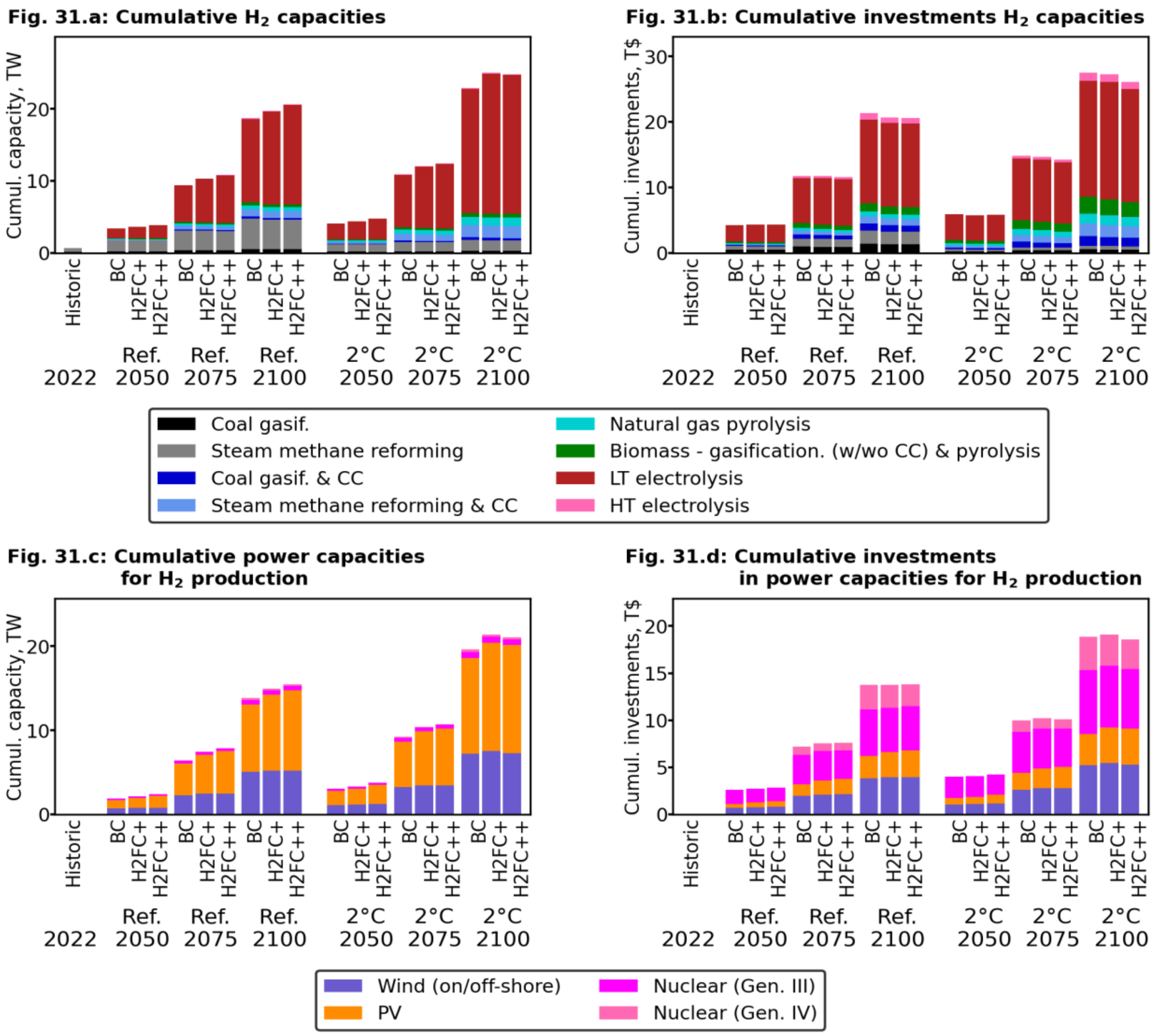
Technology cost for electrolysis

The overall investment cost for the solar and wind electrolysis considers the cost of respective solar and wind plants in addition to the cost of the electrolyser unit. Therefore, the decreasing overall investment cost for solar and wind electrolysis (**Figure 29.c**) is a combined effect of decreasing cost of the electrolyser unit and declining cost for solar and wind (Sections 2.1 and 2.2). For solar electrolysis, the overall investment cost near the floor cost level is already achieved by 2060 in the *BC* due to the rapidly dropping PV cost (**Figure 17**.b). The effect of enhanced learning is less pronounced as the cost for the solar and wind generation is the dominating factor in the total hydrogen production cost. In terms of overall investment cost, solar electrolysis is substantially cheaper compared to wind electrolysis. However, this difference is more than compensated by higher load factors associated with wind generation in most geographies. Consequently, the cost of wind-based hydrogen is lower than hydrogen from solar (**Figure 31**) and more hydrogen is produced through wind electrolysis than solar across all scenario variations (**Figure 28**), Nevertheless, more solar electrolysis capacities are required to be built (**Figure 29**.d).

Crowding out effects

The competing clean hydrogen production technologies, such as the three CC technologies and the two nuclear electrolysis technologies, are crowded out in the enhanced learning scenarios (**Figure 96** and **Figure 97** in Section AN 3.1). Although their learning rates are increased by the same factor, they cannot compete with the faster developing electrolysis routes.

Figure 31. Impacts of learning variations (*BC, H2FC+*, *H2FC++*) under the *Reference* and *2°C scenario* for hydrogen production technologies.



Source: POLES-JRC model

Production cost and investments

The global production cost of wind and PV-based hydrogen declines to about 2.6 $/kg of hydrogen in 2050 (*2°C BC scenario*) due to technology learning (**Figure 30**.a and b). With highly enhanced learning (*H2FC++*), renewable production cost falls further to about 2.1 $/kg by 2050. Moreover, enhanced learning leads to increased capacities for hydrogen production and electrolysis power. This effect is illustrated in **Figure 31**.a and b in terms of cumulative capacities.

In terms of investment needs, the enhanced learning scenarios (*H2FC+, H2FC++*) show that less funding is required to build more hydrogen production capacities (**Figure 31.a**), produce more hydrogen (**Figure 28**) and achieve lower production costs for renewable hydrogen (**Figure 30.a and b**). However, the impact on the investment needs for building the required power capacities for electrolysis is ambiguous (**Figure 31.c**). Further cost reduction for building these power capacities may be achieved by additionally considering enhanced learning for wind (*W+*, *W++*) and solar (*S+*, *S++*) as described in Sections 2.1 and 2.2.

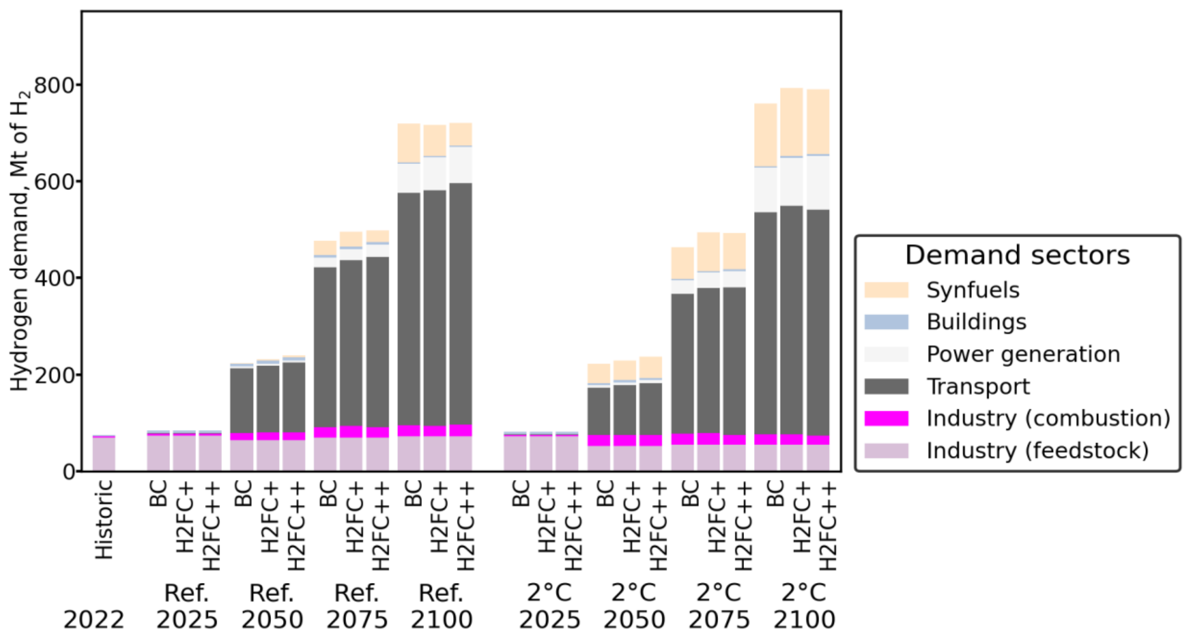
2.4.3 Hydrogen demand

Currently, almost all hydrogen demand is concentrated in the industrial sector,, mainly in refineries and chemical industry (Figure 32). Within the chemical industry, hydrogen primarily serves as a non-energy feedstock for ammonia production, which is mainly utilised in fertiliser manufacturing.

With the shift towards a green economy, global hydrogen demand is expected to surge, driven by expanding applications in transport, power generation, synfuel production and steel production (industry). As a result, worldwide hydrogen demand is expected to rise from the current 75 Mt_{H2} to about 220 Mt_{H2} by 2050 and 760 Mt_{H2} by 2100 in the *2°C scenario* BC (**Figure 32**).

In the second half of the century, in both scenarios, a large share of hydrogen is used in the transport sector where it is used for fuel cell vehicles. Moreover, a substantial share of hydrogen is used to produce synfuels of which a large part is also used in the transport sector. The use of hydrogen and synfuels in the transport sector is illustrated in **Figure 5** in Section 1.2.3.3. In the industrial sector, hydrogen demand for combustion processes increases in the coming decades before stabilising. Simultaneously, demand for feedstock experiences a slight decline until 2050. Hydrogen usage in buildings is also set to grow, but overall plays a minor role (**Figure 6** in Section 1.2.3.3.2).

Figure 32. Global hydrogen demand by sectors for learning variations (*BC*, *H2FC+*, *H2FC++*) under the *Reference* and *2°C scenario*.



Source: POLES-JRC model

The global hydrogen demand in the *Reference scenario BC* follows a similar trend to the *2°C scenario* BC, but the distribution across sectors varies. In the *Reference scenario*, the transport sector starts consuming hydrogen around 2050, when decreasing costs of hydrogen production and electrolysers improve the competitiveness of hydrogen cars and trucks (**Figure 23.c**). Hydrogen demand in buildings and synfuels appear slightly later and remain at a low level until 2100. This picture differs significantly in the *2°C scenario*, as the introduction of higher global carbon value favours the use of hydrogen in the power sector and as feedstock in synfuels.

2.4.3.1 Transport sector

2.4.3.1.1 Technology adoption pattern

Hydrogen demand

In the pursuit of decarbonising the transport sector, electrification is the prevalent strategy. According to the scenarios analysed in this study, electrification dominates cars and LCVs in the latter half of the century (**Figure 23**). However, for specific transport modes such as aviation and freight transport with HDV, hydrogen-based fuels or synfuels produced with hydrogen may provide an alternative. Assuming that the required hydrogen is produced with low carbon intensity, these options can significantly contribute to the decarbonisation of the transport sector. As a result, synfuels play an increasingly vital role in the final energy demand of the transport sector (**Figure 5** in Section 1.2.3.3).

While electrification is prevalent, fuel cells in transport serve as a viable alternative amidst the overall electrification trend in main transport modes. Hydrogen fuel cells powering cars and LCVs are expected to be more widely used than the internal combustion engine (ICE) in the latter half of the century (**Figure 23.a and b**). In the final energy demand of the transport sector, significantly more hydrogen than synfuels are consumed in both BC scenarios during this period (**Figure 5**). In the *2°C BC scenario*, hydrogen consumption even surpasses that of oil.

Overall, most of the hydrogen in the second half of the century is utilised in transport, either directly in fuel cell vehicles or indirectly to produce synfuels exclusively used in the transport sector. By 2050 (*2°C scenario* BC), fuel cells in transport account for approximately 44% (97 Mt_{H2}) of the total hydrogen demand, while synfuel production corresponds to about 18% of the hydrogen demand (40 Mt_{H2}). In 2100, hydrogen demand for fuel cells in transport and for synfuel production increases to 450 Mt_{H2} and 140 Mt_{H2}, respectively.

Fuel cell capacities

The share of fuel-cells-powered cars and LCV in the vehicle stock surges from a few percent increases today to about 14% in the *2°C scenario* by 2050 (**Figure 23**). Due to this rapid expansion and high learning rates for fuel cells in cars (15%), the overnight investment cost for fuel cells in vehicles decreases drastically in the coming decades (**Figure 33**.b). In particular, the floor cost level is already reached by 2050.

Total fuel cell capacity in transport grows to about 45 TW in 2050 and continues to expand in the latter half of the century, reaching approximately 148 TW in 2100 in the *2°C BC scenario* (**Figure 34.a**). Fuel-cells-powered cars account for roughly 31 TW which corresponds to approximately 70% of the total fuel cell capacity in the *2°C BC scenario* (**Figure 33.a** and **Figure 34.a**). Trucks powered by fuel cells account for about 20% of total capacity (2050, *2°C BC scenario*).

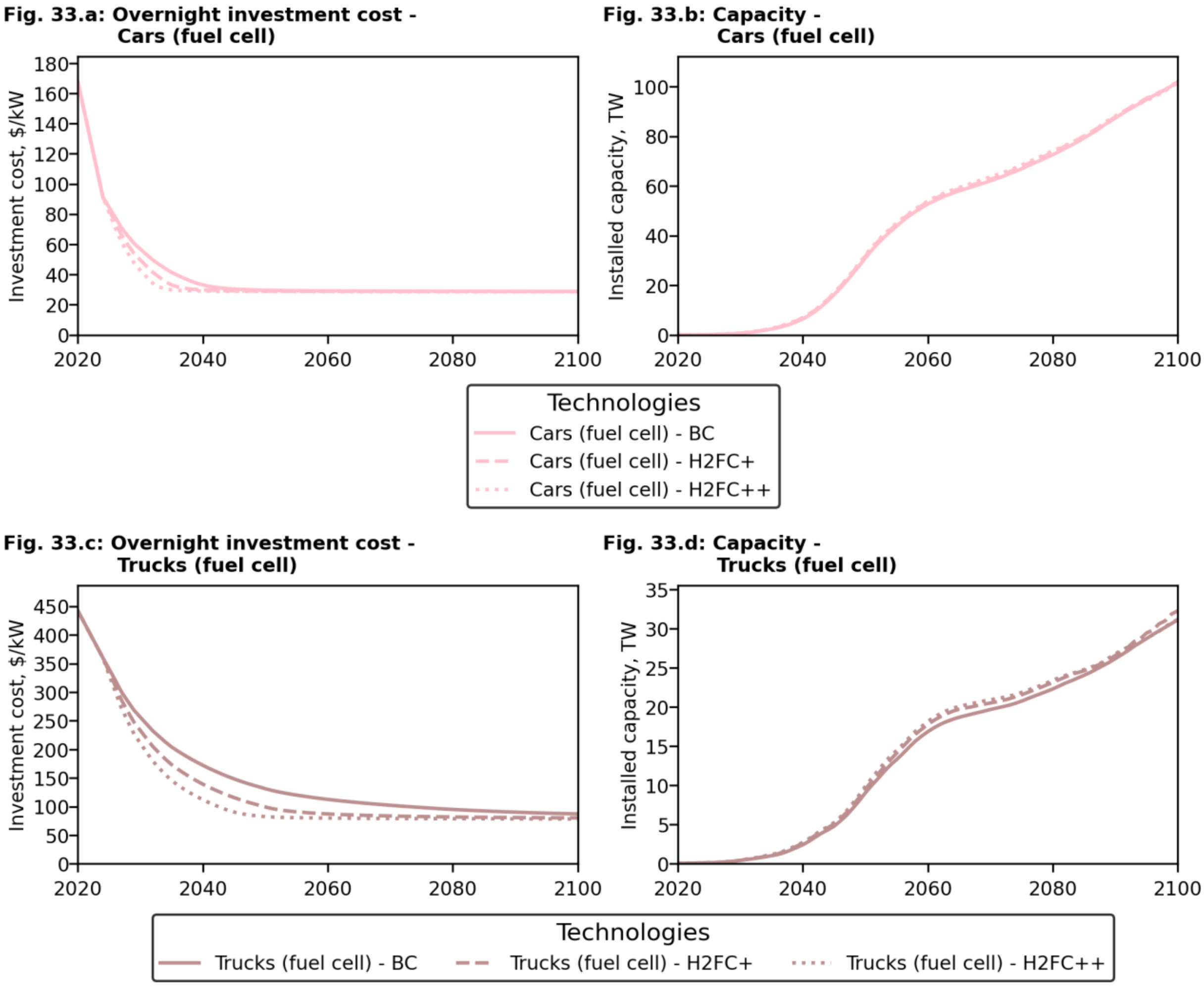
Moreover, POLES-JRC considers ships and aircraft powered by fuel cells as options for decarbonising the transport sector. The number of ships and aircrafts is comparatively low relative to cars and trucks.

Investment and cumulative investments

The difference among categories become less pronounced when examining investments. Due to the complexity of the installation of a fuel cell system, the specific fuel cell system costs (see **Table 22** in AN 5.4.1) for ships and aircrafts are more than 20 and 30 times higher than for cars, respectively. Consequently, in terms of required investments, fuel cells for ships represent a significant portion of total fuel cell investments (**Figure 34**.b). Investments for aircrafts remain at low levels due to the limited number of fuel cell aircrafts in the fleet.

Total investment needs, measured as cumulative investments (see indicator definition in 0) for fuel cells, amount to around 7 T$ by 2050 and 47 T$ by 2100. Until 2100, 44% of cumulative investments for fuel cells in transport account for cars, followed by 26% for ships, 18% for trucks and still 13% for aircraft (Figure 34.c).

Figure 33. Fuel cells in transport: evolution of (a) overnight investment cost and (b) capacities for learning variations (*BC*, *H2FC+*, *H2FC++*) under the *2°C scenario*.



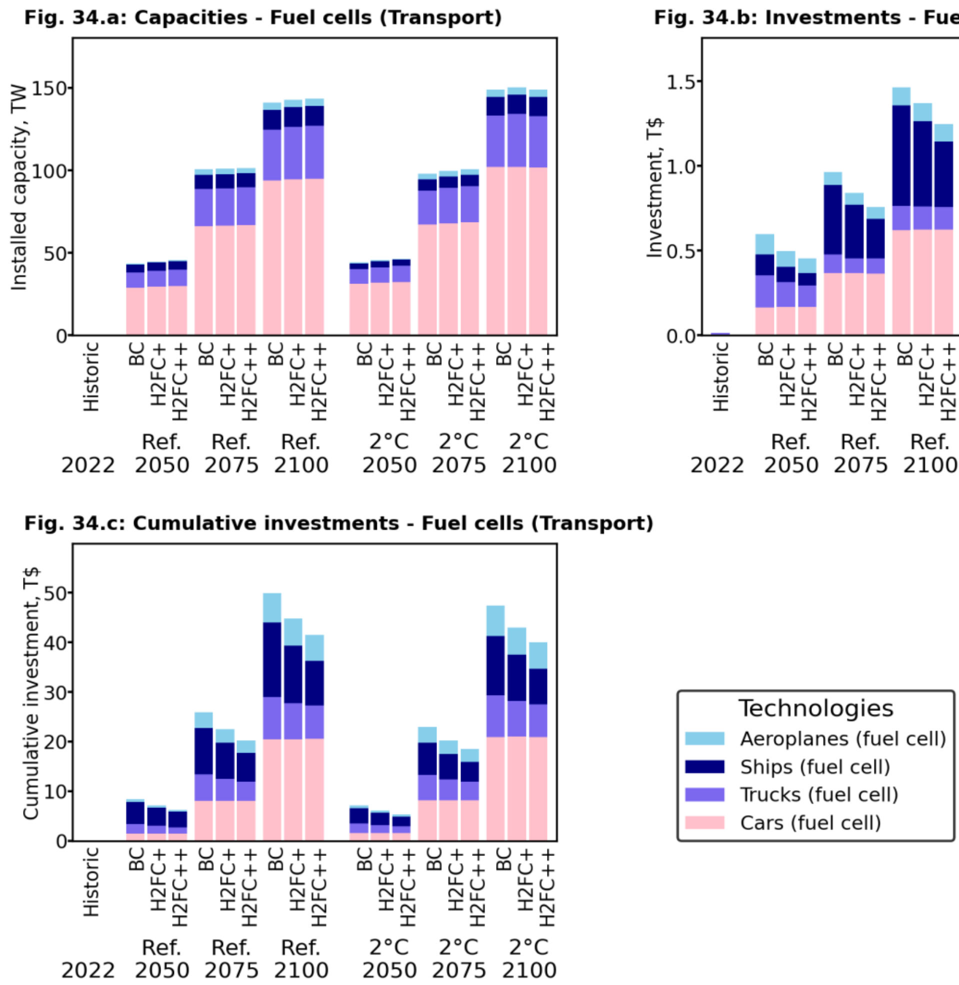
Source: POLES-JRC model

2.4.3.1.2 Impacts of enhanced learning rates

Enhanced learning (*H2FC+*, *H2FC++*) significantly reduces the cost of fuel cells (**Figure 33**.a). In the scenario with highly enhanced learning (*H2FC*), the floor cost level is reached much earlier by 2035 instead of by 2050 as in the *2°C scenario* BC. However, the impact on capacities is less pronounced. The underlying reason for this behaviour is that by the time capacity expansion accelerates significantly from 2040 onwards, costs have already decreased to relatively low levels, leading to negligible differences in capacity additions across the various enhanced learning scenarios. However, although the effect on capacities due to enhanced learning might be small, hydrogen demand does increase with enhanced learning on production technologies (**Figure 32**), as hydrogen becomes more competitive as production costs decrease.

The impact on investment needs (i.e., cumulative investments) for all enhanced learning scenarios (*H2FC+*, *H2FC++*) is substantial. About 20% less investments are required for highly enhanced learning (*H2FC++*) variations of the *2°C* and *Reference scenarios*.

Figure 34. Impacts of learning variations (*BC*, *H2FC+*, *H2FC++*) under the *Reference* and *2°C scenario* for fuel cells in transport.



Source: POLES-JRC model

2.4.3.2 Power sector

2.4.3.2.1 Technology adoption pattern

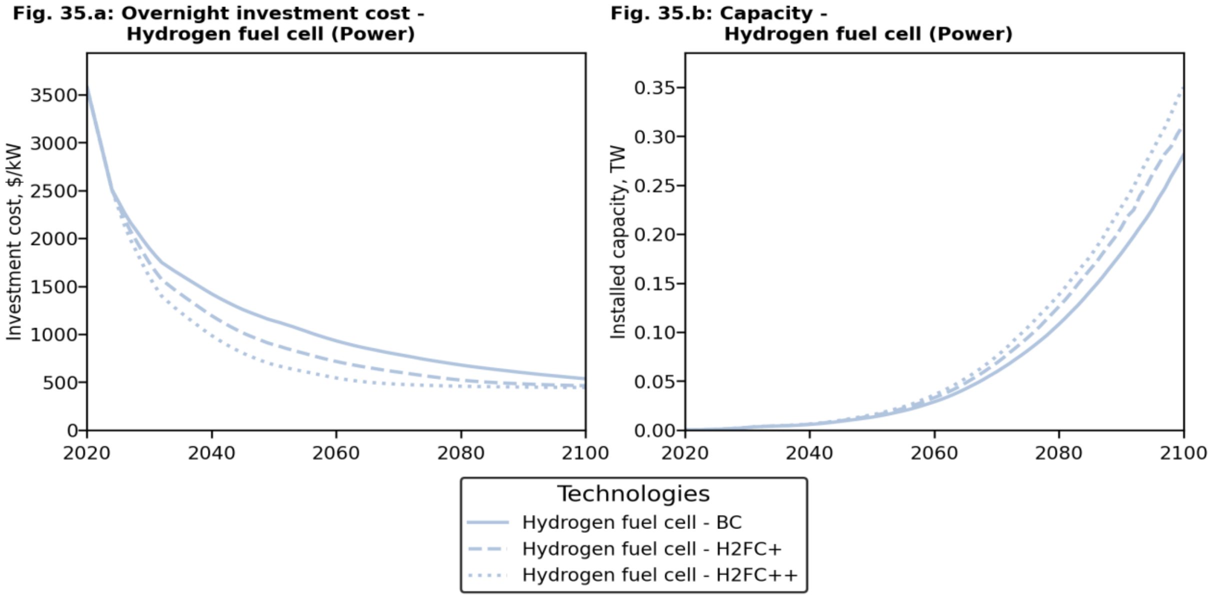
Hydrogen used for power generation increases from its virtually negligible level today to approximately 2% of global hydrogen demand by 2050 and to about 12% in 2100 in the *2°C BC scenario* (**Figure 32**). Consequently, the capacities for hydrogen fuel cells surge over the same period (**Figure 35.a**). Global power generation with fuel cells using hydrogen also increases in the coming decades (**Figure 36**.a). However, power generation with fuel cells accounts for less than 2% of the global power mix of the *2°C scenario* BC by 2100 (**Figure 3** in Section 1.2.3.2).

In the power system, merely a minor part of hydrogen is used to generate power by hydrogen fuel cells. Hydrogen-fuelled gas turbines and combined cycle plants are not considered in the current configuration of the POLES-JRC model. These technologies could likely play a significant role in the power mix, particularly for peak demand and to compensate for the variable nature of solar and wind, which could increase the role of hydrogen in the power mix by substituting a few percentage points of gas in the power mix (**Figure 3** in Section 1.2.3.2).

As fuel cell types, POLES-JRC considers two generic fuel cell types using hydrogen or natural gas. Investment cost for both types is assumed to be the same. Overnight investment cost is projected to decrease steeply from today's 3045 $/kW by about 63% by 2050 (**Figure 35**.a). This steep decline in cost for emerging fuel cell technologies results from fast endogenous learning based on two effects. Firstly, the assumed learning rate is relatively high (16%). Secondly, the initial capacities are relatively small (**Figure 35.b**), which means that even modest increases in capacity can have a pronounced impact on cost reduction through endogenous learning. However, capacities reach meaningful levels only by 2050.

Global power production of both fuel cell types reaches about 5 PWh by 2100, which equals about 4% of global power production *2°C BC scenario* (**Figure 3**). In particular, the role of hydrogen fuel cells is projected to play a minor role with about 1.6% (2.2 PWh) of global power production by 2100 in the *2°C BC scenario*. Power generation and capacities for gas-powered fuel cells are considerably higher in all scenarios compared to hydrogen fuel cells, as natural gas prices remain more competitive than hydrogen prices. Furthermore, in the *Reference scenario*, the significantly higher power generation and capacities for gas-powered fuel cells result from the lower gas price, as gas becomes expensive due to the global carbon value in the *2°C BC scenario*.

Figure 35. Hydrogen fuel cells in the power sector: evolution of (a) overnight investment cost and (b) capacities for learning variants (*BC*, *H2FC+*, *H2FC++*) under the *2°C scenario*.

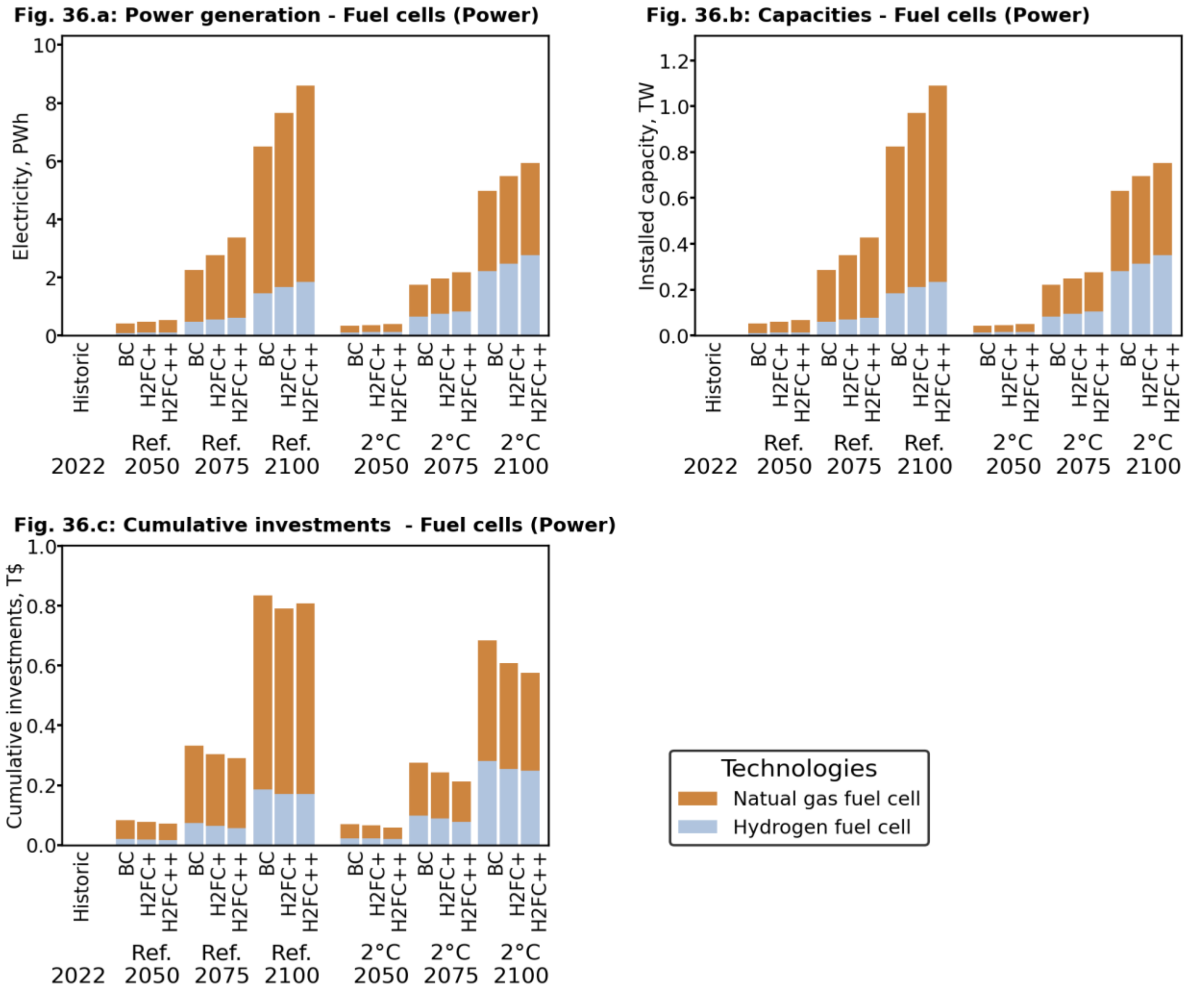


Source: POLES-JRC model

2.4.3.2.2 Impacts of enhanced learning rates

The effects of enhanced learning (*H2FC+*, *H2FC++*) are very prominent in terms of declining investment cost as well as increasing capacities and power generation (**Figure 35.a and b**, **Figure 36.a and b**). In terms of cumulative investments, the impacts of enhanced learning rates are less pronounced (**Figure 36.c**). The reason is that in the second half of the century towards 2100, the effects of enhanced learning tend to compensate each other as the cost decline approaches the floor cost, while capacities continue to increase.

Figure 36. Impacts of learning variations (*BC*, *H2FC+*, *H2FC++*) under the *Reference* and *2°C scenario* for fuel cells in the power sector.



Source: POLES-JRC model

2.5 Carbon capture in power and hydrogen production

Carbon capture and storage (CCS) technologies play a vital role in decarbonising the energy system by capturing CO_2 emissions from various sources and sequestering them in long-term storage. These technologies aim to capture CO_2 from point sources, such as fuel combustion, and from the air using techniques like direct air capture (DAC). Additionally, negative emissions can be achieved when combining bioenergy sources with CCS technologies (BECCS) or direct air capture.

The POLES-JRC model accounts for carbon capture (CC) in various sectors and processes:

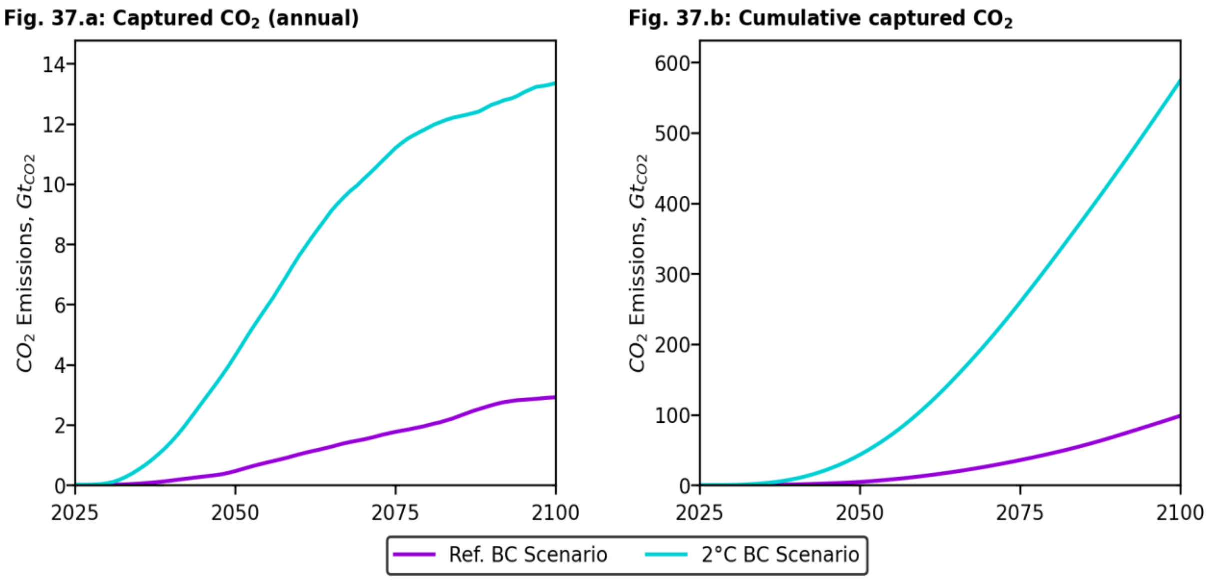
- *Power generation* from fossil fuels and biomass (Section 2.5.1)
- *Hydrogen production* from fossil fuels and biomass (Section 2.4.2.1);
- *Steel* and *cement* production in the industrial sector;
- Second generation *biofuels production* (Section 2.7.1.1.5);
- *Direct air capture* with storage and synfuels production (Section 2.6).

For the sensitivity analysis, CCS technologies are divided into two groups. The technology group *carbon capture* in power and hydrogen production and its associated learning rate variations (*CC+*, *CC++*) are addressed in this section. While the technology group *direct air capture and synfuels (DACSY)* is analysed in Section 2.6. Endogenous technology learning for CCS in biofuel production and industrial processes is modelled in POLES-JRC but is not subject to the sensitivity analysis of this study.

Regarding CO_2 storage, the model considers (i) geological sequestration, where CO_2 is injected into deep underground formations, and (ii) ocean sequestration, which involves injecting CO_2 into the deep ocean [20]. The potential for geological and ocean storage is considered in POLES-JRC. Saturation effects are anticipated by taking into account increasing costs with the exploitation of the storage. Additionally, the costs for transporting CO_2 to the storage sites are taken into account. While endogenous learning for CO_2 storage technologies is applied in the model, it is not considered in the sensitivity analysis of this study.

Figure 37.a illustrates the annually captured CO_2 resulting from all carbon capture technologies for both base case scenarios. Under the *2°C scenario*, CO_2 capture increases significantly and is pivotal in curbing overall GHG emissions during the second half of the century (compare with **Figure 1**, Section 1.2.1). By 2100, the cumulative captured CO_2 (**Figure 37.b**) amounts to approximately 570 Gt_{CO2} in the *2°C scenario*, whereas only around 100 Gt_{CO2} in the *Reference scenario*.

Figure 37. Evolution of annual captured CO_2 and cumulative CO_2 under the base cases of the *2°C scenario* and *Reference scenario*.



Source: POLES-JRC model

2.5.1 Power generation with CO_2 capture

2.5.1.1 Power technologies

POLES-JRC considers *four* power-generating technologies with CO_2 capture based on *post-combustion* or *pre-combustion* processes.

Post-combustion
In *post-combustion* processes, CO_2 is removed from the exhaust gases after the combustion of coal or natural gas. *Two* power-generating technologies with *post-combustion* are considered:
(1) Advanced pulverised coal with CO_2 capture (Adv. PC & CC) represents a conventional super-critical pulverised coal power plant coal with post-combustion CO_2 capture. The components of the capture system consist of the CO_2 absorption system, the CO_2 compression unit, and a generic balance of system (BOS) capture part (**Table 16** in AN 5.1).
(2) NGCC with CO_2 capture (NGCC & CC) consists of a conventional combined cycle gas turbine (CC) plant fuelled with natural gas (NG) and a dedicated CO_2 capture system with analogous components, as in the case above.

Pre-combustion
Pre-combustion technologies are based on conventional integrated gasification combined cycle (IGCC) plants. In a conventional IGCC plant, electricity is generated by using the hydrogen of the syngas to generate power in a combined cycle process employing a gas turbine and a steam turbine. In an IGCC with CO_2 capture, the CO of the syngas is converted into CO_2 and subsequently separated and removed. As the CO_2 is removed before burning the fuel, this capture process is referred to as pre-combustion process.

The *two* pre-combustion power technologies in POLES-JRC are based on IGCC plants fuelled by coal or biomass:
(3) Integrated coal gasification with CO_2 capture (ICG & CC) uses a CO_2 capture system, which consists of units for the water-shift reaction, CO_2 removal and CO_2 compression (see **Table 16** in AN 5.1).
(4) Integrated biomass gasification with CO_2 capture (IBG & CC) allows to achieve negative CO_2 emissions. Apart from using biomass, this technology functions analogously to the aforedescribed IGCC & CCS, but requires more complex processing for the biomass. Therefore, the cost of the components are substantial higher and the efficiency is lower (see **Table 12** in AN 5.1).

Oxy-fuel
In the POLES-JRC model, the oxy-fuel process is not explicitly considered as a CO_2 capture mechanism for power technologies, as the aforementioned generic power technologies allow to model the evolution of CO2 capture in the power sector concerning cost, fuel type, and efficiency adequately..

Retrofitting
Apart from installing new capacities with CO_2 capture, retrofitting existing plants is an effective strategy for swiftly reducing the emissions of the power sector.
Retrofitting is a particularly attractive option for countries with relatively modern fossil power fleets, as it enables the recovery of existing investments and helps to mitigate the transition costs associated with shifting to a decarbonised power system [42]. POLES-JRC considers the option to retrofit coal and biomass power technologies with CO_2 capture. A retrofit with a CO_2 post-combustion capture unit may be considered for sub-critical lignite and coal plants and advanced pulverised coal (super/ultra-super critical). NGCC plants may also retrofitted with a CO_2 post-combustion capture unit. Existing IGCC and biomass gasification plants may be retrofitted with a pre-combustion CO_2 capture unit.

2.5.1.2 Learning for CO_2 capture technologies

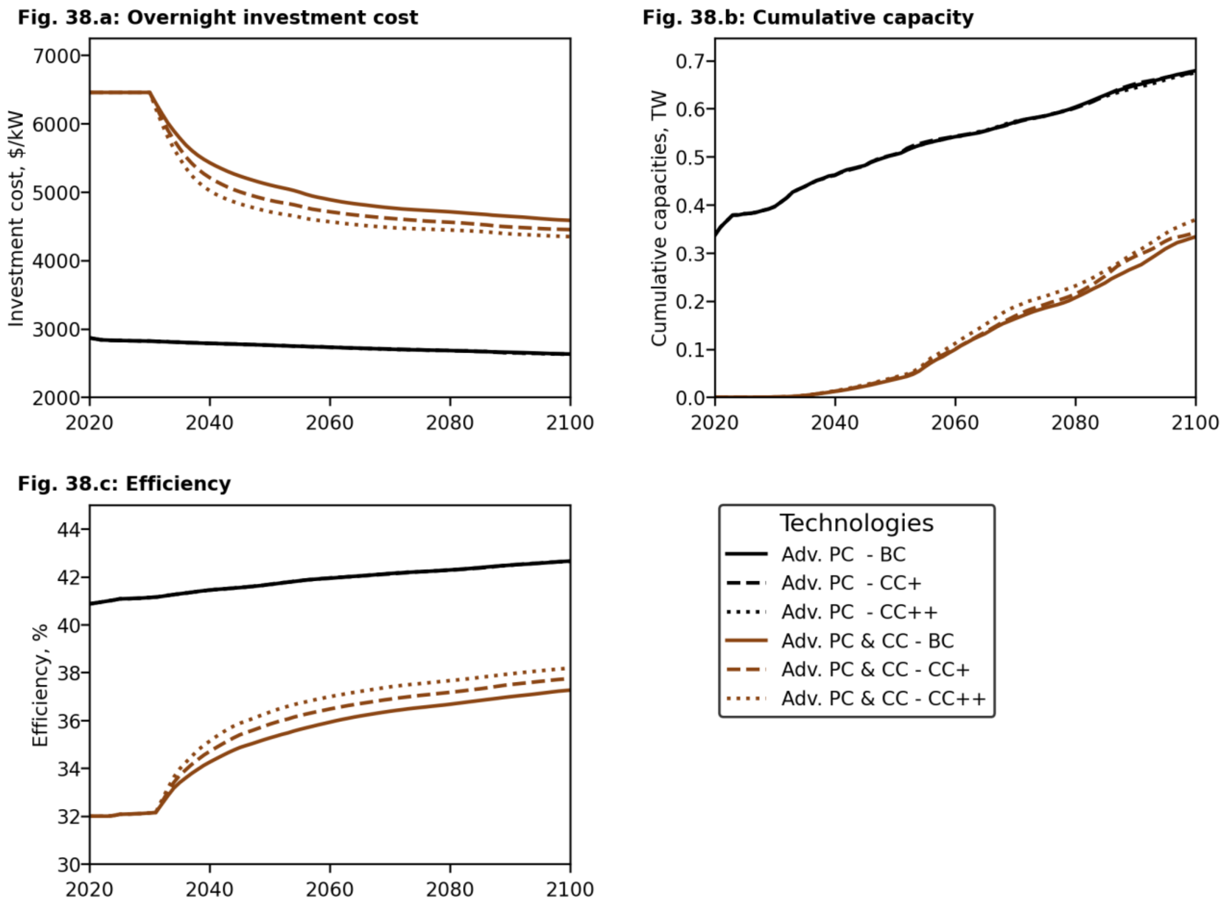
The investment cost of these technologies is broken down into several components, which are shared by several thermal power generation technologies (**Table 12** and **Table 16** in AN 5.1) and hydrogen production technologies (**Table 18** in AN 5.2). Additionally, the *CO_2 compression component* is shared with the direct air capture (DAC) technology (**Table 24** in AN 5.5).

The cost decrease of a shared component is driven by its cumulative capacities across all its shared technologies according to the component-based learning-by-doing approach (compare Section 1.3.1). Therefore, all technologies sharing a certain component benefit from the technology progress made by this component.

Figure 38 illustrates the technology progress of conventional power technology and its corresponding CO_2 capture technology, exemplarily for advanced pulverised coal with CO_2 capture (*Adv. PC & CC*) and without CO_2 capture (*Adv. PC*). The investment cost for *Adv. PC & CC* decreases substantially from 2030 onwards (**Figure 38.a**) as CCS capacities increase steadily (**Figure 38.b**). This cost decrease in the early years is very pronounced as it increases from zero, and cumulative capacities multiply various times in the early years so that endogenous learning has a substantial effect on reducing cost (see Section 1.3.1). In contrast, the cost decreases merely slowly for the conventional technology (Adv. PC). One reason is that the capacities of its components increase much more slowly in contrast to the CO_2 capture capacities (**Figure 38.b**). Moreover, conventional components are regarded as mature technologies characterised by rather low learning rates in contrast to the components of CO_2 capture, which are considered as emerging technologies with rather high learning rates (**Table 12** and **Table 16** in AN 5.1). As a result, the total cost decrease for the CO_2 capture technology (Adv. PC & CC) relates mainly to its CO_2 capture components, whereas its conventional components contribute rather little.

Analogously, the efficiency of the the CO_2 capture technology (Adv. PC & CC) increases substantially in the coming decades, while the efficiency of the mature conventional power technology (*Adv. PC*) improves merely slowly (**Figure 38.c**).

Figure 38. Evolution of (a) overnight investment cost, (b) cumulative capacity and (c) efficiencies for advanced pulverised coal power with CO_2 capture (Adv. PC & CC) and without CO_2 capture (Adv. PC) for learning variations (*BC*, *CC+*, *CC++*) under the *2°C scenario*.



Source: POLES-JRC model

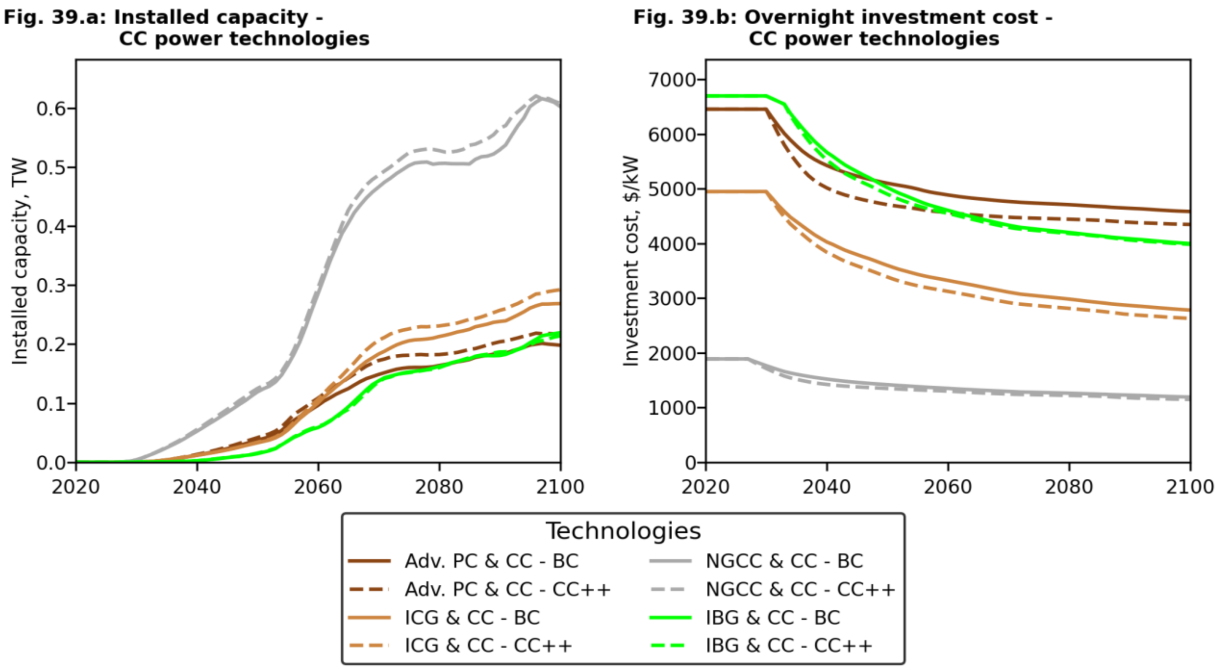
2.5.1.3 Technology adoption pattern

Within the *2°C BC scenario*, power plants with CO_2 capture expand rapidly from 2030 onwards, driven by the global carbon value (**Figure 39.a**). Combined cycle plants with CO_2 capture (NGCC & CC) are the dominating technologies throughout the century mainly due to their low investment cost compared to other technologies (**Figure 39.b**). Also, substantial amounts of coal-based technologies are built (Adv. PC & CC and ICG & CC), while biomass gasification with CO_2 capture (IBG & CC) plays merely a minor role. Although its investment cost is comparable to advanced pulverised coal with CO_2 capture (Adv. PC & CC), relatively high biomass prices impede the expansion of biomass gasification with capture.

The global electricity generation with CO_2 capture technologies increases to about 1 PWh by 2050 and further to about 5.4 PWh by 2100 in the *2°C BC scenario* (**Figure 40.c**). However, in relation to the total global electricity generation (**Figure 3**), CO_2 capture technologies account merely for 1.5% by 2050 and 4% by 2100. Cumulative CO_2 captured in the power sector amounts to about 190 Gt_{CO2} by 2100 in the *2°C BC scenario* (**Figure 40.d**), which accounts for 34% of total cumulative CO_2 captured until 2100 (**Figure 37.b**).

In the *Reference BC scenario*, not surprisingly, few power capacities with capture are built as stringent carbon policies are missing (see **Figure 40.a**). In the Reference scenario by 2100, power technologies with CO_2 capture (**Figure 40.c**) account for a very small amount of total global electricity production (0.7%). Moreover, in the *Reference BC scenario* about nine times less CO_2 is captured until the end of the century than in the *2°C BC scenario* (**Figure 40.d**).

Figure 39. Evolution of (a) installed capacity and (b) overnight investment costs for carbon capture (CC) power technologies with CO_2 capture for learning variations (*BC*, *CC+*, *CC++*) of the *2°C scenario*.



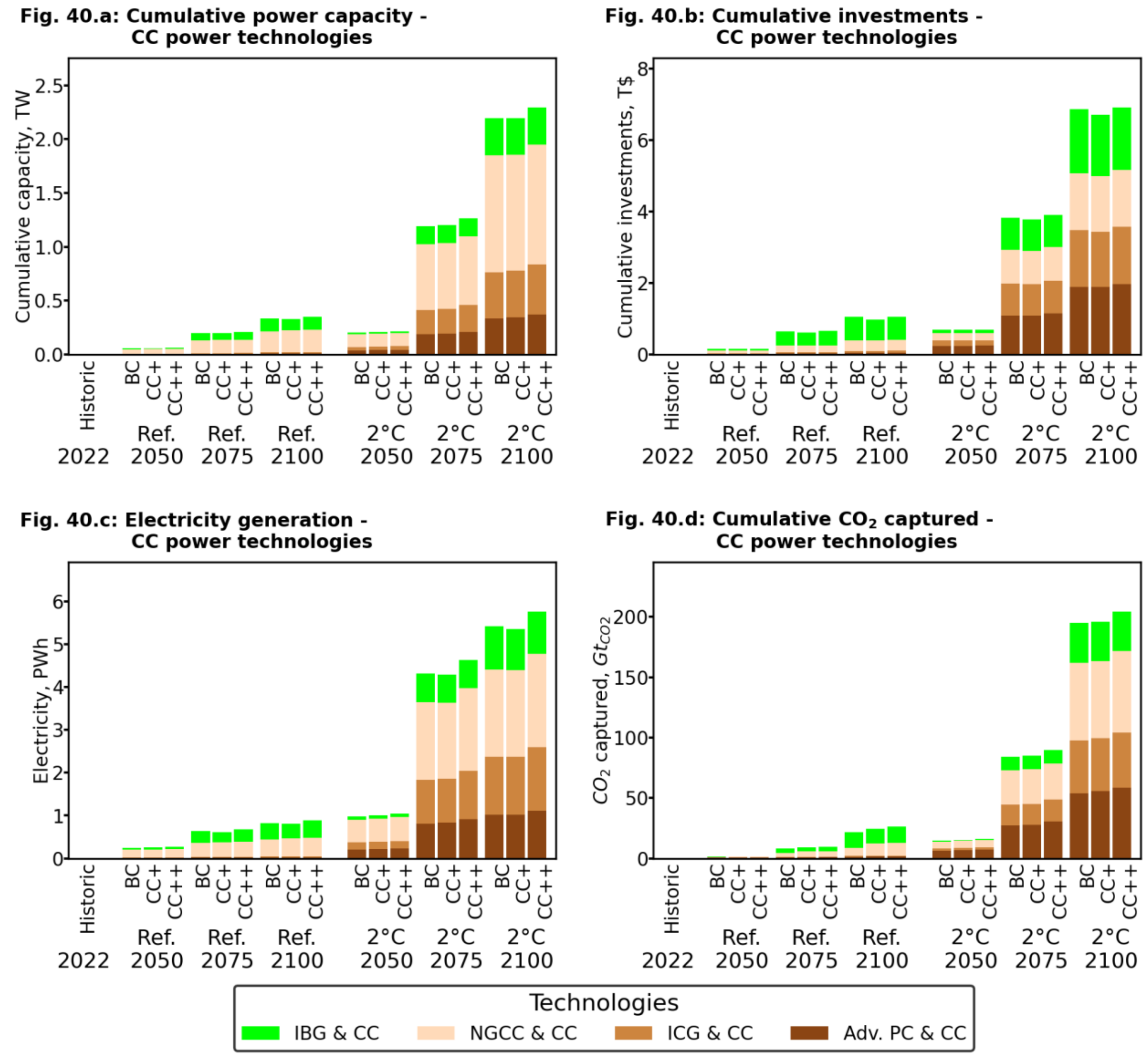
Source: POLES-JRC model

2.5.1.4 Impacts of enhanced learning rates

In the context of the 2°C base case scenario, enhanced learning of carbon capture technologies (*CC+*, *CC++*) leads to several advantages. These include increased capacities (**Figure 39.a**) and reduced investment costs, particularly for advanced pulverised coal with CO_2 capture (Adv. PC & CC), as depicted in **Figure 39.b**. Moreover, the power technologies with CO_2 capture demonstrate improved efficiencies, as illustrated in **Figure 38.c**.

Overall, the enhanced learning of carbon capture technologies (*CC+*, *CC++*) leads to increased electricity production (**Figure 40.c**) and enhanced CO_2 capture (**Figure 40.b**) across all examined scenarios. Notably, the Adv. PC & CC and ICG & CC technologies exhibit significant benefits from enhanced learning, which is reflected in the substantial reduction of investment costs (**Figure 39.b**). However, the overall impact on required investments remains ambiguous, as the increase in capacities (**Figure 39.a** and **Figure 40**.a) does not entirely offset the decrease in investment costs (**Figure 39.b**) as illustrated in **Figure 40.b** for the scenarios with enhanced learning.

Figure 40. Impacts of learning variations (*BC*, CC+, *CC++*) under the Reference and *2°C scenario* for carbon capture (CC) power technologies.



Source: POLES-JRC model

2.5.2 Hydrogen production with CO_2 capture

Hydrogen production technologies with CO_2 capture in POLES-JRC comprise steam methane reforming with CC, and gasification of coal and biomass with CC (see Section 2.4.2). The investment cost of these technologies is broken down into several conventional components, which are shared across other hydrogen technologies, and additionally capture-related components, which are shared across capture technologies for power generation (**Table 12** and **Table 16** in AN 5.1), hydrogen production (see Section 2.4.2.2 and **Table 18** in AN 5.2) and direct air capture (**Table 24** in AN 5.5).

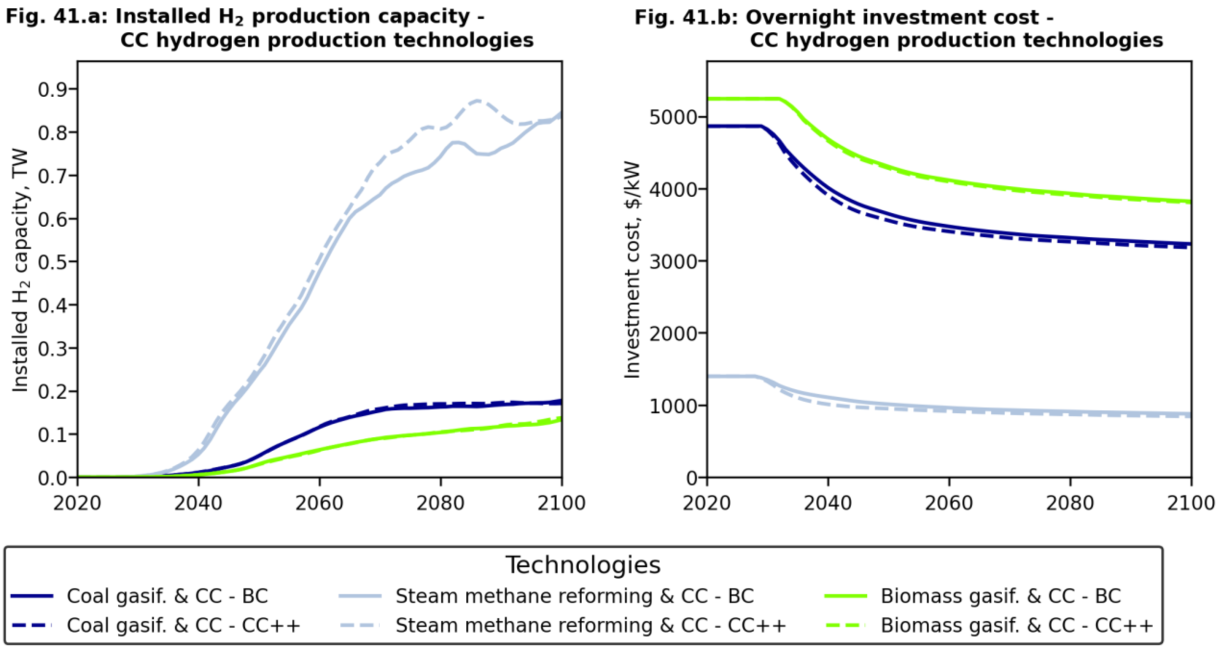
2.5.2.1 Technology adoption pattern

Hydrogen production technologies with CO_2 capture expand rapidly from 2030 onwards (**Figure 41.a**, *2°C BC scenario*). Investment costs drop significantly until 2050 due to endogenous learning as capacities start to increase from zero and cumulative capacities multiply many times in this period (**Figure 41.a** and **Figure 42.a**). After 2050, investment costs decrease more steadily as cumulative capacities multiply less quickly, although capacities reach substantial amounts in the second half of the century. For instance, cumulative capacities for steam methane reforming with CC increase about 60-fold from 2030 to 2050, while from 2050 until 2100 increase merely 6-fold.

The *adoption pattern* is similar to power technologies with CO_2 capture as the gas-based capture technologies (i.e., methane steam reforming) outperform coal and biomass technologies by far. The dominance of *methane reforming with capture* is even more pronounced than the gas-based technology (*NGCC & CC*) in power generation. Similarly, as for the power technologies, biomass gasification with CO_2 capture is the less deployed capture technology.

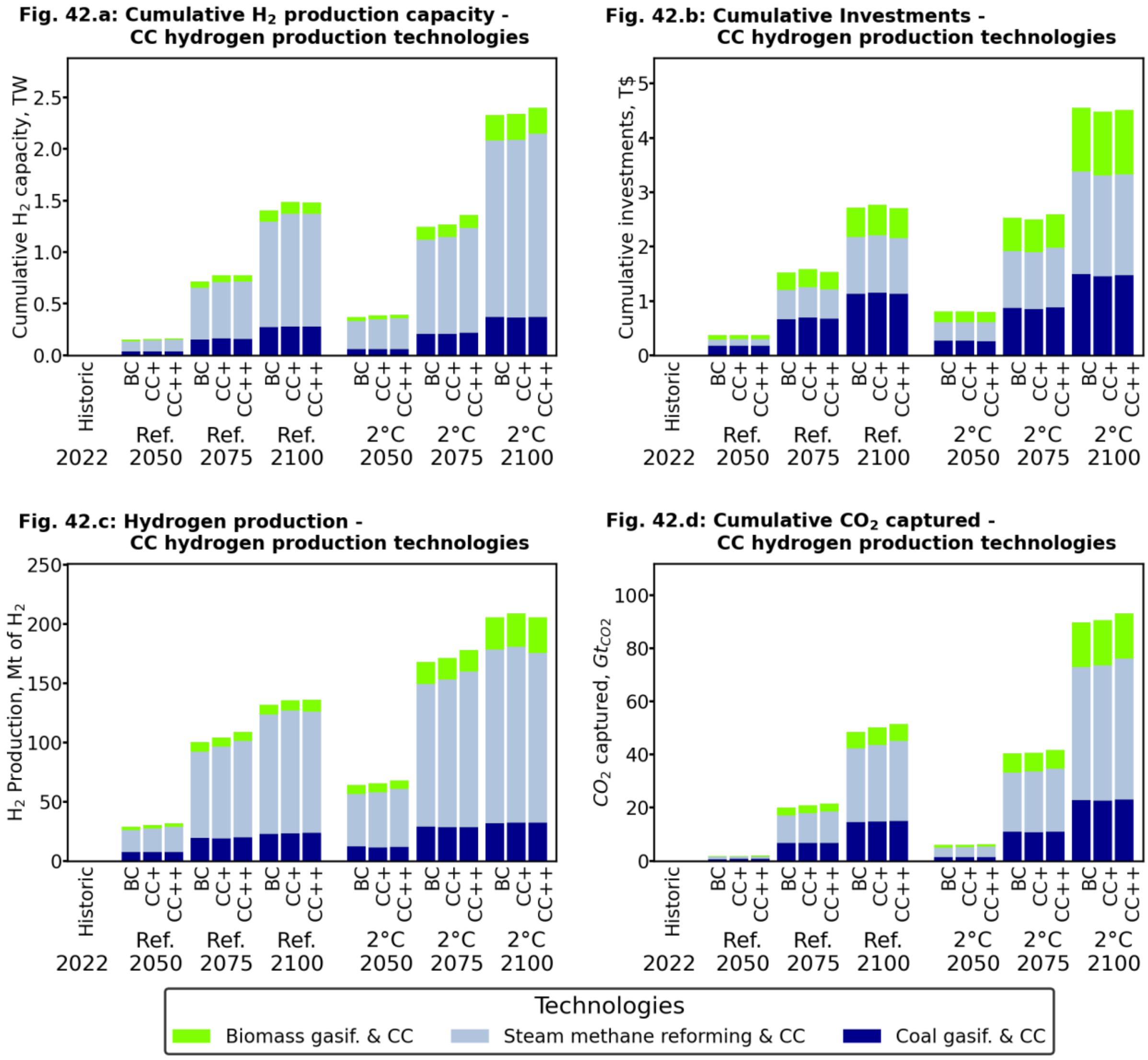
Hydrogen production with CO_2 capture in the *2°C BC scenario* increases by 2050 to about 64 Mt_{H2}, which relates to 26% of total hydrogen production of 245 Mt_{H2} (**Figure 28** in Section 2.4.2). Until 2100, hydrogen production with CO_2 capture more than triples to about 205 Mt_{H2}. The cumulative CO_2 captured amounts to about 90 Gt_{CO2} by 2100 in the *2°C BC scenario* (**Figure 42.d**). In the *Reference base case scenario*, the cumulative CO_2 captured is still half of what is captured in the *2°C BC scenario*. Notably, within the *Reference BC scenario*, carbon capture plays a more prominent role in hydrogen production than in power generation (**Figure 40.d** vs. **Figure 42.d**).

Figure 41. Evolution of (a) hydrogen production capacity and (b) overnight investment cost for carbon capture (CC) hydrogen production technologies for learning variations (*BC*, *CC+*, *CC++*) under the *2°C scenario*.



Source: POLES-JRC model

Figure 42. Impacts of learning variations(*BC*, *CC+*, *CC++*) under the *Reference* and *2°C scenario* for carbon capture (CC) hydrogen production technologies.



Source: POLES-JRC model

2.5.2.2 Impacts of enhanced learning rates

In the context of the *2°C scenario*, highly enhanced learning for hydrogen technologies with CO_2 capture (*CC++*) yields improvements compared to the base case scenarios, resulting in enhanced hydrogen production (+8%) as displayed in **Figure 42.c** and increased CO_2 capture (+4.5%) illustrated in **Figure 42.d**. However, the effects of the medium-enhanced learning variation (*CC+*) are less pronounced or even contradictory, as shown by the 2075 figures for the 2°C variations in **Figure 42.a** and **Figure 42.c**). The potential reason for this behaviour may be the relatively small cost differences between the enhanced learning variations across all hydrogen capture technologies. Furthermore, the impact on required investments is not significant for all scenario variations, as shown in **Figure 42.d**).

2.6 Direct air capture and synfuels

Direct Air Capture (DAC) of CO_2 is a technology to remove carbon dioxide directly from the ambient air. DAC is a key technology for decarbonisation for two reasons. Firstly, it is an important pathway to achieve negative emissions in combination with long-term CO_2 storage. Secondly, the captured CO_2 can be combined with hydrogen by chemical synthesis to form synfuels. Using such synfuels instead of fossil fuels would establish a carbon-neutral fuel cycle, provided that the energy needed for DAC and hydrogen production process is carbon neutral as well. The POLES-JRC model takes into account this dual functionality of CO_2 captured by Direct Air Capture (DAC), which can be either stored to achieve net negative emissions or utilised for the production of synfuels, as described in Section 2.6.2.

2.6.1 Direct air capture

2.6.1.1 Technology and modelling

State-of-the-art DAC technologies can be categorised as high-temperature aqueous solutions (*HT DAC*) and low-temperature solid sorbent (*LT DAC*) processes [43].

The *HT DAC* process typically involves liquid solvents with a high affinity for CO_2 (e.g., aqueous solutions of NaOH and KOH) for capturing CO_2. Subsequently, high-temperature heat (about 900°C) is used to regenerate the solvent and to release the captured CO_2. The *LT DAC* process uses solid sorbents (e.g., amines), which adsorb CO_2 at ambient temperature. In the subsequent desorption, the CO_2 is released at medium temperature (80-100°C). Both processes require that large volumes of air pass through the capturing unit due to the low concentration of CO_2 in the air (ca. 415 ppm). Driving the fans to pass through the air consumes substantial amounts of electricity. Moreover, in both processes, the captured CO_2 is released in the form of a concentrated stream, which will be compressed for storage or utilisation.

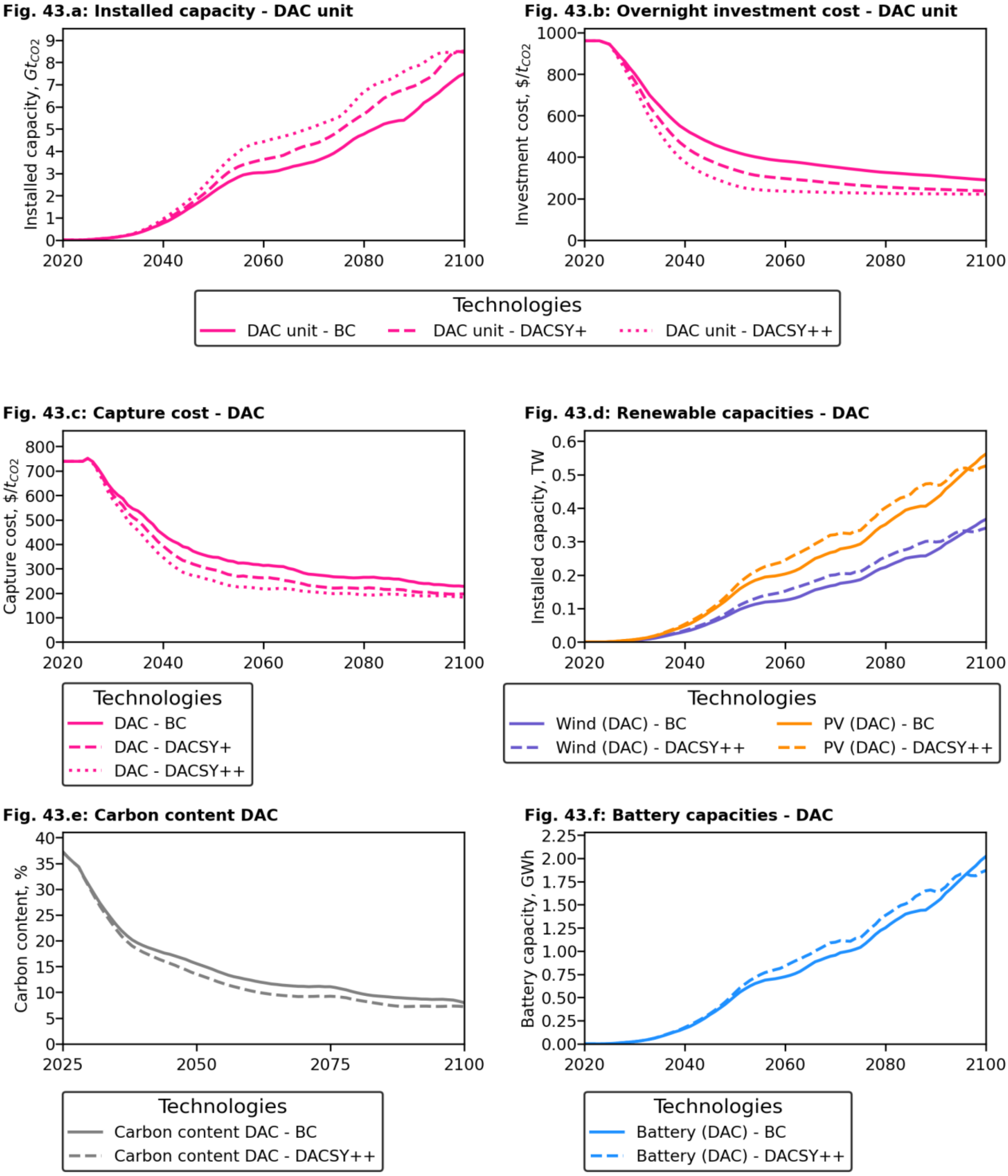
In POLES-JRC, direct air capture is implemented as a generic process that combines the techno-economic parameters and characteristics of the *HT DAC* and *LT DAC* processes. The generic process assumes a specific energy consumption of 7.8 GJ per tonne of captured CO_2 (2022), with 80% of this energy dedicated to process heat and the remaining 20% powering mechanical components. The required heat can be supplied by either natural gas or electricity, which are considered competing sources. The total DAC electricity consumption (including both heat and mechanical components) is provided exclusively by dedicated solar and wind plants in the POLES-JRC model, which are not part of the power system itself (Sections 2.1 and 2.2. Moreover, battery capacities are deployed to the solar and wind plants in order to stabilise the variable renewable generation and enhance the operational hours of the DAC process.

The investment cost for the DAC process is split by components into the actual DAC unit, accounting for over 90% of the investment, and a CO_2 compression unit (**Table 24** in AN 5.5). A learning rate of 14% is applied to the DAC unit, considering it an emerging technology, while a more modest learning rate of 3% is applied to the mature technology of CO_2 compression. Additionally, the investment costs for the dedicated wind and PV capacities and the associated battery capacities are also considered.

The resulting cost per captured tonne of CO_2 using DAC comprises (i) the investment costs for the DAC process (**Table 24** in AN 5.5), (ii) the additional investment costs for the wind or PV capacities and the battery capacities (**Table 10**, **Table 11** and **Table 15** AN 5.1), (iii) non-energy operation and maintenance costs (**Table 24** in AN 5.5) and (iv) variable costs for natural gas. Additionally, storage costs apply if the captured CO_2 is permanently removed from the atmosphere (see Section 2.5).

Two factors drive the deployment of new DAC capacities in POLES-JRC. Firstly, the increasing demand for synfuels is required to build more DAC capacities. Secondly, funds for financing the permanent removal of CO_2 from the atmosphere by DAC and subsequent storage triggered by the implementation of pricing on carbon emissions. It is assumed that as much as 10% of the revenues related to the global carbon value are available to finance the permanent removal of CO_2.

Figure 43. Evolution of (a, d & f) capacities, (b & c) costs and (e) carbon content DAC for learning variations (*BC*, *DACSY+*, *DACSY++*) under the *2°C scenario*.



Source: POLES-JRC model

2.6.1.2 Adoption patterns and learning

Technology evolution

DAC capacities are increasingly deployed from 2030 onwards in the *2°C BC scenario* due to the rising CO_2 price (**Figure 43.a**). In turn, investment cost for the DAC unit decreases fast until 2050 and continues to decline steadily in the second half of the century (**Figure 43.b**). Also, the cost of capturing CO_2 decreases substantially in the coming decades from about 750 $/$t_{CO2}$ today to 330 $/$t_{CO2}$ by 2050 and 230 $/$t_{CO2}$ by 2100 (**Figure 43.c**).

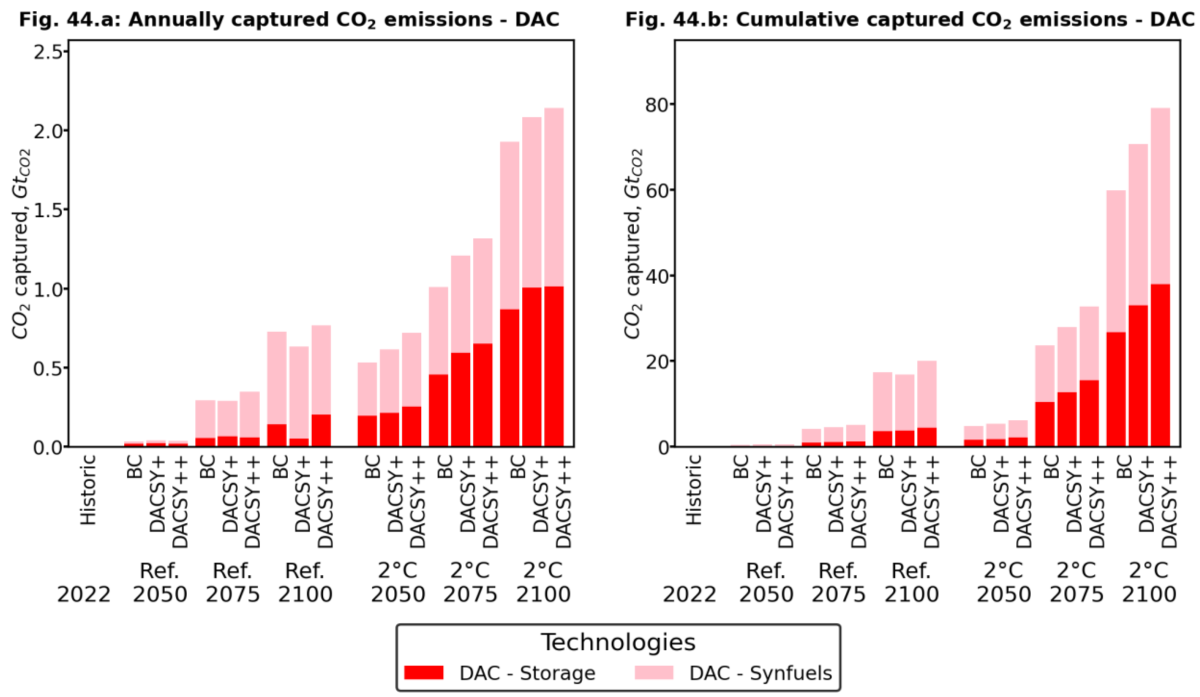
Large renewable capacities are required to power DAC (**Figure 43.d**). The dominating technologies used are on-shore wind and utility-scale photovoltaics. In 2100, the total renewable capacities amount to nearly 1 TW which is about 2% of the total installed renewable capacities (2100). Moreover, battery capacities for balancing the variable renewables increase along with the increasing renewable capacities (**Figure 43.f**).

The carbon footprint of DAC reduces continuously from initially about 37% to about 10% at the end of the century (**Figure 43.e**). The decreasing footprint reflects that natural gas is increasingly substituted by renewable electricity to produce the required heat of the process as its cost decreases continuously due to endogenous learning. Also, less energy is required for the process as its efficiency improves over time due to endogenous learning.

Annually captured CO_2 emissions under the *2°C BC scenario* account for about 0.5 Gt_{CO2} by 2050 and 1.8 Gt_{CO2} by 2100 under the *2°C BC scenario* (**Figure 44.a**). Permanently removed CO_2 using DAC with storage accounts to about 1.2 Gt_{CO2} annually by 2100 (**Figure 44.a**), which relates to 8% of the remaining annual GHG emissions (14.1 Gt_{CO2eq}) by 2100 (**Figure 1** in Section 1.2.1).

By the end of the century, the cumulative captured CO_2 emissions by DAC amount to about 60 Gt_{CO2} in the *2°C BC scenario* (**Figure 44.b**) representing around 10% of total cumulative CO_2 captured by all capture technologies by 2100 (**Figure 37.b** in Section 2.5). About 32 Gt_{CO2} cumulative CO_2 is permanently removed from the atmosphere until 2100 (**Figure 44.b**), which relates to about 3% of the cumulative CO_2 of the *2°C BC scenario* (**Figure 61.d** in Section 3.1.1.2).

Figure 44. Impacts of learning variations (*BC*, *DACSY+*, *DACSY++*) under the *Reference* and *2°C scenario* for direct air capture (DAC) technologies.



Source: POLES-JRC model

2.6.2 Synfuels

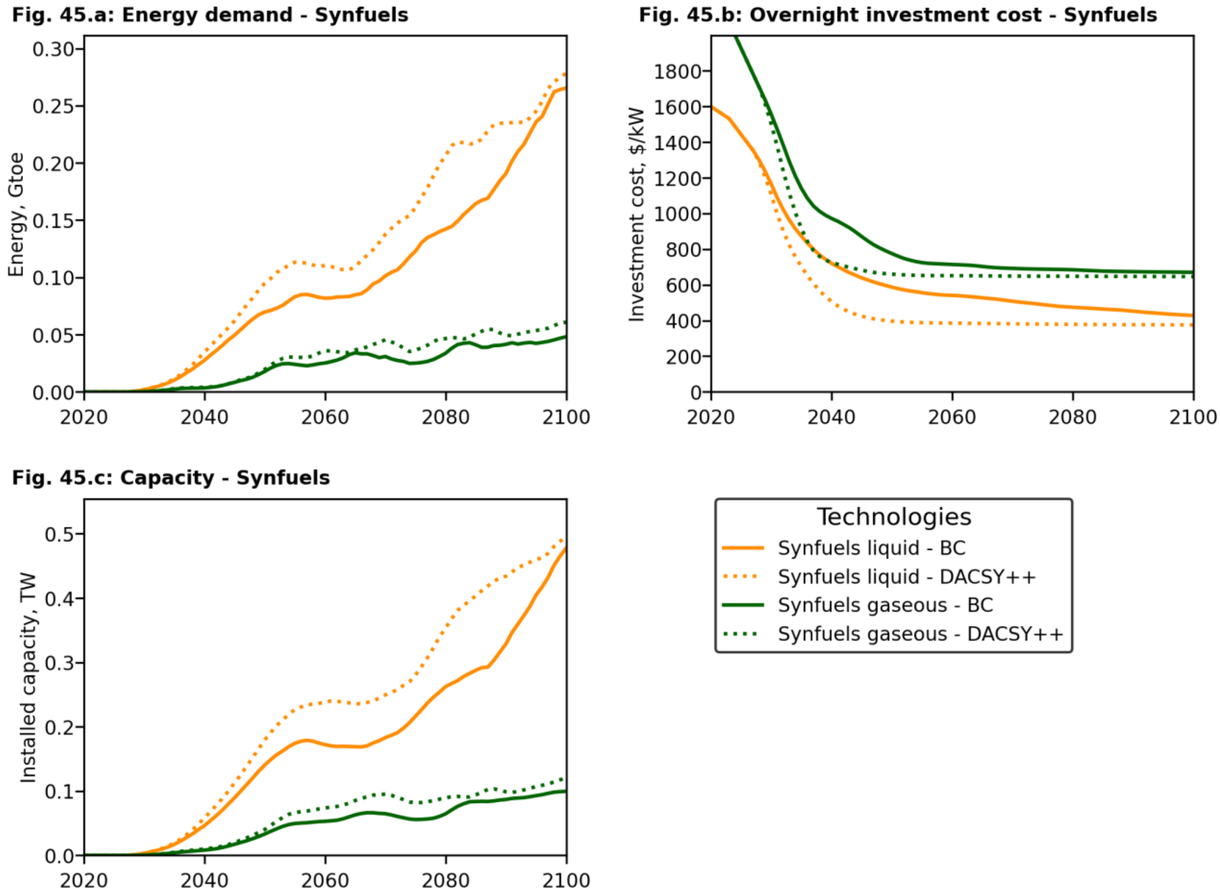
Synfuels could be gaseous or liquid and can be produced with properties very similar to natural gas and oil products. Therefore, synfuels are well suited to substitute conventional fuels in many end-uses. Using synfuels instead of fossil fuels would allow the establishment of a carbon-neutral fuel cycle given that the energy needed for the DAC and hydrogen production process is carbon-neutral as well. Synfuels, when using solely renewable energy sources for their production, are also referred to as *E-fuels*, or in an EU context, as *renewable fuels of non-biological origin* (*RFNBO*).

The production of gaseous and liquid synfuels in POLES-JRC uses solely the CO_2 from DAC as carbon feedstock, while the required hydrogen is supplied by the various hydrogen technologies (Section 2.4.2). The production process for gaseous synfuels is modelled as methanation process [44], [45], whereas liquid synfuels are produced by the Fischer-Tropsch process [43].

Within the *2°C BC scenario*, demand for synfuels emerges in the 2030s. In particular, demand for liquid synfuels surges throughout the second half of the century (**Figure 45.a**). In 2100, total synfuels production amount to about 0.3 Gtoe which is about 2% of final energy demand **Figure 4** in Section 1.2.3.3).

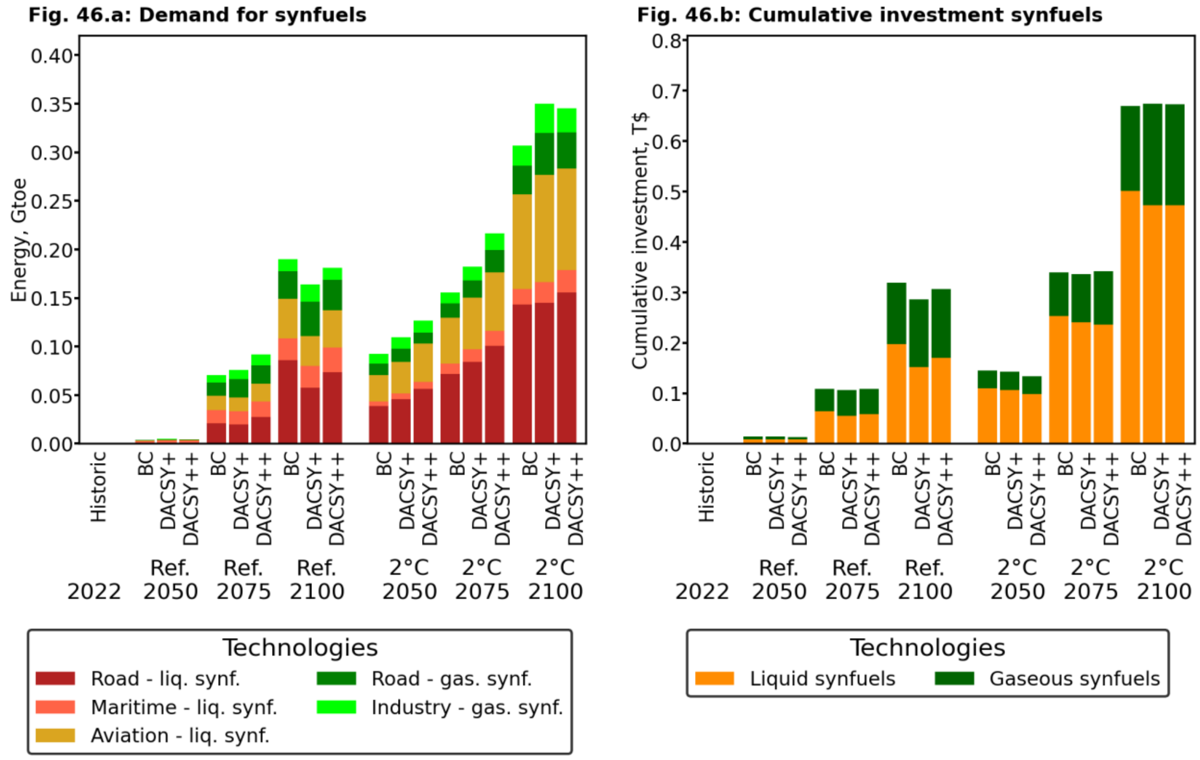
POLES-JRC calculates endogenously the demand for synfuels from various end-uses. *Liquid synfuels* are solely considered for uses in transport, with the aim of substituting oil in road traffic, aviation, and maritime shipping (**Figure 46.a**). Moreover, trade between regions allows the distribution of liquid synfuels according to regional production costs and regional demand. The transportation of liquid synfuels can use pipelines and shipping similar to oil products. *Gaseous synfuels* are mainly considered for industrial uses (**Figure 46.a**), such as producing steel and chemicals, and in the non-metallic sector (i.e., cement, ceramics, glass). To a minor extent, gaseous synfuels are used in road transport as fuel.

Figure 45. Evolution of liquid and gaseous synfuels for learning variations (*BC*, *DACSY++*) under the *2°C scenario*.



Source: POLES-JRC model

Figure 46. Impacts of learning variations (*BC*, *DACSY+*, *DACSY++*) under the *Reference* and *2°C scenario* on demand and cumulative investments for synfuels.



Source: POLES-JRC model

Demand for liquid synfuels increases substantially faster than gaseous synfuels due to the increasing demand in transport. At the end of the century, demand for liquid synfuels is about three times higher than for gaseous synfuels in 2100 (2°C BC scenario). Therefore, multiple times higher production capacities for liquid synfuel production are required (**Figure 45.c**). Consequently, investment cost decreases for liquid synfuel more aggressively than gaseous synfuels (**Figure 45.b**).

2.6.3 Impacts of enhanced learning rates

In the *2°C BC scenario*, enhanced learning for DAC and synfuel technologies (*DACSY+*, *DACSY++*) significantly increases the amount of captured CO_2.

In particular, enhanced learning allows capturing substantial amounts of CO_2 much earlier compared to the *BC scenario*. The DAC capacities by about 2055 for highly enhanced learning (*DACSY++*) are not attained before about 2075 in the *BC scenario* (**Figure 43.a**). The reason for the faster deployment of DAC capacities with enhanced learning is the faster-declining costs induced by enhanced learning (**Figure 43.b and c**). Annual captured CO_2 increase with highly enhanced learning (*DACSY++*) in 2050 by about 37% and in 2100 by about 18% (**Figure 44.a**).

Overall, the cumulative amount of captured CO_2 until 2100 increases by 35% for the highly enhanced learning variation of the *2°C scenario* (*DACSY++*) compared to the *BC scenario*. Notably, the cumulative amount of stored CO_2 increases even by 65% (*DACSY++*) compared to the *BC scenario*.

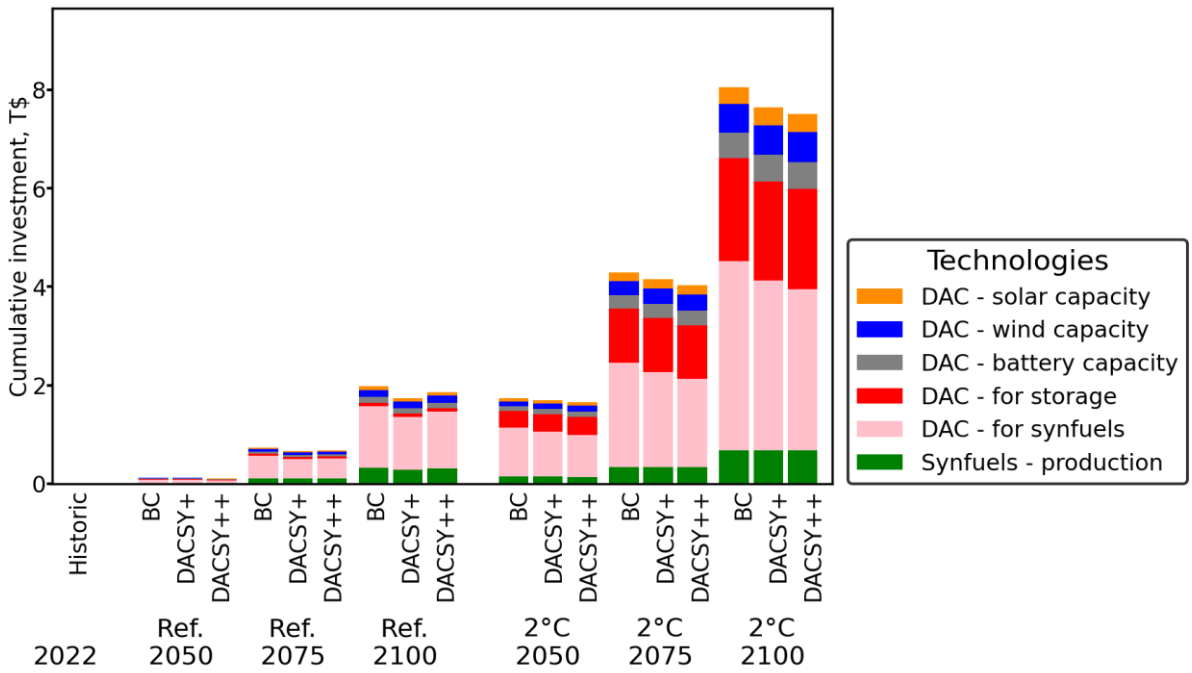
To conclude, enhanced learning for DAC in the *2°C scenario* variations allows to establish DAC as decarbonisation technology significantly earlier and has a significant impact on reducing the carbon budget.

For *synfuels*, enhanced learning increases in the *2°C scenario* the demand for synfuels as their cost decreases due to lower cost for DAC capture (**Figure 43.c**) and lower synfuel production cost (**Figure 45.b**).

Remarkably, fewer investments are required at the end of the century to capture more CO_2 and consume more synfuels with enhanced learning in the *2°C scenario*, as can be seen for the decreasing cumulative investments (**Figure 47**).

Under the *Reference scenario*, the impacts of enhanced learning rates are ambiguous. The described tendencies for the *2°C scenario* are similar in the highly enhanced learning (*DACSY++*) variation of the *Reference scenario*. However, for moderate enhanced learning (*DACSY+*) in the *Reference scenario*, even less CO_2 is captured (**Figure 44.a**) and fewer synfuels are demanded (**Figure 47**) compared to the BC. It seems that moderately accelerating learning without a substantial global carbon value is not sufficient to usher in more decarbonisation with DAC.

Figure 47. Impacts of learning variations (*BC*, *DACSY+*, *DACSY++*) under the *Reference* and *2°C scenario* on cumulative investments for direct air capture (DAC) uses and production of synfuels.



2.7 Bioenergy technologies

Biomass is a viable alternative to fossil fuels for energy use. Biomass use for energy is projected to increase in the future and its use would further expand with enhanced climate policies.
POLES–JRC distinguishes several primary biomass resources such as energy crops, short rotation crops (lignocellulosic) and wood (lignocellulosic). These biomass resources are used for different end-uses:

- Liquid biofuels are solely used in the transport sector. First generation biofuels are based on agricultural crops (non-cellulosic), and second generation biofuels are based on lignocellulosic biomass.
- Biomethane is modelled as a substitute for natural gas and is mainly used for generating electricity and heat.
- Solid biomass (lignocellulosic) is used for electricity generation (see Section 2.7.2), the production of hydrogen (see Section 2.4.2) and direct use for supplying heat for buildings and industrial processes.

Supply cost curves and maximum potentials describe primary biomass supply by resource type in POLES-JRC. Biomass supply relations and its projections for different biomass and carbon cost levels are provided by soft-linking with the specialised model GLOBIOM-G4M (Global Biosphere Management Model) [46]. Also, food production, land uses and associated GHG emissions in agriculture, forestry and other land use (AFOLU) are provided by the soft-link with GLOBIOM-G4M. As input, the soft-link with GLOBIOM-G4M is fed with biomass energy demand, which is modelled in POLES-JRC. Accordingly, biomass prices increase increases over time as more of the resource is being used. Moreover, biomass can be traded, either in solid form or as liquid biofuel.

The bioenergy technology group (*BE*) in this study encompasses three sub-technology groups, which are described in the following sections:

1. Production of liquid biofuels and biomethane;
2. Power generation;
3. Production of hydrogen.

2.7.1 Biofuels and biomethane

2.7.1.1 Liquid biofuels

Liquid biofuel supply in POLES-JRC refers to biomass conversion into liquid biofuels, ethanol and biodiesel, that can be used in transport activities. Liquid biofuels can be classified as conventional or advanced biofuels[2] (according to IEA Task 39 [48]), aiming to make a differentiation between biofuels production potentially competing with food or feed biomass (conventional) and those that use feedstock from residues or use non-agricultural land. Currently, third-generation biofuels (algae) are not included in POLES-JRC as the technology is still in an exploratory stage.

Table 3. Liquid biofuels classification for road transport, POLES Code and representative technology/process used.

Classification	**Technologies used**
1st generation, biogasoline (ethanol)	Dry Mill corn/ethanol
1st generation, biodiesel	Palm oil seed crushing & Palm oil transesterification
2nd generation, biogasoline (ethanol)	Enzymatic hydrolysis
2nd generation, biodiesel	Gasification & Fisher Tropsch

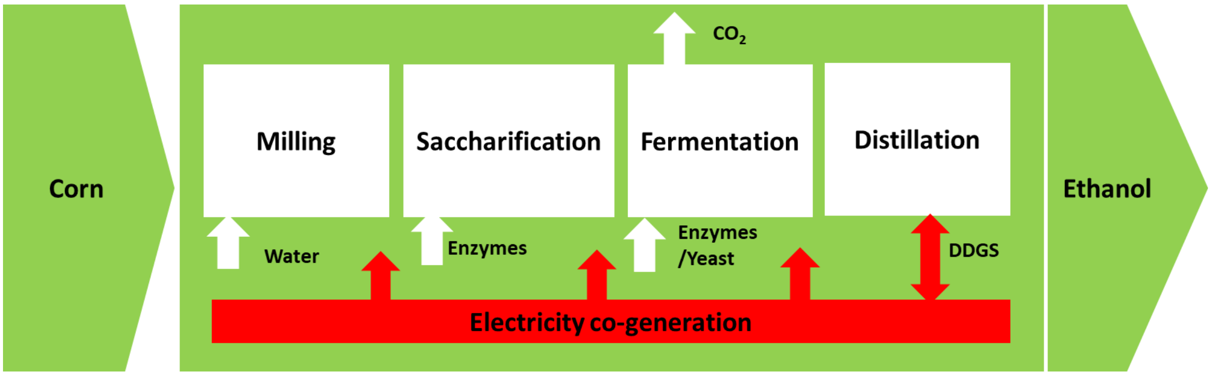
[2] Advanced biofuels correspond largely to those feedstocks in the Annex IX A and B lists of the Renewable Energy Directive II (RED II) [47].

First generation biofuels are commercially available and have reached technological maturity. New developments in feedstock generation and processing are likely to further reduce costs and achieve better environmental performance. Feedstock for conventional biofuel production can consist of sugars, starches, oil-bearing crops and animal fats, among others. Advanced biofuels use non-food crops and agricultural and forest residues, mainly based on cellulose, hemicellulose or lignin. First generation biofuels are already a mature technology, while second generation is still under development after some commercial attempts during 2010-2020.

2.7.1.1.1 First generation, biogasoline (ethanol)

First generation ethanol is produced within a dry mill plant. Ethanol, with an energy density approximately of 30% lower than gasoline, is produced from crop fermentation. In POLES-JRC, corn-to-ethanol is taken as the representative technology for the entirety of bioethanol production. Corn is milled, and then the starch or cellulose is converted into sugar. The soluble C5 and C6 sugar molecules are biologically fermented to ethanol using yeast or bacteria. Dry milling co-products of the production process include distiller dry grain solubles (DDGS) and CO_2. DDGS is usually sold as a feed; in the modelling, it is entirely used to supply all of the energy required for ethanol production in a CHP plant with 55% efficiency (self-consumption). Therefore, there is no cost for purchasing electricity or heat from external utilities, nor co-products credits.

Figure 48. First generation ethanol production input/output scheme.



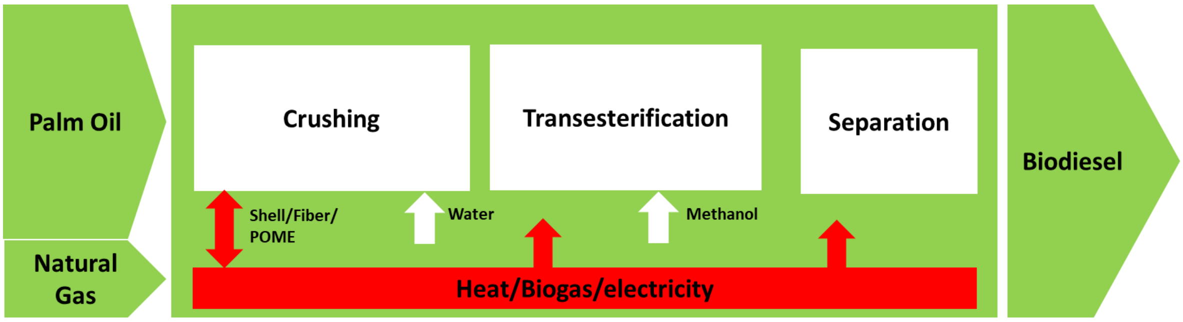
Source: POLES-JRC model

2.7.1.1.2 First generation, biodiesel

First generation biodiesel is produced by a crushing + transesterification process. Biodiesel refers to esterified oils produced form vegetable oils, animal fat and waste fat. Generally, about 50% of the existing biodiesel plants do not rely on one feedstock type and use multiple sources to ensure optimal feedstock supply security [49]. In POLES-JRC, palm oil seeds has been the feedstock selected for the representative process for biodiesel production in the model. All the co-products and waste in the mill (crushing) are converted into heat and electricity to feed the process. Shell and fibre are used as an alternative fuel in the boiler to produce steam. Palm oil mill effluent (POME) is treated by anaerobic digestion to produce biogas that is then used to provide electricity for the transesterification process (self-consumption); this covers the total internal need for heat and electricity within the crushing + transesterification process, improving the economics of biodiesel production. In addition, natural gas has to be purchased for methanol production in a process called transesterification[3] [50].

[3] Methanol is used to convert the triglycerides in different types of oils into usable biodiesel fuel

Figure 49. First generation biodiesel production input/output scheme.

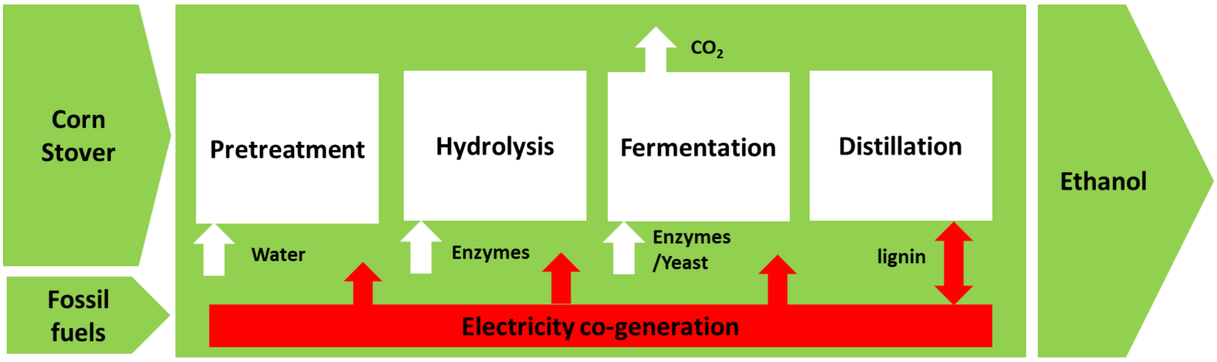


Source: POLES-JRC model

2.7.1.1.3 Second generation, biogasoline (ethanol)

Second generation ethanol is produced via enzymatic hydrolysis from lignocellulosic feedstock, which can be corn stover or woody biomass. In POLES-JRC, corn stover to ethanol is taken as the representative technology for the entirety of advanced bioethanol production. Biomass feedstock is subjected to thermal and/or chemical pre-treatment. This is typically followed by separation of the lignin fraction, and then hydrolysis using enzymes to convert the cellulose and hemicellulose fractions to sugars. The soluble C5 and C6 sugar molecules are biologically fermented to ethanol using yeast or bacteria [51]. The lignin, the main co-product, is burnt onsite for heat & power generation in a CHP plant with 55% efficiency, covering all the steam and electricity required for ethanol production (self-consumption) and eventually producing an electricity surplus. Therefore, there is no cost for purchasing electricity or heat from external utilities, nor co-product credits. Furthermore, other fossil fuels are required to produce lime and sulphuric acid for corn stover pre-treatment and hydrolysate condition as well as for the ammonia production for enzyme production. Therefore, different fossil fuels (natural gas, heavy fuel oil, hard coal, and light fuel oil) are purchased to produce the chemicals needed at the pre-treatment and enzyme production phases [52].

Figure 50. Second generation ethanol production input/output scheme.

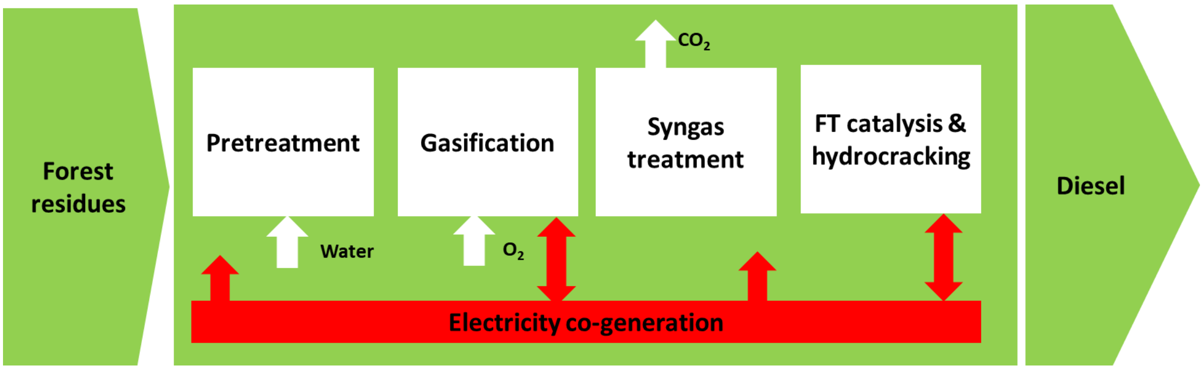


Source: POLES-JRC model

2.7.1.1.4 Second generation, biodiesel

Second generation biodiesel is produced by gasification using the Fischer-Tropsch (FT) process from lignocellulosic biomass. In POLES-JRC, forest residues to biodiesel are taken as the representative technology for the entirety of advanced biodiesel production. Biomass is typically pre-treated and then processed in a gasifier. Gasification converts the biomass into syngas. The syngas is then cooled and cleaned, the carbon dioxide is removed, and the syngas is compressed. During the Fischer-Tropsch synthesis, the conditioned syngas is reacted to produce diesel and generate excess electricity [51].

Figure 51. Second generation biodiesel production input/output scheme.



Source: POLES-JRC model

2.7.1.1.5 Carbon capture for second generation biofuels

The POLES-JRC model includes carbon capture and storage (CCS) for second-generation biofuels. Capturing of CO_2 in second-generation biofuel production applies to the emissions generated during their production:

- 2nd generation biogasoline (ethanol): capturing CO_2 emissions from the fermentation process
- 2nd generation biodiesel: removing CO_2 from the syngas

The deployment of carbon capture capacities for second-generation biofuels is primarily driven by the carbon value and the comparative production costs of biofuels with and without carbon capture. Consequently, second-generation biofuel production with CCS thrives under the *2°C scenario* but remains uncompetitive under the *Reference scenario*.

Under the *2°C scenario*, the share of second-generation biofuels with CCS increases steadily from 2030 onwards, reaching approximately 8% by 2050 and 40% by 2100. However, despite this growth, the total amount of captured CO_2 remains relatively modest, accounting for less than 1% of total cumulative CO_2 captured by 2100.

2.7.1.2 Biomethane

Biogas is produced by the breakdown of organic matter in an oxygen-free environment, a process known as anaerobic digestion. The resulting biogas is a mixture of mainly methane (CH_4) and carbon dioxide (CO_2). To produce a high-quality, grid-compliant fuel, biogas must undergo an upgrading process, which involves the separation of methane from carbon dioxide and other impurities, resulting in a purified biomethane product. After the upgrading process, the resulting biomethane can be directly mixed with fossil gas in the existing natural gas network, offering a low-carbon alternative for heating, power generation, and transportation.

Various biomass types can be used for producing biomethane, ranging from agriculture products like corn, over agricultural waste (manure, crop residues) to waste (biodegradable municipal waste, sewage). In POLES-JRC the biomethane produced is used to generate electricity and heat for various end-uses.

2.7.1.3 Technology adoption pattern

Biofuels

The demand for biofuels in transport is expected to increase in the coming decades due to their growing role in substituting oil in road transport (**Figure 5** in Section 1.2.3.3). By approximately 2040, biofuels demand reaches a preliminary peak; in the subsequent decades, biofuels are partially displaced by the massive expansion of electric vehicles (**Figure 5**). The growth in biofuel demand during the latter part of the century is primarily driven by the increasing demand for biofuel in international air transport.

First-generation biofuels currently dominate the market in terms of capacity (**Figure 52.a**) and production (**Figure 53.b**). In the *2°C BC scenario*, first-generation biofuel capacities are projected to reach a maximum in the 2030s, followed by a continuous decline until the end of the century, falling below current levels.

Second-generation biofuels are projected to experience significant growth in the next two decades, reaching a temporary peak by about 2050. In the second half of the century, biodiesel demand surges due to the increasing demand for international air transport, while biogasoline declines due to extensive electrification in road transport.

The transition from first-generation to second-generation biofuels can be primarily attributed to the significant cost advantage of lignocellulosic feedstock over agricultural biomass. Two key factors drive this shift:
Firstly, the cost of lignocellulosic feedstock is substantially lower than that of agricultural biomass, making second-generation biofuels more economically viable. Secondly, agricultural biomass costs are expected to increase faster than lignocellulosic feedstock throughout the century. This trend is driven by the decreasing potential of first-generation biofuels, which face intense competition from agricultural food production. Moreover, as second-generation biofuel technologies mature, agricultural biomass production becomes less attractive.

The investment costs for first-generation biofuels decrease marginally, reflecting the maturity of the technology (**Figure 52**.**b**). In contrast, investment costs for second-generation biofuels decrease significantly in the coming decades as substantial capacities are built up from a low starting point (**Figure 52.d**).

Total biofuel production in the *2°C BC scenario* increases from about 0.1 Gtoe today to nearly 0.25 Gtoe in 2050 and approximately 0.4 Gtoe in 2100 (**Figure 53.b**). From 2040 onwards, first-generation fuel production declines continuously for the reasons previously mentioned.

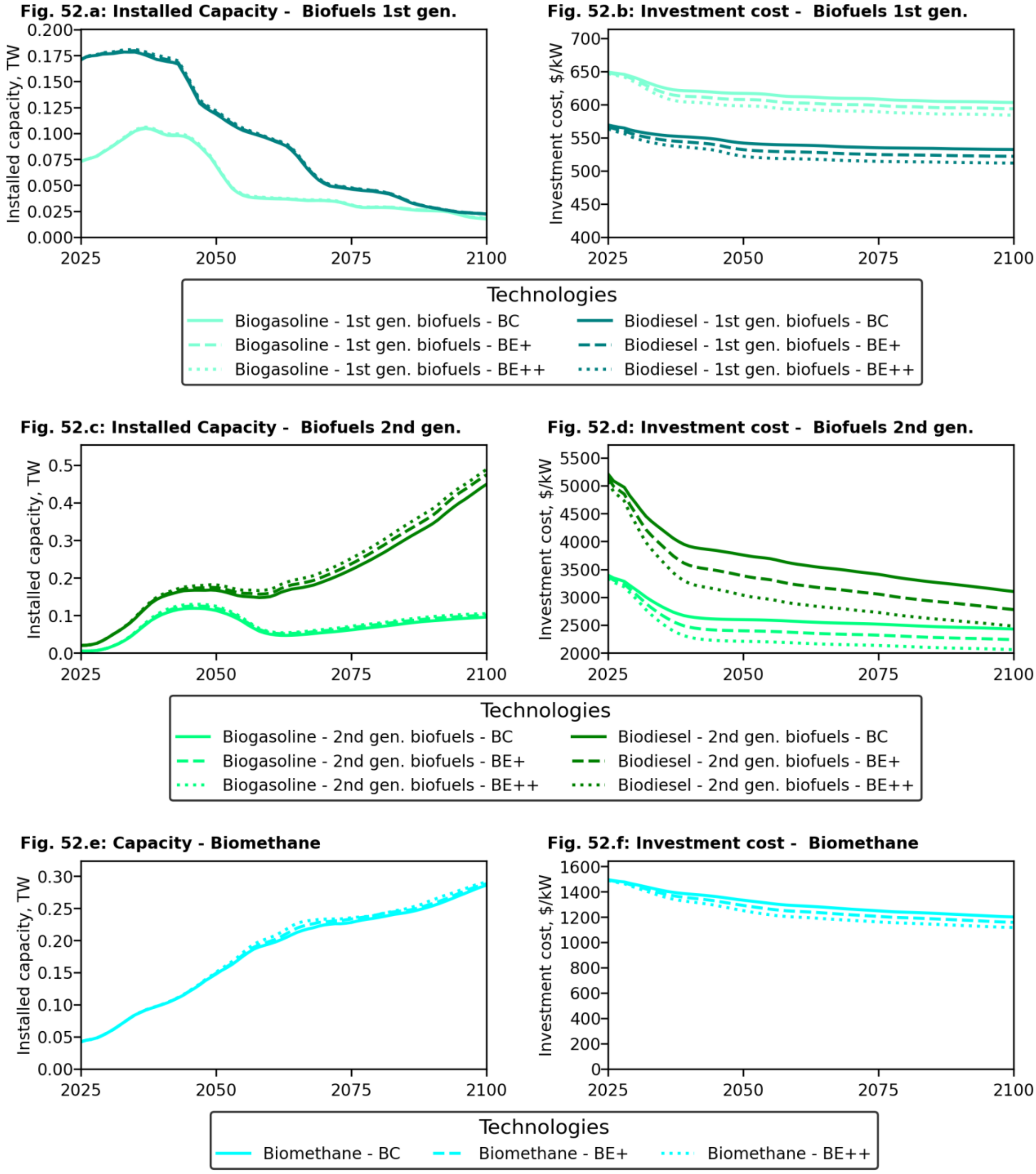
Under the *Reference scenario*, biofuel production follows a similar trajectory but remains approximately 10% lower in 2050 and 2100 compared to the *2°C BC scenario* (**Figure 53.b**).

Biomethane

Biomethane capacities grow steadily in the coming decades (**Figure 52.e**). By 2050, biomethane production increases nearly fivefold, and by 2100, it almost reaches nine times the current levels in the *2°C BC scenario* (**Figure 53.b**).

The primary driver behind the expansion of biomethane is the increasing demand for carbon-neutral gas for electricity generation and industrial applications. Additionally, resource costs play a lesser role in biomethane production, as it primarily utilises residues and waste materials.

Figure 52. Evolution of installed capacity (left) and overnight investment cost (right) for biofuel and biomethane technologies for learning variations (*BC*, *BE+*, *BE++*) of the *2°C scenario*.



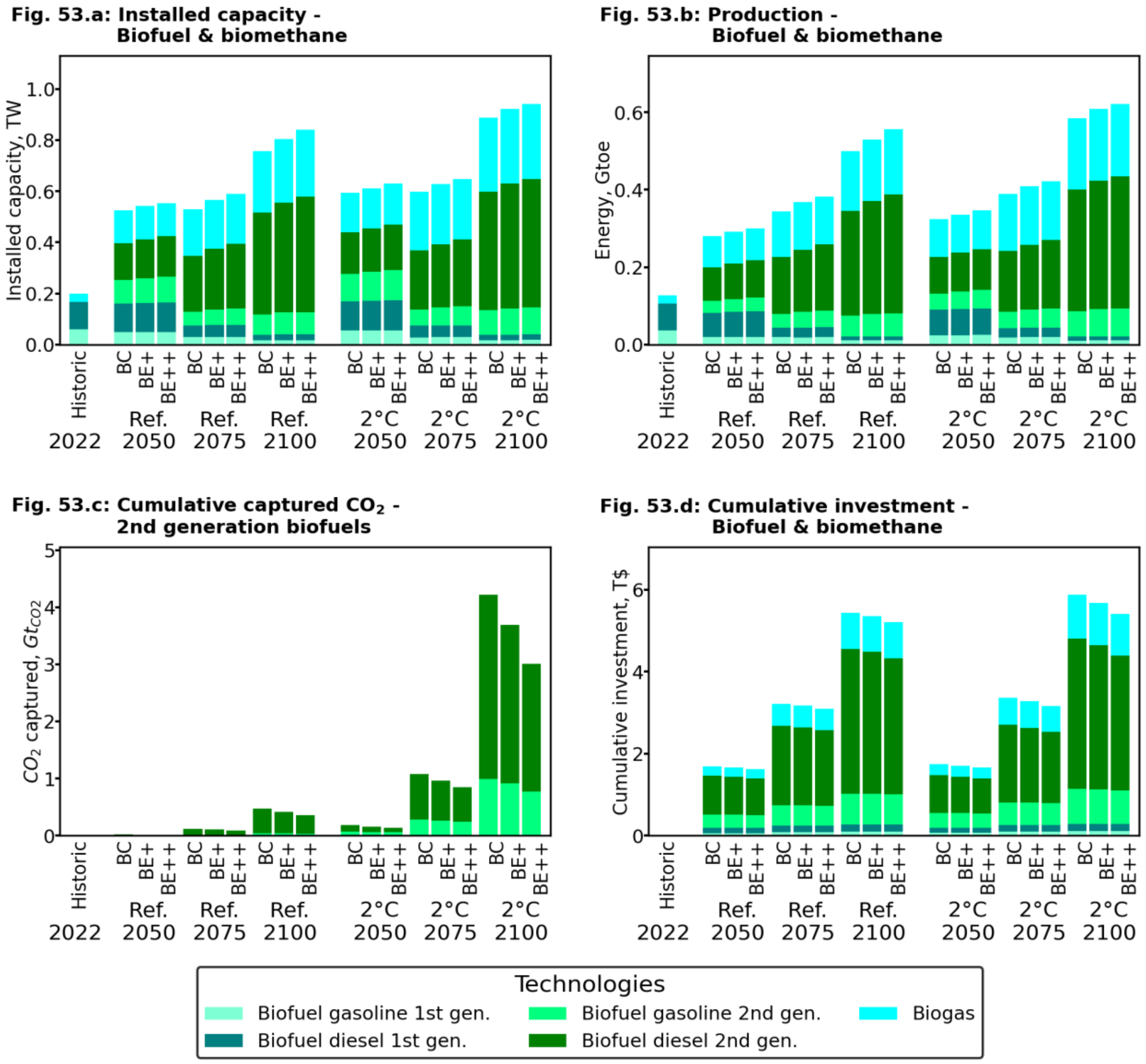
Source: POLES-JRC model

2.7.1.4 Impact of enhanced learning

In all scenario variations, enhanced learning for bioenergy technologies (*BE+*, *BE++*) leads to increased production and capacities for biofuels and biomethane (**Figure 53.a and b**), with less investment (**Figure 53.d**). In the *2°C scenario* with highly enhanced learning (*BE++*), total production increases by approximately 7% in 2100 compared to the base case scenario (**Figure 53.b**) for which around 7% fewer investments are needed over the century to construct the associated production capacities (**Figure 53.d**).

This positive response to enhanced learning is primarily attributed to second generation biofuels as their significant cost reductions (**Figure 52.c**) and capacity increases (**Figure 52.d**) are induced by enhanced learning. In particular, the impact on second-generation biodiesel is substantial due to its high demand in the transport sector.

Figure 53. Impacts of learning variations (*BC*, *BE+*, *BE++*) under the *Reference* and *2°C scenario* for biofuel and biomethane technologies.



Source: POLES-JRC model

2.7.2 Power generation based on biomass

2.7.2.1 Technology adoption pattern

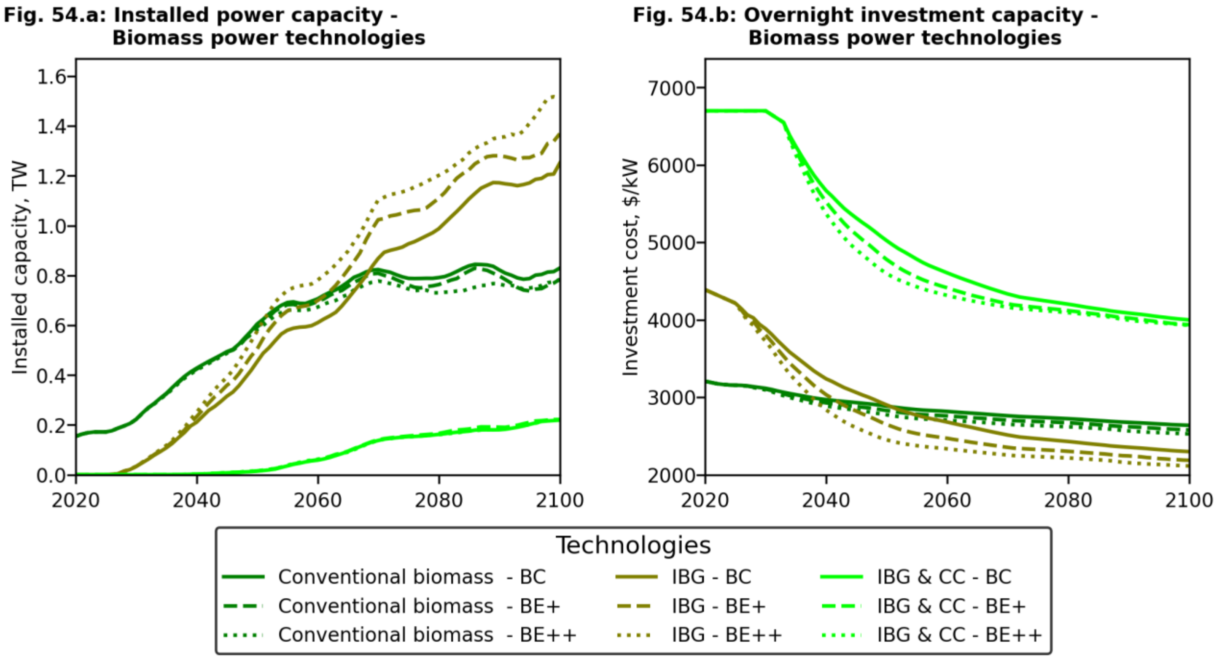
In the POLES-JRC model, three power-generating technologies using bioenergy are considered:
(1) Integrated biomass gasification with CO2 capture (IBG & CC) as introduced in Section 2.5.1.1;
(2) Integrated biomass gasification without CO2 capture (IBG);
(3) Conventional biomass power firing biomass and solid waste in a boiler and generating electricity with a sub-critical steam turbine.

Figure 54.a illustrates the projected evolution of the bioenergy power generating technologies under the *2°C BC scenario*. Conventional biomass power currently holds the largest share of installed biomass power capacities, accounting for approximately 170 GW. Moreover, conventional biomass power is projected to remain the most widespread biomass technology until the middle of the century due to substantial advantages in investment cost (**Figure 54.b**). However, from 2030 onwards, IBG emerges and becomes the dominant biomass power technology in the latter half of the century. This development is mainly driven by differences in investment cost. IBG's investment cost decreases fast due to higher learning rates of its components, whereas conventional biomass enjoys less cost improvements by learning as it is already a widely deployed technology with mature components. Additionally, IBG has the advantage of higher efficiencies (**Table 12** in AN 5.1).

Decreasing costs for IBG components spill-over to IBG & CC as biomass-related components are shared. Additionally, the costs for the CC-related components of IBG & CC decrease rapidly as its capacities expand from scratch and its cumulative capacities multiply several times until 2050 (**Figure 40.a** in Section 2.5.1). Consequently, the investment cost for IBG & CC decreases **Figure 54.b** However, as investment costs remain significantly higher and efficiencies lower compared to competing technologies, installed capacities for IBG & CC remain small.

Biomass power technologies account for about 6% (3.8 PWh) of the total global electricity production by 2050 under the *2°C BC scenario* (**Figure 55.b** and **Figure 3** in Section 1.2.3.2). The cumulative CO_2 captured by IBG & CC amounts to approximately 32 Gt_{CO2} by 2100 in the *2°C BC scenario* (**Figure 55.c**), representing 6% of the total cumulative CO_2 captured (**Figure 37.b** in Section 2.5).

Figure 54. Evolution of (a) installed capacity and (b) overnight investment cost for bioenergy power technologies for learning variations (*BC*, *BE+*, *BE++*) of the *2°C scenario*.



Source: POLES-JRC model

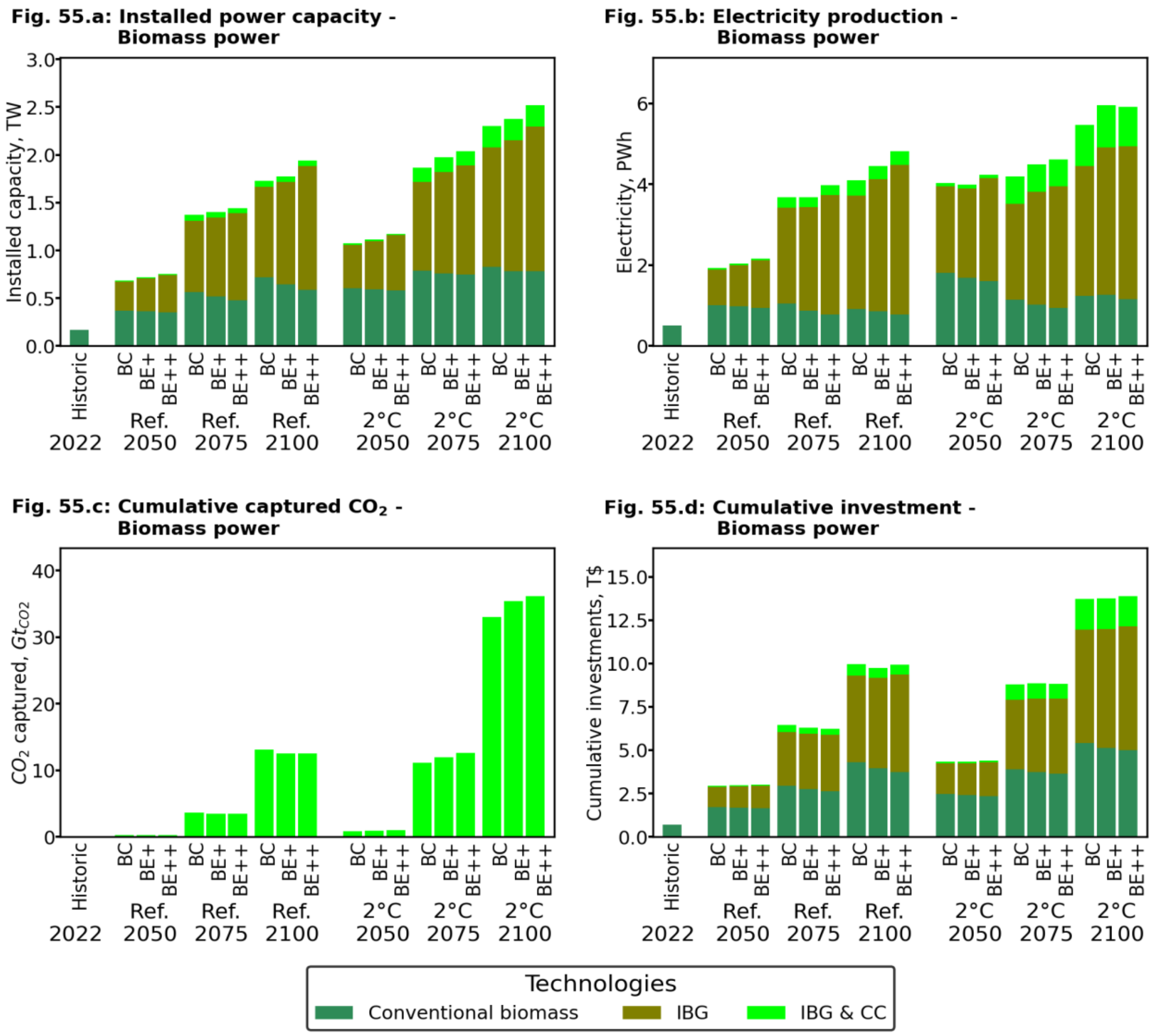
In the *Reference BC scenario*, biomass power technologies are less prominent compared to the 2°C BC scenario. By 2050, electricity production and capacities in the *Reference BC scenario* are approximately 50% and 38% lower than those in the *2°C BC scenario*, respectively. Moreover, the cumulative CO_2 captured in the *Reference BC scenario* accounts for only 41% of the *2°C BC scenario*.

2.7.2.2 Impact of enhanced learning

Integrated biomass gasification (IBG) is the most positively impacted technology by enhanced learning of bioenergy technologies (*BE+*, *BE++*). Enhanced learning for IBG results in substantially lower costs **Figure 54.b**, leading to much higher capacities (**Figure 55.a**) and electricity generation (**Figure 55.b**) because conventional biomass power is further crowded out. Overall, enhanced learning results in higher total capacities (**Figure 55.a**) and total electricity generation (**Figure 55.b**) at the end of the century for both the *Reference* and *2°C* variations compared to their respective base cases.

The effect of enhanced learning on cumulative CO_2 capture (**Figure 55.c**) is relatively modest and somewhat ambiguous, as the integrated biomass gasification (IBG) pathway with CO_2 capture struggles to compete economically with its counterpart without CO_2 capture. The impact of higher learning rates on total cumulative investments (**Figure 55.d**) is ambiguous primarily due to the faster increase in IBG capacities as its investment costs decline (**Figure 55.a and b**).

Figure 55. Impacts of learning variations (*BC*, *BE+*, *BE++*) under the Reference and *2°C scenario* for bioenergy power technologies.



Source: POLES-JRC model

2.7.3 Hydrogen production based on biomass

Hydrogen technologies using biomass in POLES-JRC refer to (1&2) biomass gasification with and without CO_2 capture and (3) biomass pyrolysis. Their technology characteristics are outlined in Section 2.4.2.
However, these technologies play a minor role in the overall hydrogen production as described in Section 2.4.2.3.

Biomass gasification with CO_2 capture and biomass pyrolysis are the dominating biomass hydrogen production technologies (**Figure 56.a** and **Figure 57.b** Biomass pyrolysis offers substantial advantages in terms of investment costs. Biomass gasification with CO_2 capture is preferred over its variant without CO_2 capture due to revenues gained from permanently removing CO_2 from the atmosphere.

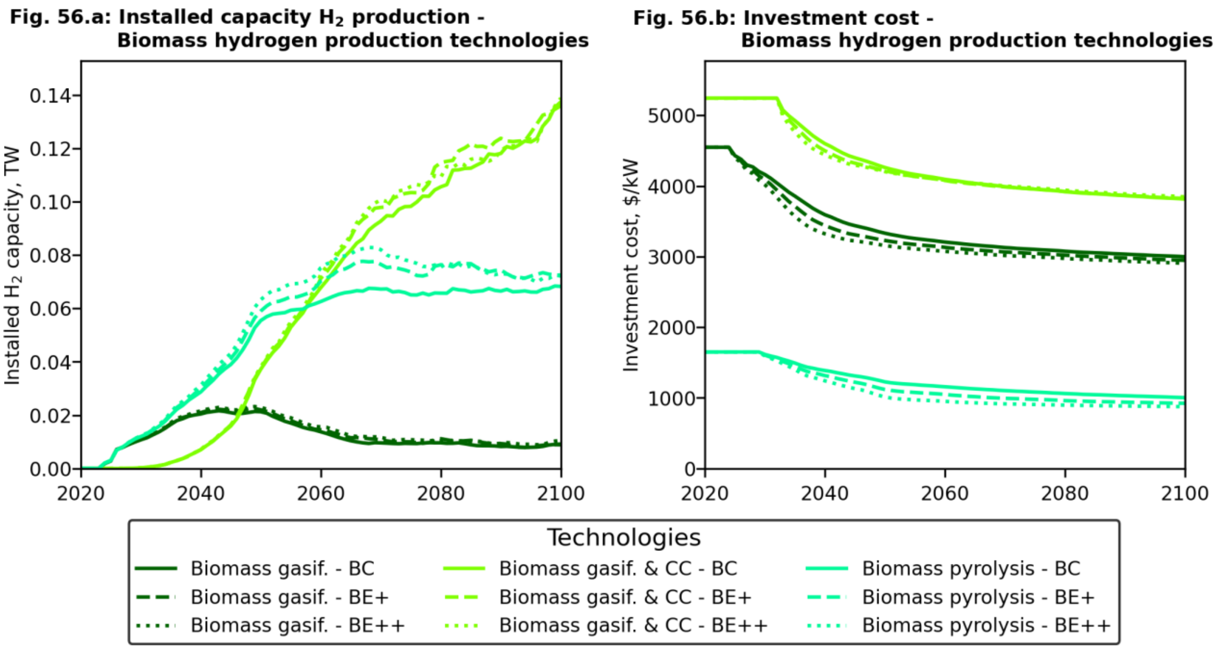
The cumulative CO_2 removed permanently from the atmosphere by biomass gasification with CO_2 capture and biomass pyrolysis, amounts to about 28 Gt_{CO2} by 2100 in the *2°C BC scenario* (**Figure 57.c**), accounting for 5% of the total cumulative CO_2 captured (**Figure 37.b** in Section 2.5).

2.7.3.1 Impact of enhanced learning

Enhanced learning for biomass hydrogen technologies (*BE+*, *BE++*) has positive impacts on capacities (**Figure 56.a** and. **Figure 57.a**) and production (**Figure 57.b**) until 2075 compared to the base case scenarios. In particular, biomass pyrolysis is positively affected in terms of capacities (**Figure 56.a**).

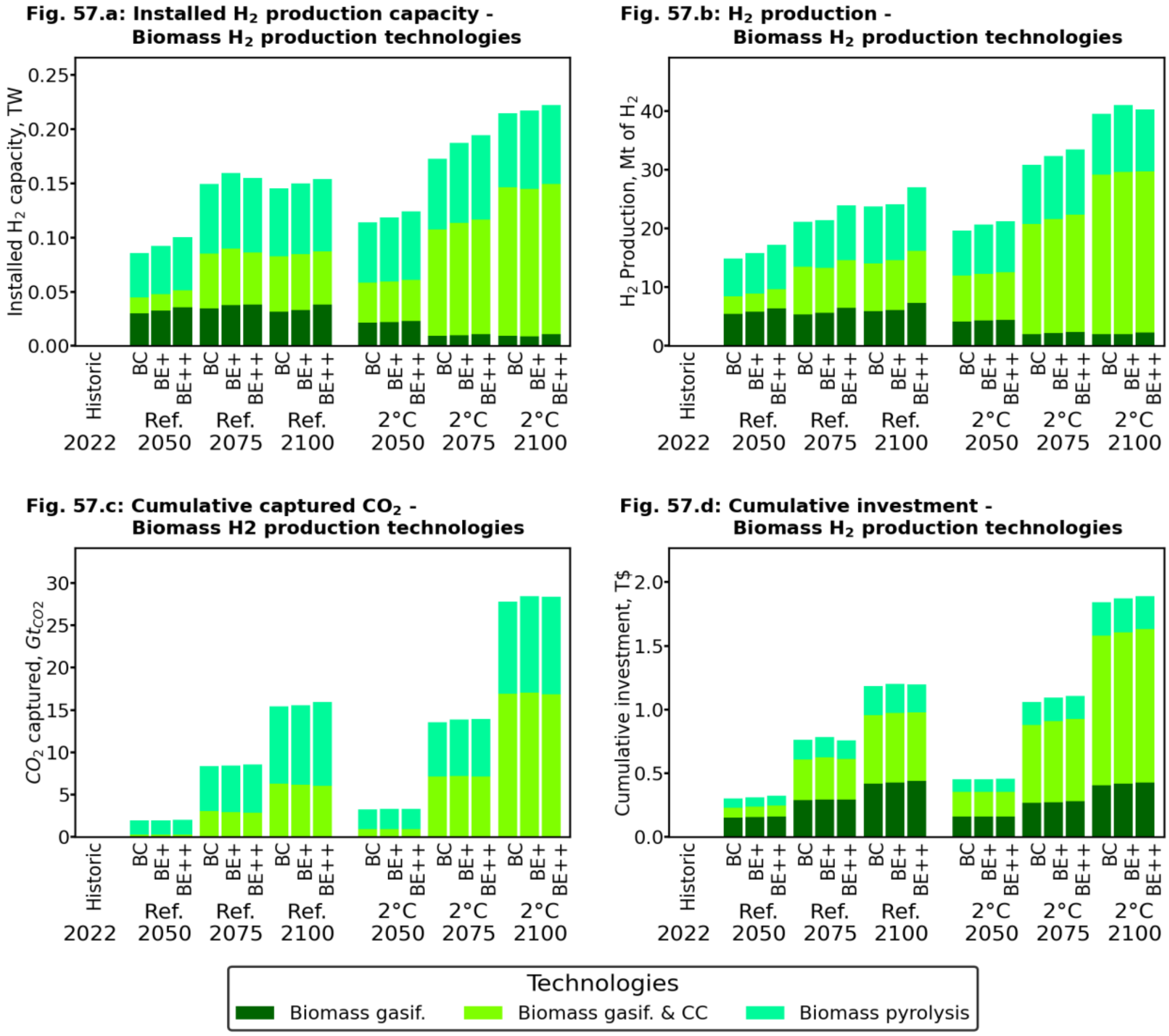
However, the impacts of enhanced learning rates on total capacities and production for the last quarter of the century remain ambiguous. Moreover, the impacts of enhanced learning rates on cumulative CO_2 captured and cumulative investments are not significant.

Figure 56. Evolution of (a) hydrogen production capacity and (b) overnight investment cost for Biomass hydrogen production technologies for learning variations (*BC*, *BE+*, *BE++*) of the *2°C scenario*.



Source: POLES-JRC model

Figure 57. Impacts of learning variations (*BC*, *BE+*, *BE++*) under the *Reference* and *2°C scenario* for bioenergy hydrogen production technologies.



Source: POLES-JRC model

2.8 Heat pumps

Heat pumps are pivotal in electrifying energy demand in both the building and industrial sectors to decarbonise its energy use. This section focuses on the crucial role that heat pump technologies play in electrifying heating and cooling within the building sector, particularly in residential and service buildings (e.g., offices).

Industrial heat pumps are a key technology in POLES-JRC and play in its scenarios an important role in the electrification of the industrial sector [53]. However, within the scope of this study industrial heat pumps are not considered for enhanced learning.

2.8.1 Heating and cooling demand

Heating and cooling needs constitute the most significant portion of final energy consumption within the building sector. The energy demand for heating and cooling is determined by the useful energy made actually available to consumers [54]. In the POLES-JRC model, the calculation of the useful energy demand takes into account diverse factors, including per capita dwelling area, building envelope insulation, GDP per capita, regional climatic conditions quantified through heating degree days (HDD) and cooling degree days (CDD), and other regional-specific economic parameters [1].

The model differentiates between the residential and service sectors, employing sector-specific drivers and parameters. Consequently, POLES-JRC provides distinct modelling outcomes for heating and cooling energy requirements in the residential and service sector.

Heating

The regional *final energy demand* for heating is obtained by satisfying the *useful energy* demand of various heating technologies ranging from oil, gas and electric boilers to heat pumps taking into account their respective efficiencies. The resulting *global final energy demand* for the base case (BC) scenarios (2°C and Reference) is depicted in **Figure 58.a**.

In general, final energy consumption for heating declines substantially over the coming decades as (i) less useful energy is needed due to better insulation, and (ii) heat pumps become more attractive due to decreasing cost and increasing efficiencies.

In the *2°C BC scenario*, the final energy demand for heating is significantly lower compared to the Reference scenario, driven by the rising global carbon price, which increases fuel costs and leads to reduced consumption, improved insulation, and a greater adoption of heat pumps. In detail, the effects for residential and service heating demand are illustrated for the *2°C BC scenario* in the left column of **Figure 59**. The residential sector accounts 2025 for the largest part of the final energy demand for heating in buildings, with 0.67 Gtoe. Residential and service sector energy demands for heating are expected to decline significantly over the coming decades, with reductions of approximately 60% by 2050 and over 80% by 2100, compared to current levels.

POLES-JRC applies seasonal coefficients of performance (SCOP) to describe heat pump efficiencies. Variations in climate are taken into account by applying a SCOP depending on HDDs of the region. The benchmark for 2022 is a SCOP of 3.3 for an average climate with 2570 HDDs. This benchmark SCOP refers to the average SCOP of air-water heat pumps classified as A++ for a heating temperature of 55°C [55] according to the European standard EN 14825 [56]. The SCOP for the regions varies as a function of regional HDDs over a range from a SCOP of 2.3 for a cold climate with 6500 HDDs to a SCOP of 4.0 for a mild climate with 800 HDDs (see **Table 23** in AN 5.4.2). Over time, regional SCOPs vary according to climate-induced HDDs following a RCP 4.5 climate trajectory. Moreover, the SCOPs improve over time by endogenous learning. This is modelled as relative efficiency improvements with a learning rate of 10% for heat pumps for heating. Compared to 2025, the relative efficiency increases by about 30% by 2050, as illustrated in **Figure 59.c** for the *2°C BC scenario*.

Overall, the heat pump share in global useful heating energy demand increases strongly in the coming decades from less than 2% today to about 40% by 2050 and 52% by 2100 (**Figure 59.g**).

Cooling

The only cooling technology considered in the model refers to cooling appliances based on heat pump technology. Consequently, the energy demand for cooling is exclusively electric. Cooling requirements are projected to increase due to several drivers. The general trend for more comfort needs, in combination with wealthier societies, drives up demand for cooling. In particular, cooling demand will increase substantially for countries with hot climates due to their expected economic growth. Moreover, increasing temperatures induced by climate change strongly drive increasing cooling demand. For the presented scenarios, increasing CDDs derived from temperature increase due to climate change follow a RCP 4.5 climate trajectory.

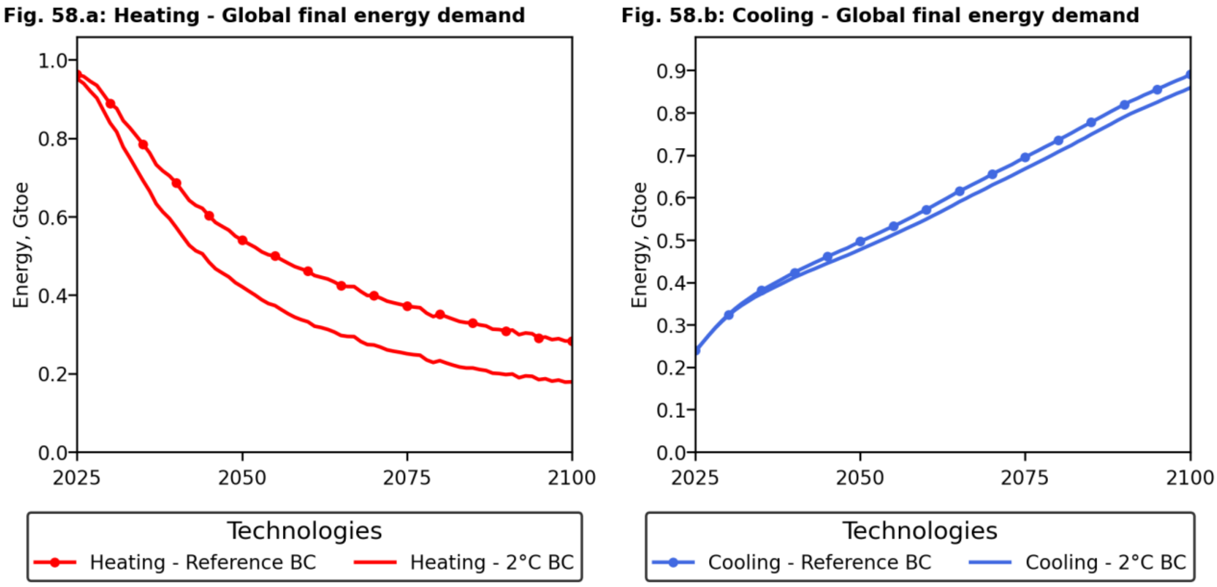
As a result, the global final electricity demand for cooling quadruples until the end of the century in both scenarios as shown in **Figure 59.b**. The surging electricity demand for cooling is significant and accounts for about 8% of global power generation in 2050 (**Figure 3**). The difference between both scenarios is relatively as – in difference to heating - competing technologies do not exist, and improvements in insulation play a minor role.

The residential sector accounts for the vast part of the surge in cooling demand. In the services sector, the cooling demand is assumed to be rather saturated and projected to increase by merely 25% until the end of the century.

The efficiency variation for cooling is modelled analogously to heat pumps for heating. For cooling, the seasonal coefficients of performance (SCOP) benchmark is 3.7 for a climate corresponding to 1150 CDDs. The SCOP for the regions varies over a range of a SCOP of 3.9 for a template climate with 200 CDDs to a SCOP of 3.0 for a hot climate with 4000 CDDs (see **Table 23** in AN 5.4.2).

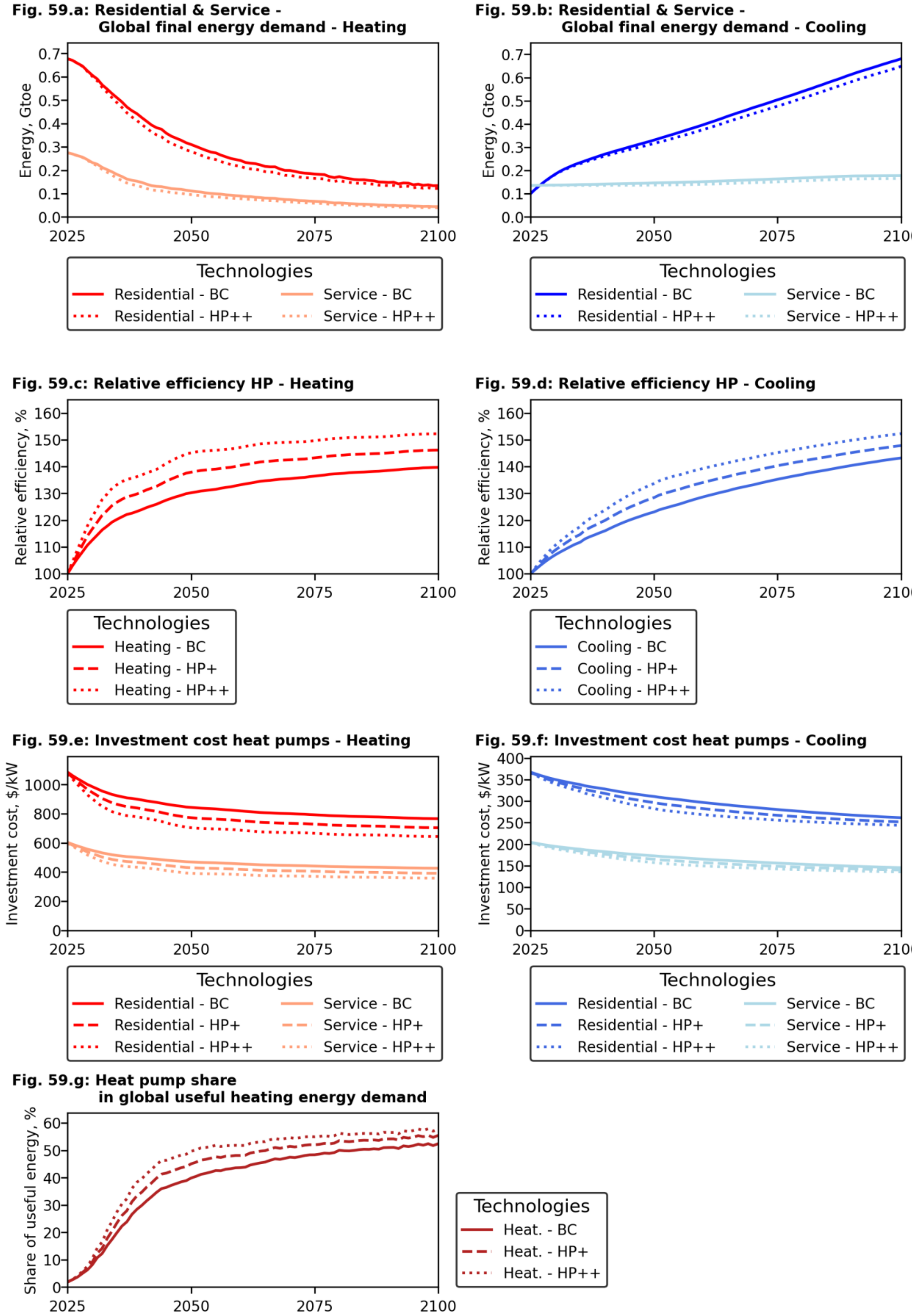
Over time, regional SCOPs for cooling *decrease* slightly as CDDs increase according to rising temperatures due to climate change. On the contrary, SCOPs *increase* over time due to endogenous learning. In relative terms, SCOP improve by endogenous learning compared to 2025 by about 23% by 2050 and by 43% by the end of the century in the the *2°C BC scenario* (**Figure 59.c**)

Figure 58. Global final energy demand for heating and cooling under the base cases (BC) under the Reference and *2°C scenario*.



Source: POLES-JRC model

Figure 59. Heating and cooling in the residential and service sector: Evolution of (a & b) global final energy demand, (c & d) relative efficiency, (e & f) overnight investment cost and (g) share of heat pumps (heating) for learning variations (*BC*, *HP+*, *HP++*) of the *2°C scenario*.



Source: POLES-JRC model

Total demand heating and cooling

While for heating the final energy demand decreases by about 80% until the end of the century, the cooling demand increases about 4-fold, as illustrated in **Figure 58.a. and b** (2°C BC). As a result, the *total* final energy demand for heating and cooling decreases in the coming decades. It reaches a minimum by 2060 with about 24% less demand compared to today (not shown).

Investment cost

Figure 58.e and f (2°C BC scenario) show the evolution for investment cost per kW installed thermal power. In general, investment costs in the services sector are assumed to be lower than in the residential sector as economies of scale favour larger installations for services buildings. For instance, the cooling needs for residential buildings are predominantly satisfied by air conditioning units; while larger devices (e.g., chillers) are commonly used in the services sector.

Compared to today's cost, the investment costs for heat pumps for *heating* decrease by about 27% by 2050, as illustrated in **Figure 59.e** (2°C BC), while for cooling appliances, investment cost decrease by merely about 17% by 2050 (**Figure 59.f**). Faster decreasing cost for heat pumps for *heating* results from more substantial capacity growth compared to cooling appliances (**Figure 60.b**).

2.8.2 Impacts of enhanced learning rates

Highly enhanced learning (*HP++*) drives investment costs further down and improves efficiencies. In 2050, investment costs decrease by an additional 12 percentage points for heat pumps for heating and by an additional 8 percentage points for cooling appliances, according to **Figure 59.e and f** (2°C HP++ variation). Relative efficiencies increase by about 8 and 5 percentage points for heating and cooling devices, respectively (**Figure 59.c and d**).

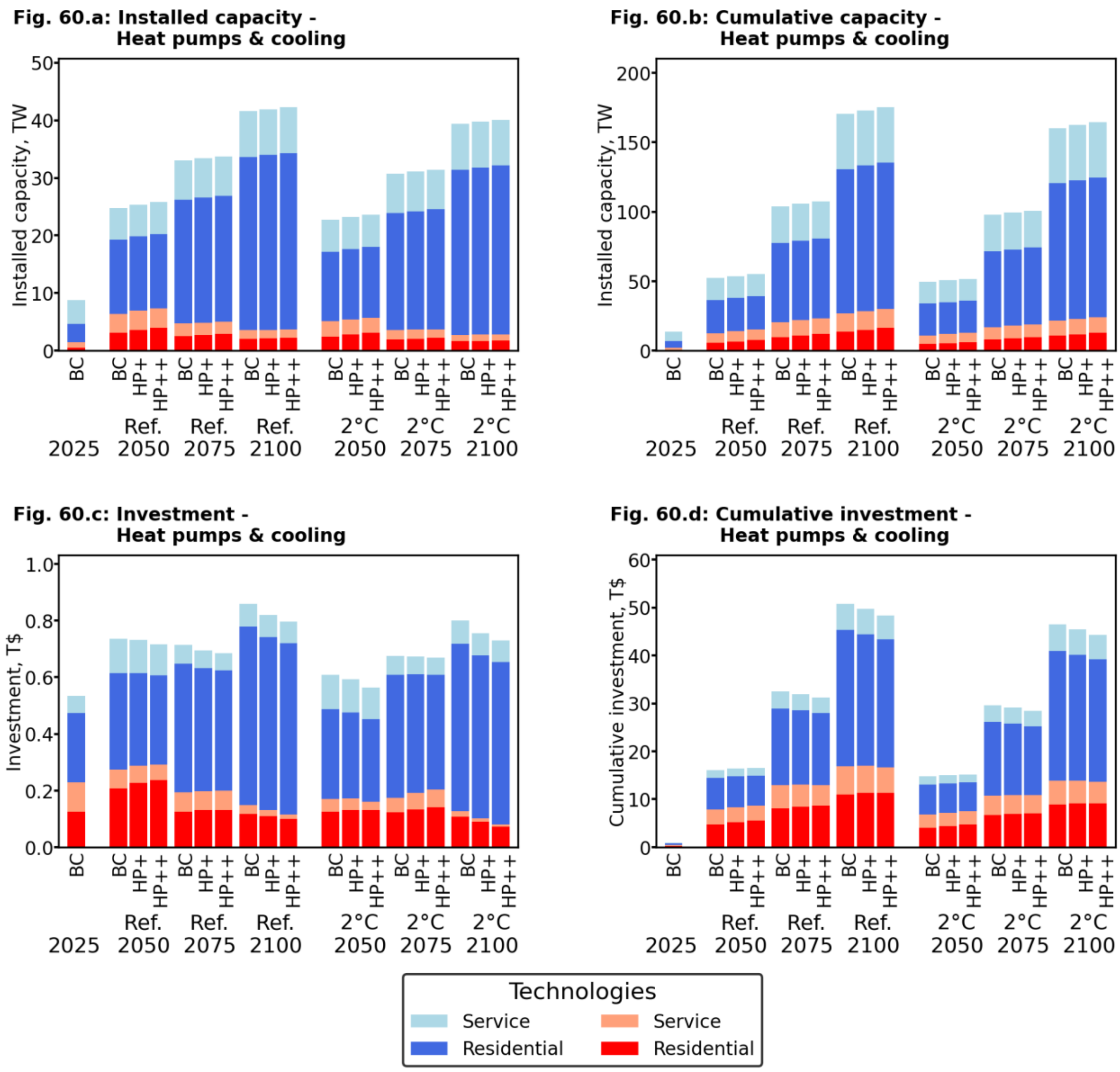
These improvements make it more attractive to use heat pumps for heating, and as a consequence, competing heating technologies are increasingly crowded out (e.g., boilers, electric resistance heating). As a result, the share of heat pumps in the useful energy demand in 2050 increase to 50% for highly enhanced learning (*HP++*) compared to 40% in the *2°C BC scenario* (**Figure 59.g**).

In terms of final energy, highly enhanced learning (*HP++*) results in less energy demand for heating and cooling (**Figure 59.a. and b**). Quantitatively, the savings in energy demand for cooling are higher than for heating due to the underlying opposite trends in terms of energy needs.

In terms of capacities, enhanced learning leads to substantially more deployment of heat pumps for heating by 2050 in the 2°C and *Reference scenarios* (**Figure 60.a**). In particular, residential capacities for heat pumps for heating increase by 24% (2050) with highly enhanced learning (*HP++*), while the capacities for residential air conditioning are merely slightly affected as the model considers only one cooling technology.

Overall, less money has to be spent on heating and cooling appliances in all enhanced learning scenarios, as illustrated in **Figure 60.d** by the decreasing cumulative investments. The overall decreasing investment needs are driven by cooling appliances as the decreasing cost overcompensates the slight increase in capacities. However, for heat pumps, slightly more investments in the coming decades are required for enhanced learning compared to the *BC scenarios* as the increase in deployment (**Figure 60.a**) is not compensated by the decreasing cost (**Figure 59.f**).

Figure 60. Impacts of learning variations (*BC*, *HP+*, *HP++*) under the *Reference* and *2°C scenario* for heat pump technologies.



Source: POLES-JRC model

2.9 Conclusions on the analysis of technology groups

Chapter 2 '*Analysis by technology group'* investigated the eight thematic technology groups in separate sections. Firstly, for each thematic group, the technology modelling approach used in POLES-JRC was described, and the technology adoption patterns of the base case scenarios (*2°C scenario*, *Reference scenario*) were discussed. Secondly, the impacts of enhanced and highly enhanced learning within the respective technology group were analysed. Finally, for wind and solar technologies, the R&I expenditures associated with the enhanced learning were estimated.

Wind and solar power expand massively in the coming decades until mid-century in the *2°C BC* and the *Reference BC scenario*. Wind power continues to increase at a slower pace until 2100. On-shore wind capacities outpace off-shore wind capacities more than 10-fold throughout the entire century. Rooftop and utility PV capacities experience a further lower increase between 2050 and 2100. The dominating solar technologies are PV technologies throughout the century.
Decreasing overnight investment costs of batteries push electric vehicles into transport fleets, making them the prevailing technology in transport, which is slightly challenged by fuel cells in the second half of the century. Biofuel demand in transport is expecting to increase in the coming decades due to their growing role in substituting oil in road transport. Biofuels reach a peak by approximately 2040 and will be displaced afterwards by electric and fuel cell vehicles.
Electrolysis becomes, under both scenarios, the prevailing hydrogen production technology. However, under the Reference scenario, hydrogen production remains fossil-prone throughout the whole century, while under the *2°C scenario*, hydrogen production is virtually decarbonised by 2050.
In the second half of the century, carbon capture technologies start playing a relevant role in electricity generation and hydrogen production, as well as in DAC and synfuels. The competitiveness of carbon capture technologies requires stringent climate policies. Consequently, carbon capture technologies are substantially less used under the *Reference scenario* compared to the *2°C scenario*.
Heat pumps for heating increase primarily in the first half of the century as fossil boilers are substituted, whereas heat pumps for cooling evolve throughout the entire century.

A key result of the analysis on the impacts of enhanced learning rates shows that enhancing learning results in: significantly decreasing costs for all technologies and in a substantial expansion of capacities and production for several relevant technologies (e.g., PV, wind, electrolysers, heat pump technologies, DAC and synfuels);
Certain highly dynamic technologies are projected to reach their minimum cost (or "floor cost") as early as 2055-2080 under base case scenarios, assuming default learning rates. However, with highly enhanced learning, floor cost levels can be reached about 20 to 35 years earlier. As a result, the beneficial impacts of these technologies anticipate about two decades earlier.
For instance, with highly enhanced learning, the floor cost level of batteries for electric vehicles (42$/kWh) is already reached 2035 instead of 2055 as for the default learning rate. For PV modules, the minimum investment cost (40$/kW) is already reached by 2045 for highly enhanced learning instead of by 2080 for the default learning rate.

The analysis on research and innovation expenditure illustrates the important role of R&I for the decrease of overnight investment cost of energy technologies. For instance, between 2010 and 2020, global R&I expenditures for wind technologies, both private and public investments, oscillated between 4 billion USD. The *2°C BC scenario* projects a steady increase in cumulative R&I expenditures to about 213 billion USD by 2050. For the additional progress made under the highly enhanced learning (*W++*) variant of the *2°C scenario*, cumulative R&I expenditures are projected to increase by 2050 to 335 billion USD. In annual terms, these additional R&I expenditures amount to roughly 4 billion per year which is equivalent to approximately doubling the current global R&I expenditures. From a monetary perspective, these additional 122 billion USD in R&I expenditures are required to reduce cumulative investments until 2050 by approximately 1 trillion USD.

3 Overall impacts of enhanced technology learning

This chapter examines the overall impacts of enhanced learning rates on the global energy system. To this end, a comprehensive framework of *key indicators* is introduced to assess the effectiveness of enhanced learning. The analysis in this chapter builds on the thematic technology learning groups specified in Chapter 2 and examines in three subsequent sections the overall impacts of enhanced learning rates:

- for unpaired technology learning (i.e., solely within a thematic group);
- for synergies in technology learning considering selected combinations of enhanced learning across the different thematic groups;
- using a sensitivity analysis that considers all combinations of enhanced learning from *eight* thematic groups.

3.1 Key indicators

The key indicators are designed to evaluate the overall impacts of enhanced learning rates along three main dimensions:

- CO_2 emissions;
- Overall investment needs;
- Energy supply costs.

The CO_2 dimension aims to investigate to what extent enhanced learning of clean energy technologies could close the gap to climate targets. In contrast, the other two dimensions focus on the economic implications of the green transition, examining how enhanced learning can help mitigate its financial burden. The overall investment needs indicator measures the financial resources required over a certain period, while the energy supply costs indicator measures the annual energy expenditures.

In the analysis sections of this chapter, the overall impacts are examined as relative changes to the base cases of the *Reference* and *2°C scenario*.

3.1.1 CO_2 emissions

3.1.1.1 Emission perimeters

The projected total global greenhouse gas (GHG) emissions introduced in **Figure 1** (Section 1.2.1) are illustrated in **Figure 61.a** for the *Reference* and *2°C scenario* base cases. The largest share of global GHG emissions refers to CO_2 emissions from all sectors are as shown in **Figure 61.c**. Furthermore, the largest share of *all* CO_2 emissions refers to *energy-related CO_2* emissions, as illustrated in **Figure 61.b**. In 2022, *energy-related CO_2* emissions account for about 84% of *all* CO_2 emissions).

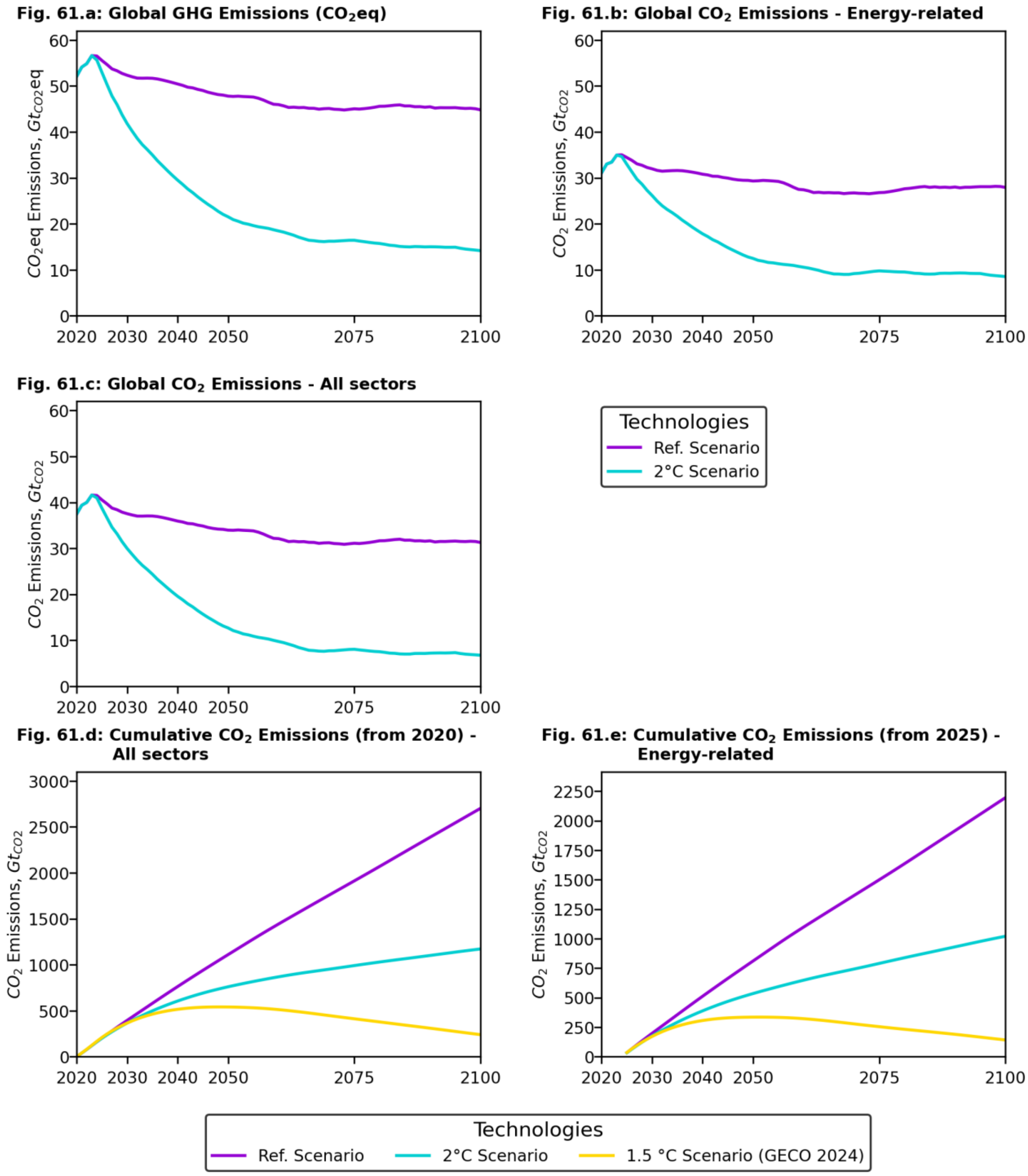
The perimeter of *energy-related CO_2 emissions* (**Figure 61.b**) comprises CO_2 emissions from:

- Power generation;
- Transport, including international air and maritime transport;
- Residential and services sector;
- Industrial sector (i.e., combustion emissions);
- Energy transformation sector (e.g., coke, hydrogen production).

The perimeter of *all* CO_2 emissions (**Figure 61.c**) additionally includes emissions from:

- Industrial CO_2 process emissions as these emissions are not energy-related. Process-related CO_2 emissions occur in the chemical industry and non-metallic mineral industry (e.g., decomposition of carbonates in the cement industry). POLES-JRC considers carbon capture technologies for these emissions. However, these carbon capture processes are not affected by the learning variations of this study.
- CO_2 fugitive emissions and emissions from waste.
- CO_2 emissions from land use and forests (LULUCF).

Figure 61. Evolution of global (a) GHG emissions (in CO_2eq), (b) energy-related CO_2 emissions, CO_2 emissions of all sectors (incl. LULUCF), (d) cumulative CO_2 emissions of all sectors (incl. LULUCF) from 2020 onwards and (e) cumulative energy-related CO_2 emissions from 2025 onwards under the *Reference* and *2°C scenario* base cases of this study and under the *1.5°C scenario* of the GECO 2024 report [53].



Source: POLES-JRC model

3.1.1.2 Cumulative CO_2 emissions

The interlinkage between GHG emissions and temperature increase is quite complex. Due to the long lifetime of CO_2 in the atmosphere, the rise in global temperature is mainly determined by the cumulative CO_2 emissions. The carbon budget is commonly linked to a specific temperature increase above pre-industrial levels by the end of the 21st century. Therefore, the carbon budget is a suitable indicator for evaluating impacts on climate mitigation efforts. In the literature, the carbon budget is expressed as cumulative CO_2 emissions from all sectors between 2020 and 2100.

Indicator: Cumulative CO_2 emissions – all sectors (from 2020)

Cumulative emissions aggregate emissions from a given year until a particular year. Under the *2°C scenario* base case, cumulative CO_2 emissions (**Figure 61.d**) continuously increase, resulting in a carbon budget of almost 1170 $GtCO_2$ by 2100. In the *Reference scenario* base case, total cumulative emissions at the end of the century amount to approximately 2700 $GtCO_2$. This study uses cumulative CO_2 emissions of all sectors *from 2020* onwards to verify that the carbon budget is kept by 2100.

CO_2 Emissions under a 1.5°C scenario

According to the *1.5°C scenario* outlined in the *GECO 2024 report*, global total GHG emissions become negative by the early 2060s [53]. As shown in **Figure 61.d**, cumulative CO_2 emissions (all sectors) under this scenario peak in 2050, ultimately resulting in a carbon budget of approximately 240 $GtCO_2$ by 2100.

Under the 1.5°C scenario of the GECO 2024 report [53], a substantially deeper decarbonisation is achieved compared to the *2°C scenario* base case by:

- A considerably higher use of renewables and a higher electrification in all sectors resulting in a significant reduction in fossil energy use.
- A very prominent role of negative emissions. In the energy sector, negative emissions are achieved by substantially deploying bioenergy with carbon capture and storage (BECCS) and direct air capture (CO_2 storage). Moreover, land use and forests (LULUCF) act increasingly as CO_2 sinks on top of negative emissions in the energy sector.

Indicator: Cumulative energy-related CO_2 emissions (from 2025)

Enhanced learning of clean energy technologies primarily affects CO_2 emissions within the energy sector perimeter. Therefore, cumulative energy-related CO_2 emissions are used as an indicator to assess the overall and long-term emission impact of enhanced technology learning. This indicator encompasses emissions *from 2025*, onwards as this year marks the starting point of the enhanced learning (2025-2050) (**Figure 61.e**).

3.1.2 Energy-related investment needs

The overall energy-related investment needs for the green transition are crucial for its success as they determine the amount of financial funds required. Therefore, this study investigates the impact of enhanced learning on these investment needs.

This study adopts a cumulative investment approach to quantify the overall investment requirements. Cumulative energy investment needs are calculated by summing undiscounted annual energy investments (see Section 1.2.4) from *2025 onwards* (the starting year of the learning period) until a particular year. The cumulative energy investments are measured in constant US dollars of 2022 and do not take into account any interest. Operation and maintenance (O&M) costs are not considered for calculating cumulative energy investments. This method allows for aggregating of multi-year data into a single indicator, providing a comprehensive view while minimising the influence of investment cycles and associated biases. Cumulative energy investments are an indicator measuring the overall financial funds required for the investments to deploy energy capacities.

The cumulative investments are calculated based on the annual investments for energy supply, as illustrated in **Figure 8** and **Figure 9** (Section 1.2.4), and for energy demand in transport and heat pump technologies, as illustrated in **Figure 10** (Section 1.2.4). Three indicators of cumulative energy investments are used for the analysis, taking into account (a) *energy supply* investments, (b) *energy demand* investments and (ci) overall energy investments as sum of investments for energy supply and demand.

(a) Indicator: Cumulative energy supply investments

This indicator comprises investments in *all* energy supply technologies, including clean and fossil technologies:

- Power technologies (technology overview see Section AN 5.1):
  - Clean technologies (renewables, nuclear, electricity storage);
  - Fossil technologies (including CCS);
- Hydrogen production:
  - Clean hydrogen production including associated power investments (wind, solar) ;
  - Fossil hydrogen production;
- Biofuels and biomethane production;
- Synfuels production and DAC for CO_2 storage, including associated power investments (wind, solar and batteries).
- Fossil fuel production (upstream and transformation)

The evolution of cumulative energy supply investments is illustrated in **Figure 62** for the *Reference* and *2°C scenario* base cases.

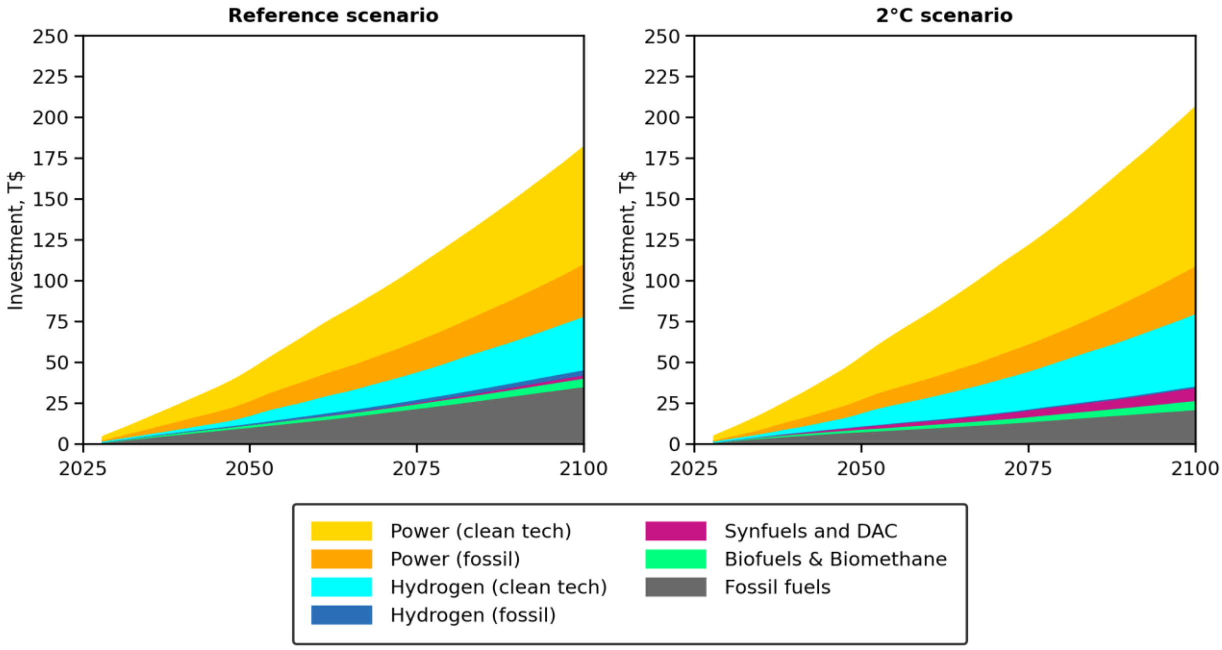
(b) Indicator: Cumulative clean energy demand investments

The indicator comprises investments in clean energy technologies on the demand side. The scope of technologies is limited to the technologies covered in this report, namely:

- Heat pumps for heating and cooling in the residential and services sector;
- Batteries in the transport sector;
- Fuel cells in the transport sector.

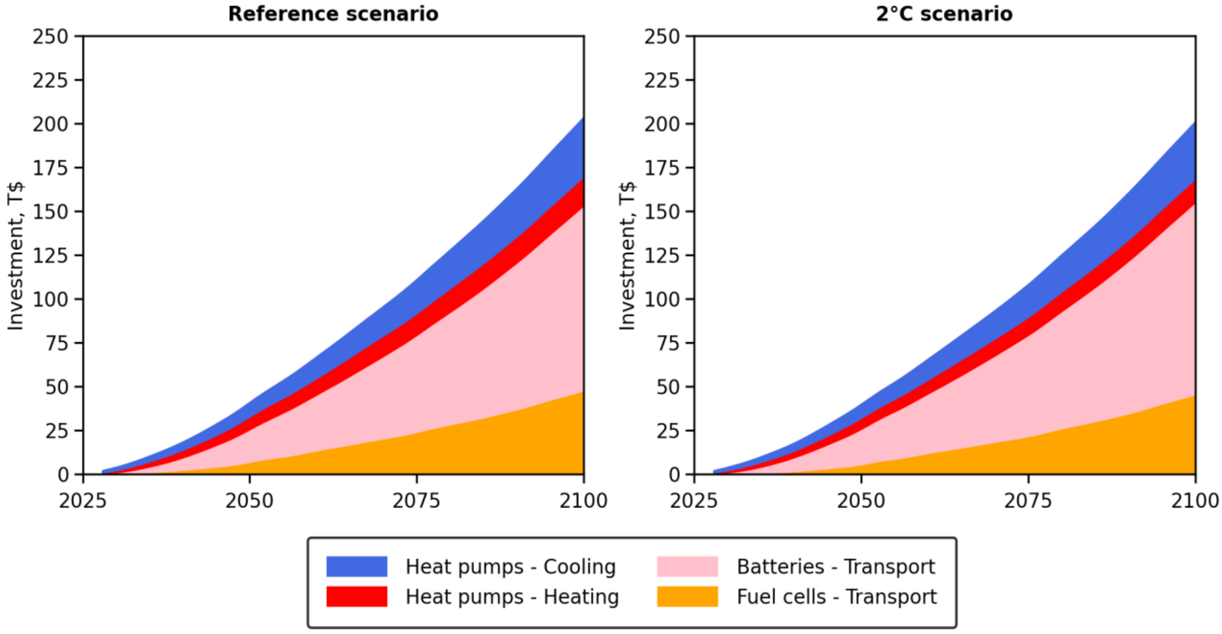
The evolution of cumulative clean energy demand technologies is illustrated in **Figure 63** for the *Reference* and *2°C scenario* base cases.

Figure 62. Cumulative energy supply investments broken down by energy type under the *Reference* and *2°C scenario* base cases.



Source: POLES-JRC model

Figure 63. Cumulative clean energy demand investments by demand type under the *Reference* and *2°C scenario* base cases.



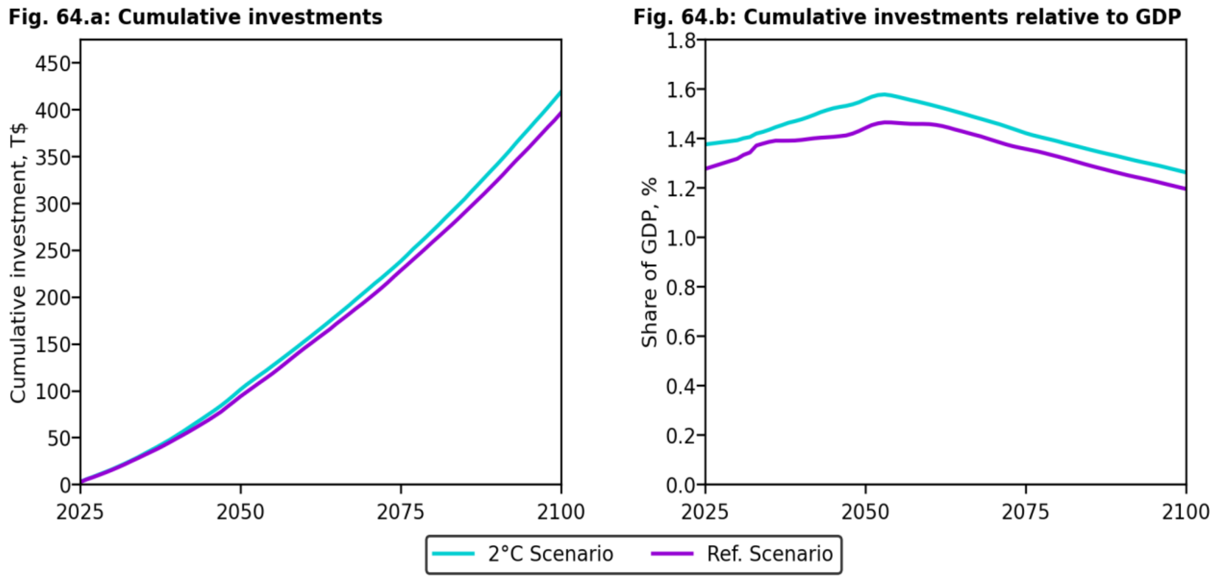
Source: POLES-JRC model

(c) Indicator: Cumulative overall energy investments

This indicator measures the overall investments and is the sum of the above-specified indicators for cumulative energy supply investments and cumulative clean energy demand investments. The evolution of overall cumulative energy investments is illustrated in **Figure 64.a**, revealing surprisingly small differences between the scenario base cases. Under the *2°C scenario,* cumulative overall investments are about 8% higher than in the *Reference scenario* by 2050 and 2100.

Figure 64.b shows the cumulative overall energy investments in relation to GDP. In terms of GDP, the difference between both scenarios in overall investment needs does not exceed 0.2% of annual GDP over the course of the century. Moreover, as GDP is expected to grow faster than investment needs, the overall energy investments in relation to GDP decrease in the second half of the century.

Figure 64. Cumulative investments in absolute terms (T$) and relative to GDP under the *Reference* and *2°C scenario* base case (cumulated from 2025 onwards).



Source: POLES-JRC model

3.1.3 Energy supply costs

From an economic perspective, the green energy transition not only impacts investments but also influences the cost of supplying energy. Consequently, the third dimension of the indicators measures the overall annual energy supply cost for the energy system.

Indicator: Energy supply costs

The overall energy supply costs (*ESC*) is a composite indicator calculated as:

(Eq. 7)
$$ESC = \sum_{f \in F} \sum_{s \in S} \sum_{u \in U_s} c_f^{s,u} FEC_f^{s,u}$$

taking into account:

- *energy cost* $c_f^{s,u}$ for fuel f for energy use *u* in sector s;
- *final energy consumption* $FEC_f^{s,u}$ for energy use *u* in sector s;
- the index f stands for all fuel types in POLES-JRC (i.e., coal, oil, gas, biomass, electricity, hydrogen, biofuels, biomethane and synfuels);
- s stands for all sectors of the POLES-JRC model (industry, transport, residential, services, agriculture, energy transformation as well as international air and maritime transport) and all its corresponding energy uses u_s (e.g., diesel cars or air traffic in transport).

The *energy cost* $c_f^{s,u}$ of fuel f comprises:

- *Fossil fuel costs* (secondary) for coal $c_{coal}^{s,u}$, oil $c_{oil}^{s,u}$ and natural gas $c_{gas}^{s,u}$ including its delivery costs, transformation costs and carbon value (if applicable).
- *Biomass fuel costs* (secondary) $c_{bm}^{s,u}$, based on its primary biomass costs and costs for transformation and transport.
- *Electricity generation costs* $c_{ele}^{s,u}$, as average electricity generation cost considering all power technologies of the POLES-JRC (including fossil, nuclear, renewable and storage technologies, technology overview see Section AN 5.1) and including distribution costs for the fossil power technologies, the carbon value of the used fossil fuels is considered (if applicable).
- *Hydrogen production cost* $c_{ele}^{s,u}$, as the average production cost for the hydrogen production mix considering all hydrogen production technologies (Section 2.4.2), and the costs for transport and distribution. For fossil fuel consumption in hydrogen production, the carbon value is considered (if applicable).
- *Synfuels production cost* $c_{sy}^{s,u}$, for liquid and gaseous synfuels (Section 2.6.2) considering costs for the actual production and the costs for its input factors (DAC, hydrogen production, renewable generation).
- *Biofuels and biomethane production cost* $c_{bfg}^{s,u}$, for the production of biofuels and biomethane (Section 2.7.1) including its primary biomass costs.

The cost components of the energy supply costs take into account all relevant cost components for supplying energy (if applicable), such as investment costs (as annuities), fixed O&M costs, and as variable cost components non-energy-related O&M costs, fuel costs and carbon value. In order to focus on the plain cost impact on the energy system, the energy supply costs indicator does not take into account other policy-related cost factors, which are considered in POLES-JRC, such as taxes, tariffs or subsidies.

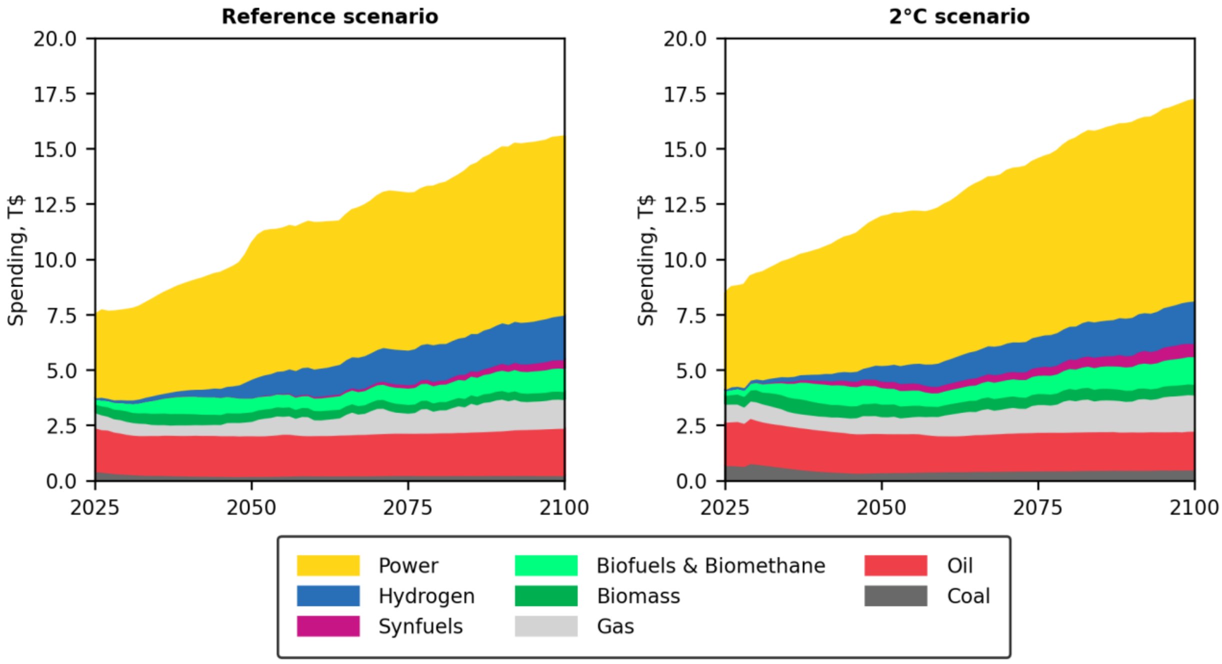
Energy supply cost vs. cumulative investment indicators

Energy supply cost is an indicator that describes the plain overall annual cost of energy consumption. Moreover, energy supply cost can be interpreted as a measure of the overall annual cash flows required for the energy mix in the respective scenario. Whereas the cumulative investment indicators focus on the mere investment for the deployment of energy capacities aiming to provide a measure for the funds required to be financed.

Evolution of annual energy supply costs

The evolution of annual energy supply costs by energy type is illustrated in **Figure 65** for the *Reference scenario* and *2°C scenario*. Under both scenarios, energy supply costs are projected to roughly double by the end of the century, while final energy demand increases only by slightly more than half (2020-2100, **Figure 4** in Section 1.2.3.3). Several factors contribute to the doubling of energy supply costs. The dominant part of the energy supply costs is the electricity component which more than doubles from today's 4.3 T$ (2025) to 9.1 T$ by 2100. This doubling is attributed to a four-fold rise in electricity demand (**Figure 4** in Section 1.2.3.3), offset by a tremendous decrease in electricity costs of wind and solar power (**Figure 13** and **Figure 19**), which account for the vast majority of power generation by 2100. Moreover, the shares of some fuels within the energy supply costs appear disproportionately high compared to their share in final energy demand due to their relatively high costs. This cost difference is the case for hydrogen and synfuels, which emerge in the second half of the century but are relative expensive fuels. Similarly, despite a substantial decline in demand for oil (in both scenarios) and gas (in the *2°C scenario*), their share in energy supply costs remains high by 2100. The latter is because oil and gas costs increase throughout the century due to scarcity (in both scenarios) and the increasing carbon value in the *2°C scenario*.

Figure 65. Energy supply costs (2025-2100) by energy type under the *Reference* and *2°C scenario* base case.



Source: POLES-JRC model

Under the *2°C scenario*, energy supply costs are at most about 20% higher than under the *Reference scenario* over the century (**Figure 66.a**). The steep cost increase in the 2020s is caused by the introduction of the single global carbon value and, to a lesser extent, by the increased deployment of low-carbon energy technologies (Section 1.2.4). In particular, for the years 2050 and 2100, the energy supply costs under the *2°C scenario* are about 11% higher than under the *Reference scenario*.

Annual energy supply costs are projected to increase over the century in increase in absolute terms (**Figure 66.a**). However, energy supply costs in terms of GDP are projected to decrease (**Figure 66.b**) as GDP is expected to grow significantly faster than energy supply costs. Moreover, the higher energy supply costs under the *2°C scenario* become relatively smaller compared to the *Reference scenario*.

Role of carbon value

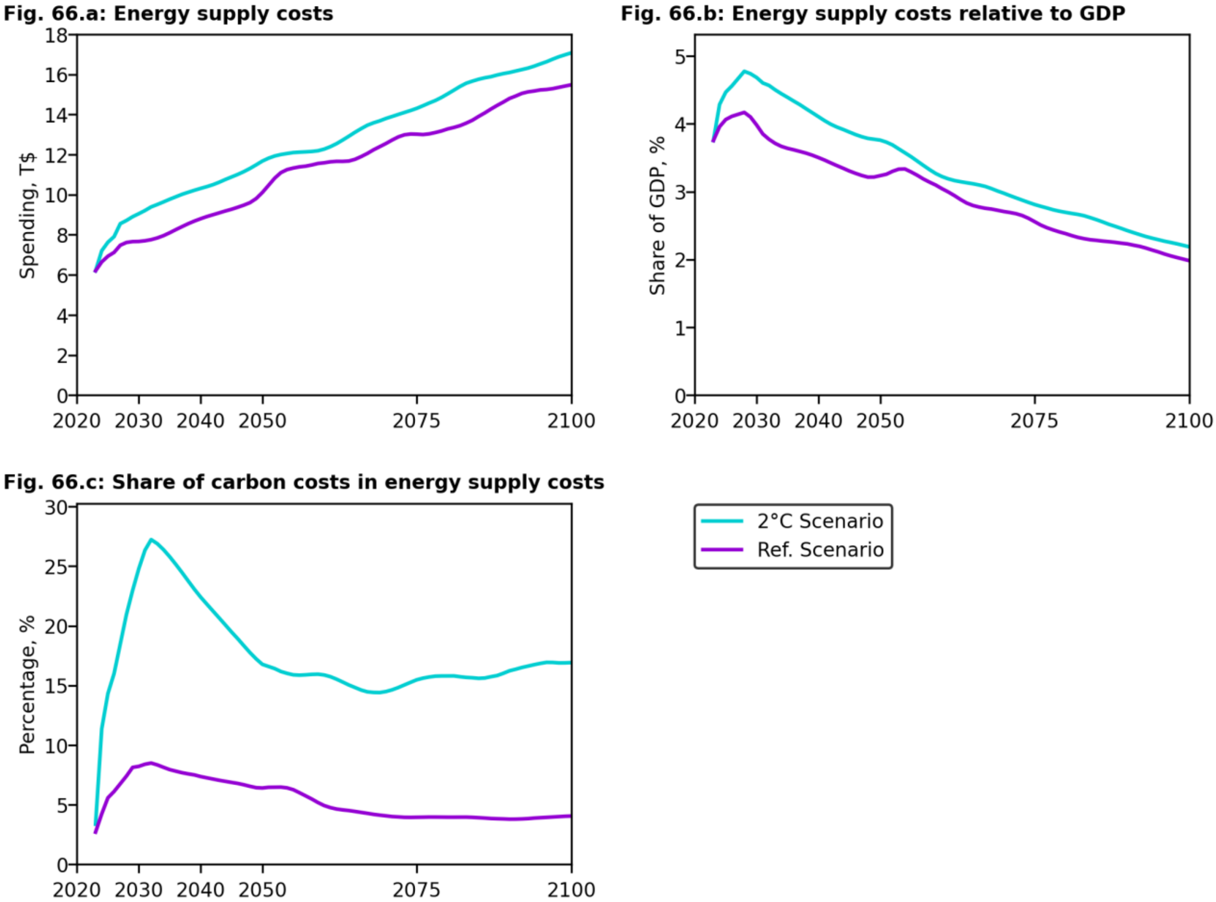
In POLES-JRC, carbon values act effectively as a tax aiming to promote the mitigation of GHG emissions. Moreover, POLES-JRC uses a stylised modelling approach in which carbon value trajectories implicitly simulate stringent carbon policies. In the real world, decarbonising the economy typically involves the implementation of carbon pricing mechanisms in conjunction with a comprehensive range of other policy measures. Such policy measures could include regulatory standards (e.g., emission standards), restrictions (e.g., phase-outs, bans), incentives and subsidies for clean technologies (e.g., feed-in tariffs, tax incentives). Therefore, the carbon value in the POLES-JRC scenarios is not directly comparable to carbon prices in actual carbon pricing mechanisms.

In the *Reference scenario,* some of the already legislated GHG policies and targets are simulated as low carbon value trajectories for some countries (Section 1.2). In the *2°C scenario*, a single global carbon value trajectory is used to simulate a stringent climate policy on top of the already legislated GHG policies and targets of the *Reference scenario*.

The share of carbon cost in energy supply costs for both scenarios is shown in **Figure 66.c**. Under the *2°C scenario*, the share of carbon cost in energy supply costs increases steeply until 2030 to about 28% and subsequently plateaus in the second half of the century at approximately 15%. Whereas for the *Reference scenario,* the carbon value, which simulates already legislated policies, is reflected in a substantially lower share of carbon cost in energy supply costs.

Due to the stylised carbon value modelling in POLES-JRC, the share of carbon costs within energy supply costs should be regarded as a modelling artefact rather than an actual monetary value.

Figure 66. Energy supply costs (2023-2100) under the *Reference* and *2°C scenario* and its relation to GDP and carbon costs.



Source: POLES-JRC model

In principle, carbon revenues generated from carbon pricing schemes can be redistributed throughout the economy. However, the POLES-JRC model, being a partial-equilibrium model of the energy system, is not suited to capture the distribution of these revenues and their broader economic implications. Economic models capturing the entire economy are required to fully assess the economic outcomes of carbon revenue recycling. Therefore, in this study the modelling results for the energy system calculated with POLES-JRC are fed into the general equilibrium model JRC-GEM-E3 to evaluate the overall economic impacts of the *2°C scenario* and the *Reference scenario* (Chapter 4).

3.2 Unpaired technology learning

This section focuses on the overall impacts of unpaired technology learning which, considers merely enhanced learning within each of the eight thematic technology groups of Chapter 2. The analysis of this section is continued in the Sections 3.3 and 3.4 by taking into account additional combinations of enhanced learning across the various technology groups.

3.2.1 Impacts on CO_2 emissions

The impacts of enhanced learning rates on CO_2 emissions for each of the eight technology groups are presented relative to the base cases (BC) of the *2°C scenario* (**Figure 67**) and the *Reference scenario* (**Figure 68**). These impacts are illustrated in three snapshots for the years 2050, 2075, and 2100. The year 2050 marks the end of the enhanced learning period (2025-2050), while the subsequent years (2075 and 2100) demonstrate the long-term effects of enhanced learning on investments.

Wind generation

Under the *2°C scenario*, the *wind* learning variation (*W+*, *W++*) has the most significant and persistent impact on cumulative energy-related CO_2 emissions (**Figure 67.a**). The impact of enhanced wind learning is very pronounced until 2075 but rather stagnates in the last quarter of the century as minor differences near floor cost have little effect (**Figure 11.e and f** in Section 2.1.2). Under the *Reference scenario*, enhanced wind learning has an even higher relative impact on emission reductions throughout the entire century (**Figure 68**.a). Emission reductions at the end of the century are still substantial.

Solar generation

Surprisingly, enhanced solar learning (*S+*, *S++*) shows ambiguous impacts on CO_2 emissions in the variations of the *2°C scenario* (**Figure 67.a**). Cumulative energy-related emissions until 2050 remain close to the base case level but increase until 2075. This surprising behaviour results from the need to balance the substantially higher solar capacities within the power system for the enhanced learning variations from 2050 to 2075 (**Figure 17** in Section 2.2.2). The reason is that gas power is the preferred technology for balancing electricity demand and supply in the POLES-JRC power system model within the coming decades. As increasing levels of intermittent renewables require more balancing, more natural gas is required compared to the base case (**Figure 67.b**, 2050), which results in higher emissions. Moreover, compared to wind power the balancing needs for solar power are higher due to larger variations throughout the day.

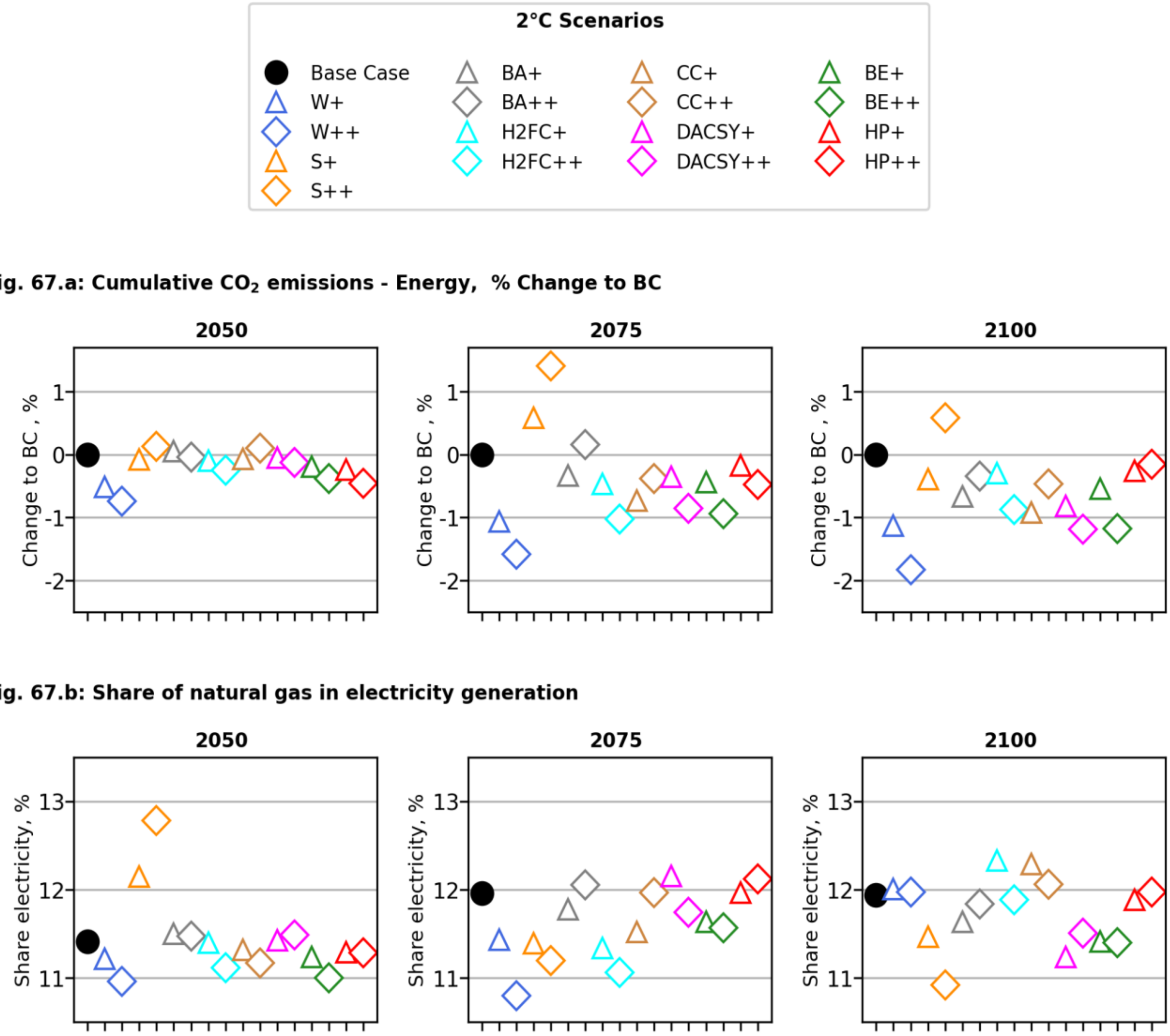
This effect fades out in the latter half of the century for various reasons. Firstly, enhanced learning (*S+, S++*) results in a slower increase of PV capacities but in a significant increase of concentrated solar power (CSP) as illustrated in **Figure 18.a** (Section 2.2.2) for 2075 & 2100. As POLES-JRC considers for CSP a thermal storage, the increase of its capacities requires less balancing gas power. Secondly, highly efficient combined cycle gas plants with CCS become more competitive and substitute increasingly conventional gas turbines, which results in less fuel usage (**Figure 67.b**, 2075 & 2100) and emissions from balancing gas power. Finally, battery energy storage becomes increasingly competitive (**Figure 25.a** in Section 2.3.2.1) and substitutes gas power as a balancing mechanism.

Under the *Reference scenario*, energy-related emissions are significantly reduced with highly enhanced learning (*S++*) until the end of the century and moderately enhanced learning until 2050 (*S+*), as illustrated in **Figure 68.a**. The relative reduction is higher than under the *2°C scenario* as solar substitutes fossil power in a predominantly fossil power mix (**Figure 3** in Section 1.2.3.2). Moreover, in the scenario without a single global carbon value (*Reference scenario*), the cost of solar has to decrease substantially (as in *S++*) to have a long-term impact.

Batteries

Until 2050, enhanced battery learning (*BA+*, *BA++*) has no significant impact for both, the *2°C scenario* (**Figure 67.a**, 2050) and the *Reference scenario* (**Figure 68.a**, 2050). However, at the end of the century, under the *2°C scenario*, cumulative energy-related emissions decrease due to enhanced battery learning (**Figure 67.a**, 2100). The reasoning is that within a decarbonised electricity mix (**Figure 3** in Section 1.2.3.2) lower battery costs act as an additional incentive to increasingly use batteries in transport and for electricity storage (e.g., balancing renewables), resulting in higher emission reductions. However, under the *Reference scenario*, emissions increase slightly towards the end of the century (**Figure 68.a**, 2075 & 2100) as slightly more demand for electric vehicles (**Figure 23** Section 2.3.1) leads to more emissions as the power sector is less decarbonised.

Figure 67. Emissions-related impacts of unpaired learning variations under the *2°C scenario*.



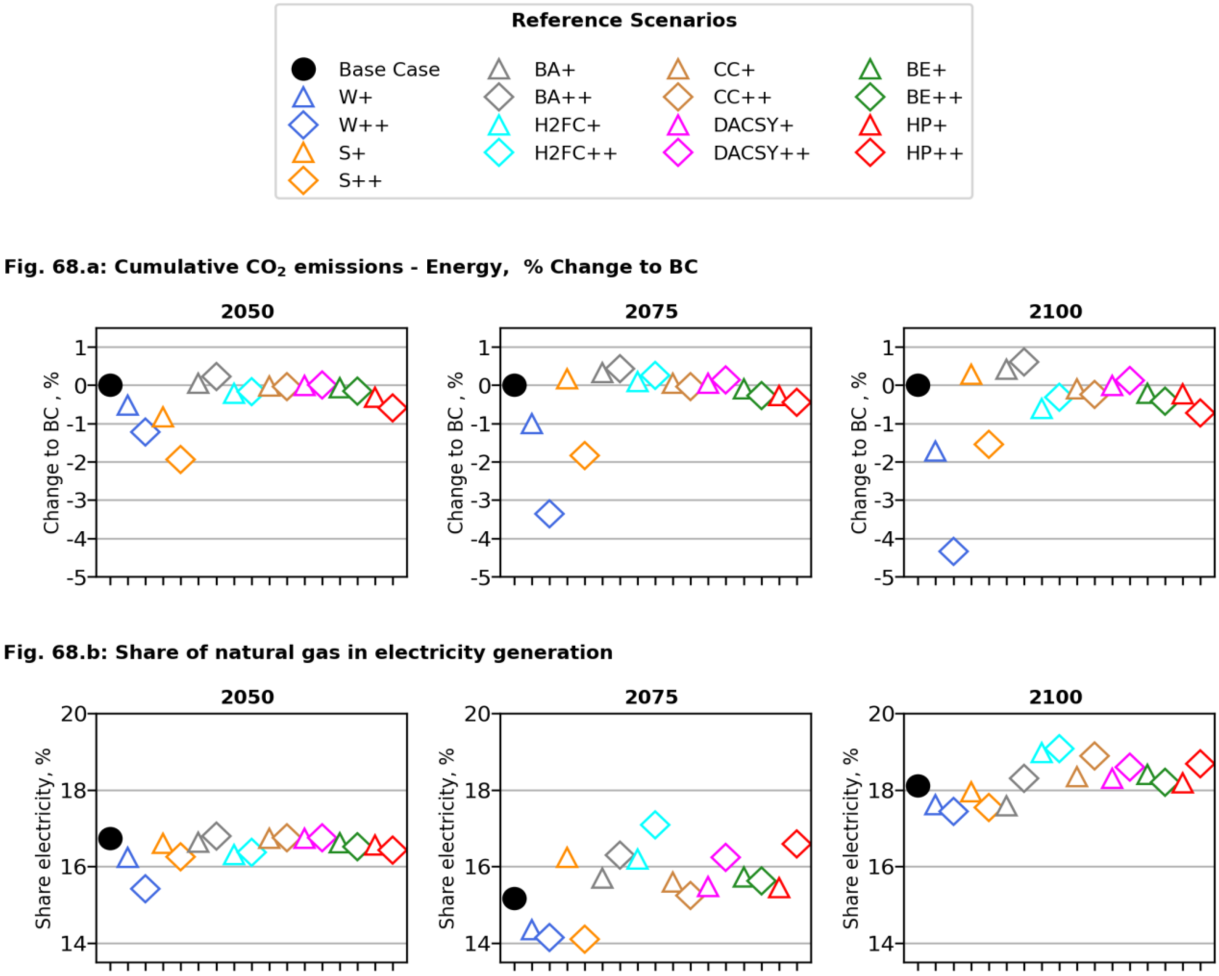
Source: POLES-JRC model

Furthermore, under the *2°C scenario*, highly enhanced learning (*BA++*) leads to higher emissions than moderate enhanced learning (*BA+*) in the second half of the century. The reason is that hydrogen production is crowded out with highly enhanced battery learning, which makes synfuels less attractive to substitute oil in the transport sector, eventually resulting in higher emissions. Notably, battery capacities in transport (**Figure 24** in Section 2.3.1) exceed by far those in the power system (**Figure 26** in Section 2.3.2.2), with a more than 10-fold difference. As a result, the primary impact of battery learning on CO_2 emissions is concentrated in the transport sector rather than contributing significantly to the decarbonisation of the power system through improved balancing of intermittent renewables.

Hydrogen and fuel cells

Under the *2°C scenario*, moderate energy-related emission reductions are achieved at the end of the century for the hydrogen and fuel cell learning variations (*H2FC+*, *H2FC++*) as shown in **Figure 67.a** for 2100. The emission reduction effect increases until about 2075 (**Figure 67.a**) as learning significantly impacts reducing costs and increasing hydrogen capacities within this period (**Figure 29.c** in Section 2.4.2.3).

Figure 68. Emissions-related impacts of unpaired learning variations *Reference Scenario*.



Source: POLES-JRC model

Under the *Reference scenario*, the impacts of enhanced learning rates on cumulative energy-related emissions are relatively neutral until 2075, followed by a moderate reduction by the end of the century (**Figure 68.a**). This outcome can be attributed to two contrasting effects. Until 2075, enhanced learning leads to a slight increase in green hydrogen production, albeit within a predominantly fossil-based hydrogen production (**Figure 28**, in Section 2.4.2.3). However, it also promotes the adoption of more fuel cell powered cars, which are mainly supplied by grey hydrogen (created from natural gas using steam methane reformation without capturing the greenhouse gases). In contrast, during the last quarter of the century, the hydrogen production mix becomes significantly cleaner, allowing learning to have a positive impact on reducing cumulative emissions.

Carbon capture technologies

In the 2°C scenario, the impact of enhanced learning for capture-related technologies (*CC+*, *CC+*, *DACSY+*, *DACSY++*) on cumulative energy-related emissions increases over the century and results by 2100 in moderated reductions (**Figure 67.a**). Enhanced learning in DAC and synfuels (*DACSY+*, *DACSY++*) has a strong impact towards the end of the century (**Figure 67.a and b**, 2100).

Surprisingly, highly enhanced learning for carbon capture (*CC++*) results in higher cumulative emissions than under the moderately enhanced variation (*CC+*). The reason is that emission-free power and hydrogen technologies are crowded out to some extent for highly enhanced learning for carbon capture technologies (*CC++*). As a result, the residual CO_2 emissions of capture technologies (ca. 90% capture rate) result in higher emissions for highly enhanced learning (*CC++*) compared to moderately enhanced variation (*CC+*).

In the *Reference scenario,* enhanced learning in carbon capture technologies has no significant impact on cumulative energy-related emissions (**Figure 68.a and b**). This is because, despite the benefits of learning, carbon capture technologies remain non-competitive in the absence of a global carbon value.

Bioenergy technologies

Under the *2°C scenario*, enhanced learning of bioenergy technologies (*BE+*, *BE++*) has a significant and increasing impact on reducing emissions (**Figure 67.a**), in particular in the second half of the century, as capacities and production of bioenergy technologies expand significantly for biofuels (**Figure 53** in Section 2.7.1.4), electricity production (**Figure 55** in Section 2.7.2.2) and hydrogen production (**Figure 57** in Section 2.7.3.1).

Notably, the *Reference scenario* reveals no significant impact of enhanced learning on energy-related emissions (**Figure 68.a and b**). The absence of a global carbon value hinders the widespread adoption of carbon-neutral or carbon-negative bioenergy technologies, thereby limiting the potential benefits of enhanced learning.

Heat pump technologies

Under the *2°C scenario*, enhanced learning in heat pump technologies (*HP+*, *HP++*) reduces moderately cumulative energy-related emissions until 2075 (**Figure 67.a**, 2050 & 2075). The reason is that with enhanced learning more fossil boilers, which provide a substantial amount of the high heating demand in the first half of the century (**Figure 59.a** in Section 2.8.1), are substituted by heat pumps.

However, in the second half of the century, this effect fades out (**Figure 67.a**, 2075 & 2100) as the heating demand decreases substantially (i.e., better insulation) and the power mix becomes more decarbonised (**Figure 3** in Section 1.2.3.2). As a result, cumulative emissions in 2100 are not significantly affected despite enhanced heat pump learning.

Under the *Reference scenario*, the impact of enhanced learning on emission reduction is slightly higher compared to the *2°C scenario*, as the power mix is less decarbonised. For the less effective reduction until 2075 compared to 2050, a similar reasoning applies to the case of the *2°C scenario*. In the last quarter of the century, more emissions are reduced as less carbon-based electricity is consumed due to improved heat pump efficiencies.

Preliminary conclusion

Enhanced learning for wind (*W+*, *W++*) and for the hydrogen and fuel cell group (*H2FC+*, *H2FC++*) positively impact cumulative CO_2 emissions in 2100 under both the *2°C scenario* and the *Reference scenario*. For heat pump technologies, the enhanced learning has a rather small emission reduction effect under both scenario cases.

A stringent carbon policy (i.e., *2°C scenario*) is required to unleash significant emission reductions by applying enhanced learning for:

- Battery technologies (*BA+*, *BA++*);
- Carbon capture for hydrogen production and power generation (*H2FC+*, *H2FC++*);
- DAC and synfuel technologies (*DACSY+*, *DACSY++*);
- Bioenergy technologies (*BE+*, *BE++*).

3.2.2 Impacts on investment needs

Figure 69 (*2°C scenario*) and **Figure 70** (*Reference scenario*) illustrate the impacts of enhanced learning rates on cumulative investments within each of the eight technology groups. The Figures depict cumulative investments in energy supply and clean demand-side technologies as well as overall investments for the years 2050, 2075, and 2100: 2050, marking the end of the enhanced learning period (2025-2050), as well as 2075 and 2100, which demonstrate the long-term effects of enhanced learning.

Batteries

Among the unpaired enhanced learning variations, enhanced battery learning (*BA+*, *BA++*) has the most significant and long-lasting impact on cumulative investments of energy demand and overall investments (**Figure 69**.b and c). Enhanced learning also significantly affects investments in energy supply (**Figure 69**.a). However, the impact on energy demand investments is much more significant due to higher investments in batteries for transportation (**Figure 63**) compared to energy supply investments in battery electricity storage (**Figure 62** and **Figure 8** in Section 1.2.4.1). The actual impact on investment needs is concentrated in the first half of the century as battery costs are close to floor cost levels in the second half of the century (**Figure 22** and **Figure 25** in Section 2.3.2.1). Consequently, the impact of cumulative investments decreases in the latter half of the century.

Solar and wind

Enhancing learning for solar (*S+, S++*) and wind (*W+, W++*) affects solely investments on the supply side (**Figure 69.a** and **Figure 70.a**) and results in substantially lower overall investment needs until 2075 in both scenario cases (**Figure 69**.c and **Figure 70.c**). In the last quarter of the century, this tendency is reversed for the variations of W+, *S+* and *S++* as the increased capacity triggered by enhanced learning is not anymore overcompensated with reductions in cost as floor cost levels have been approached (**Figure 11** in Section 2.1.2 and **Figure 17** in Section 2.2.2).

Hydrogen and fuel cell technologies

Cumulative investments on the demand side are substantially reduced in both scenario variations (**Figure 69**.b and **Figure 70.b**) by enhanced learning for hydrogen and fuel cell technologies (*H2FC+*, *H2FC++*). The reason for this behaviour is that costs for fuel cells powered vehicles decrease significantly, whereas capacities rather stagnate (**Figure 33**.b and **Figure 34**.a and c in Section 2.4.3.1).

Surprisingly, enhanced learning in hydrogen and fuel cell technologies leads to increasing in investment needs on the supply side in the second half of the century, as shown in **Figure 69**.a and **Figure 70.a**. This trend may seem counterintuitive, given that the *H2FC++* variation in **Figure 31** (Section 2.4.2.4) suggests a slight decrease in cumulative investments for hydrogen production and *dedicated* power capacities. However, the explanation lies in the significant expansion of grid-powered electrolysis, which drives a substantial increase in power capacities within the power system. Although investments in these power capacities are not captured in **Figure 31**, they are reflected in the cumulative energy supply investments presented in **Figure 69**.a and **Figure 70.a**.

Cumulative overall investment needs decrease over several decades with enhanced learning (*H2FC+*, *H2FC++*) as the cost decrease of most hydrogen and fuel cells technologies outweighs its additional capacities under the *2°C scenario* (**Figure 69.c**) and the *Reference scenario* (**Figure 70.c**.). Under the *2°C scenario*, this process lasts until about 2075, whereas under the *Reference scenario*, the decrease in overall investment needs continues until the end of the century.

Heat pump technologies

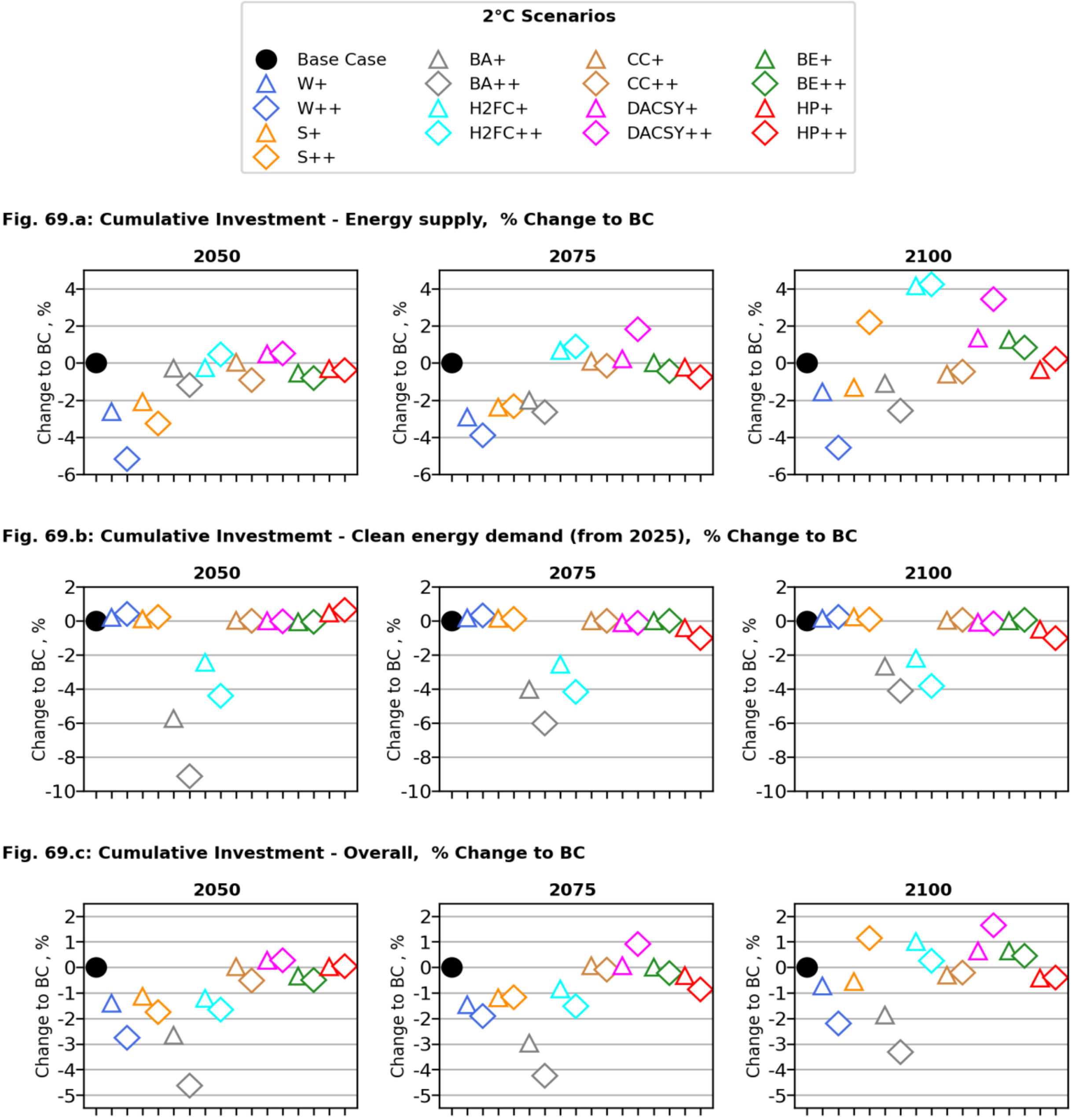
Enhanced learning, for heat pump technologies has slight investment impacts on the supply and demand side. As enhanced learning increases the efficiencies of heat pumps (**Figure 59.c and d**), less electricity is required, which reduces investment needs for electricity generation. On the demand side, cumulative investments increase slightly until 2050 (**Figure 69.b** and **Figure 70.b**, 2050) as the quantity effect of higher capacities, mainly for heat pumps for heating, is not overcompensated by falling investment costs (**Figure 60.b and d** for 2050 in Section 2.8.2).
However, in the second half of the century, demand investments decrease (**Figure 69.b** and **Figure 70.b**, 2075 & 2100) mainly as for heat pumps for cooling applications costs still decrease (**Figure 59.f** and

Figure 60.b, 2075 & 2100 in Section 2.8). These effects appear in both scenario cases and result in a slight reduction of overall investment needs in the latter half of the century (**Figure 69.c** and **Figure 70.c**).

Carbon capture and bioenergy technologies

Enhanced learning for carbon capture (*CC+, CC++*, *DACSY+*, *DACSY++*) and bioenergy technologies (*BE+, BE++*) affect predominantly investments in energy supply.

Figure 69. Impact on cumulative investments of unpaired learning variations under the *2°C scenario*.



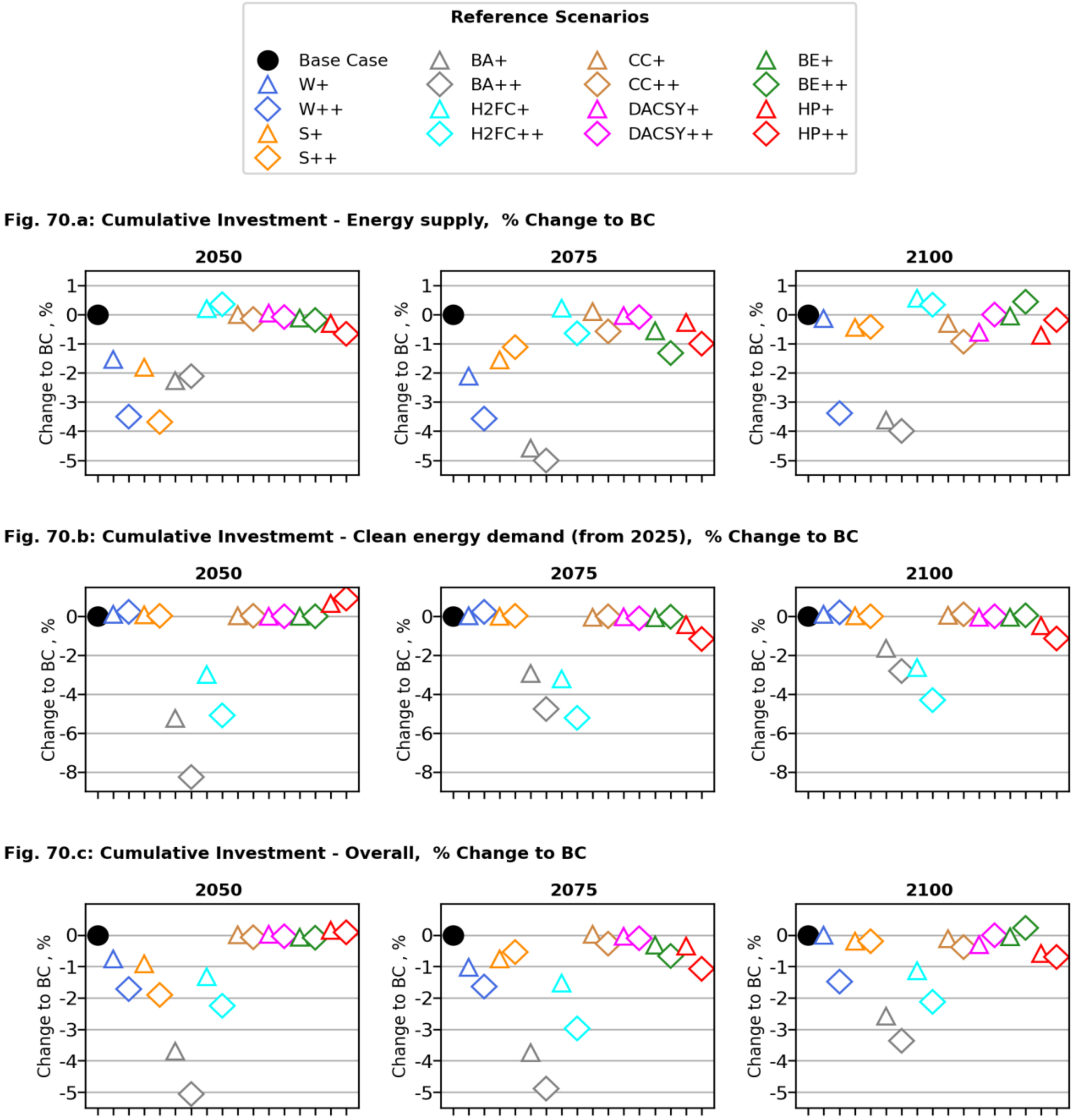
Source: POLES-JRC model

<u>*2°C scenario*</u>

Enhanced carbon capture learning (*CC+, CC++*) under the *2°C scenario* has a rather neutral effect on cumulative energy supply investments (**Figure 69.a**). This is consistent with the cumulative carbon capture investments shown in Section 2.5.1.4 for power technologies (**Figure 40.b**) and hydrogen production (**Figure 42**). In contrast, enhanced learning for DAC and synfuels (*DACSY+*, *DACSY++*) under the *2°C scenario* appears to lead to

increasing energy supply investments, mainly in the second half of the century, as shown in (**Figure 69.a**). However, this trend seems to contradict the slightly decreasing cumulative investments shown in **Figure 47** (Section 2.6.3). The explanation for this discrepancy lies in the significant expansion of grid-powered electrolysis, which triggers additional power capacities in the power system for hydrogen production required for the increased synfuel production, not accounted for in **Figure 47**. This is similar to the case of increased hydrogen and fuel cells (see above).
Enhanced bioenergy learning under the *2°C scenario* has a rather neutral impact on cumulative energy supply investments until 2075, mainly due to decreasing cumulative investments for biofuels and biomethane (**Figure 53** in Section 2.7.1.4), offset by slightly increasing cumulative investments for biomass-related hydrogen capacities (**Figure 57.d** in Section 2.7.3.1). However, other model interactions play a role, leading to additional investments in non-biomass power capacities (e.g., gas power). As a result, enhanced bioenergy learning effectively leads to higher energy supply investments in the second half of the century compared to the actual cumulative investments for biofuels and biomethane, as well as biomass-related power and hydrogen as shown in Section 2.7.1.

Figure 70. Impact on cumulative investments for unpaired learning variations under the *Reference scenario*.



Source: POLES-JRC model

Reference Scenario

The impacts on cumulative energy supply investments (**Figure 70.a**) under the *Reference Scenario* are relatively small for enhanced learning for carbon capture (*CC+, CC++*, *DACSY+*, *DACSY++*) and bioenergy technologies (*BE+, BE++*).

Preliminary conclusion

Enhanced learning in the most dynamic technologies, such as batteries, wind, PV, and hydrogen and fuel cells, leads to significant additional reductions in cumulative overall investments compared to the base case. This is because the cost savings resulting from enhanced learning outweigh the quantity effect of expanding capacities, ultimately driving down investment needs even further.

3.2.3 Impacts on energy supply costs

The impacts on *annual energy supply costs* resulting from enhanced learning within each of the eight technology groups are illustrated in **Figure 71.a** (*2°C scenario*) and **Figure 72.a** (*Reference scenario*). Additionally, global weighted averages of the main annual energy production cost components affected by enhanced learning of clean energy technologies are depicted in **Figure 71** and **Figure 72**:

- Electricity generation costs;
- Hydrogen production costs;
- Biofuel and biomethane production costs;
- Synfuels production costs.

The cost impacts are illustrated for the year 2050, marking the end of the enhanced learning period (2025-2050) and for the years 2075 and 2100, which demonstrate the long-term effects of enhanced learning.

2°C scenario – energy supply costs

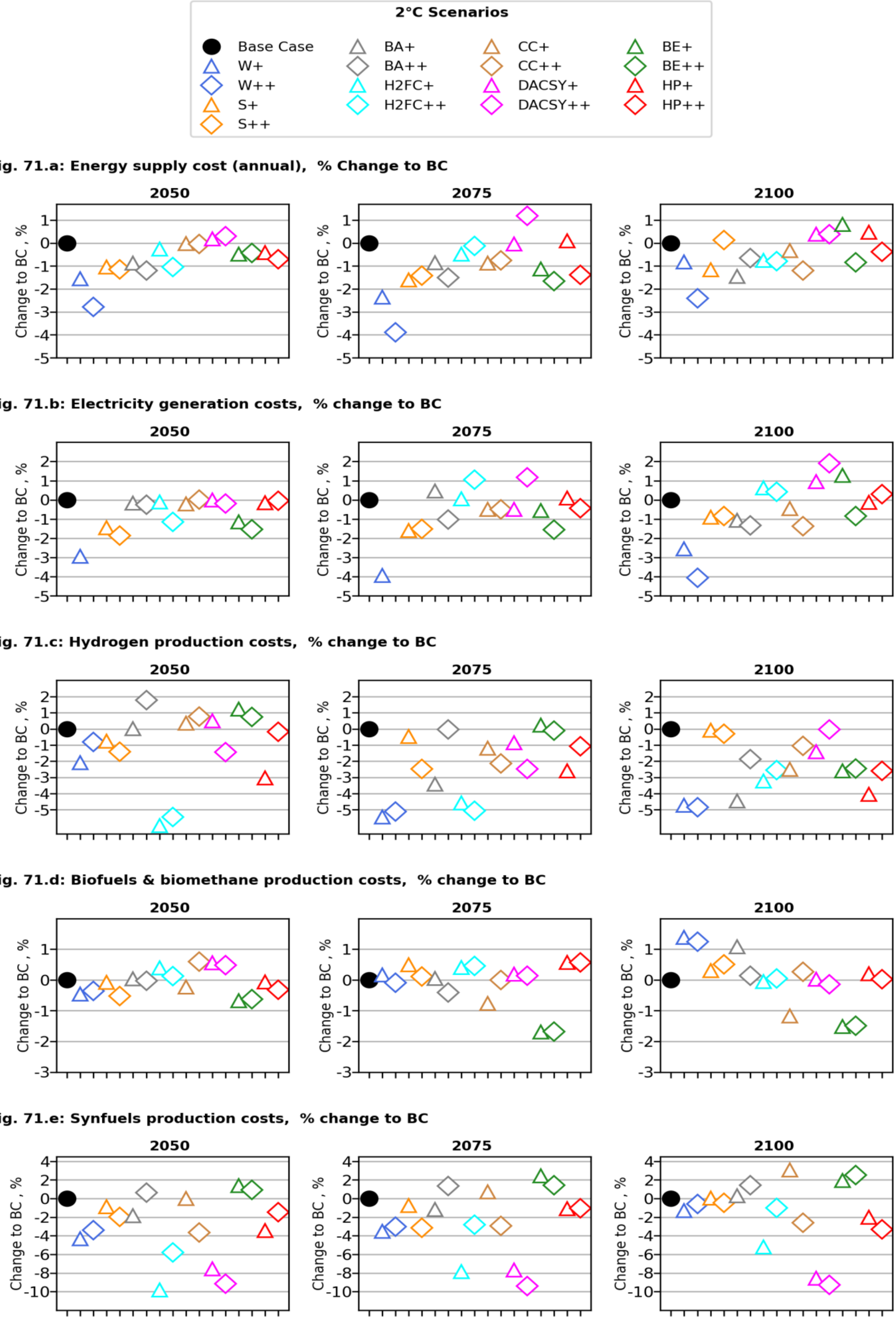
Enhanced learning for wind technologies (*W+*, *W++*) has a profound and lasting impact on reducing annual energy supply costs in the *2°C scenario* (**Figure 71.a**). This results primarily from significantly lower electricity generation costs throughout the century (**Figure 71.b**). Also, enhanced solar learning (*S+*, *S++*) results in significantly lower energy supply costs until 2075 mainly due to its cost reduction impact on electricity generation costs in the coming decades (see section *Electricity generation cost* below).

Battery learning (*BA+*, *BA++*) also reduces significantly energy supply costs. However, this reduction results from an interaction of increased electrification in the transport sector and lower electricity costs. With enhanced battery learning, electric vehicles become more cost-competitive, crowding out other vehicle types. As a result, the lower energy supply costs are a consequence of two factors: the quantity effect, which stems from reduced consumption due to the higher efficiencies of electric vehicles compared to other types, and the lower electricity costs.

Reference scenario – energy supply costs

In the *Reference scenario*, battery learning (*BA+*, *BA++*) has the most significant reduction impact on energy supply costs by far (**Figure 72.a**). This reduction is caused by the aforementioned interaction of more electrification in transport induced by lower battery and electricity costs **Figure 72.b**. However, by 2050, the shift towards more electrification (**Figure 23** in Section 2.3.1) is more pronounced under the *Reference scenario* as battery floor cost levels are reached later than under the *2°C scenario*. Moreover, by 2075, the lower electricity costs become more important for reducing energy supply costs (**Figure 72.a and b**, 2075).

Figure 71. Impacts on energy supply costs and major components for unpaired learning variations under the *2°C scenario*.



Source: POLES-JRC model

Enhanced wind learning has a positive impact on reducing energy supply costs throughout the century **Figure 72.a**, 2050-2100). Notably, the reduction effect increases for highly enhanced wind learning (*W++*) over time. This positive impact is primarily driven by lower costs for electricity **Figure 72.b**) and, to a lesser extent, for hydrogen **Figure 72.c**). Moreover, the decreasing synfuel costs from enhanced wind learning in the latter half of the century have additionally a positive effect on energy supply costs.

For enhanced solar learning, energy supply costs decrease by 2050 due to the decrease in electricity costs **Figure 72.a and b**, 2050).

Electricity generation cost

2°C scenario

Enhanced learning for wind (*W+*, *W++*) under the *2°C scenario* induces significant reductions in electricity costs until the end of the century. The impact is also significant for enhanced solar learning (*S+*, *S++*) but less pronounced than for wind. Enhanced bioenergy learning (*BE+*, *BE++*) has a slightly positive impact on electricity costs until 2075. The other learning variations, including battery learning, have a relatively small impact on electricity generation costs by 2050. Enhanced learning for DAC and synfuels (*DACSY+*, *DACSY++*), and hydrogen and fuel cells (*H2FC+*, *H2FC++*) result in the second half of the century in higher electricity costs due to increasing power investments of
grid-powered electrolysis (see 'Hydrogen and fuel cell technologies' in Section 3.2.2).

Reference scenario

Similarly to the *2°C scenario*, enhanced wind learning (*W+*, *W++*) significantly reduces electricity costs. Enhanced learning for solar and batteries results in decreasing electricity costs until 2050 and 2075, respectively. However, the impacts for the remainder of the century are less straightforward. The ambiguity arises because once floor costs are reached (as is the case for PV and batteries from 2050 onwards), learning no longer influences investment decisions, whereas other factors, such as capacity cohort effects due to lifetime, which are shaped by the scenario modelling path, become more prominent.

Hydrogen production costs

Enhanced learning for hydrogen and fuel cell technologies (*H2FC+*, *H2FC++*) has a substantial impact on reducing hydrogen costs until 2075. By 2100, the impact of learning diminishes substantially as electrolyser costs converge towards floor cost levels, particularly in the last quarter of the century (**Figure 30** in Section 2.4.2.3). Moreover, enhanced wind learning significantly impacts reducing hydrogen costs in the second half of the century. The reason is that in this period substantial wind capacities dedicated to electrolysis are deployed in combination with still decreasing wind investments costs.

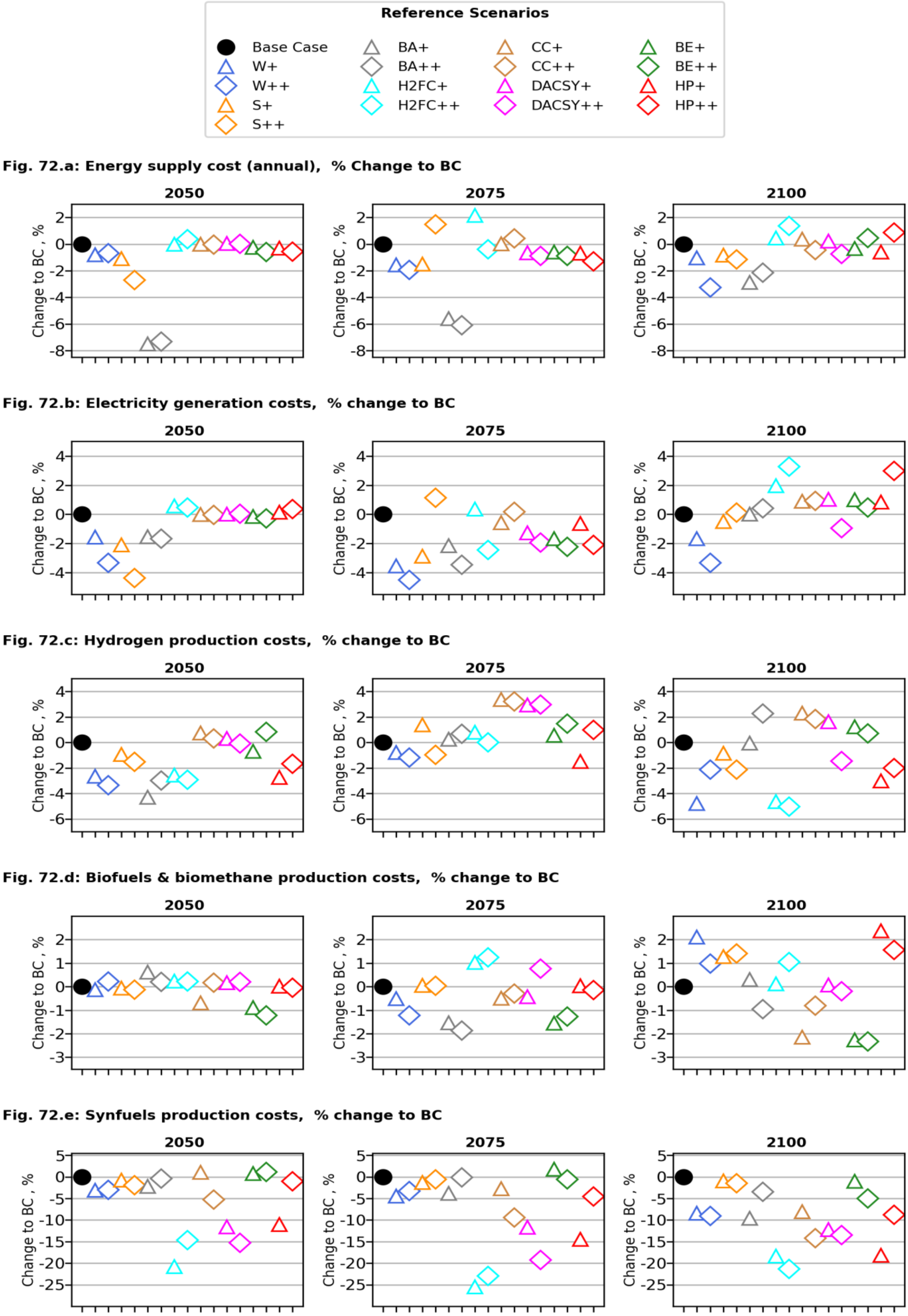
Biofuels and biomethane costs

Among the *2°C* learning variations, enhanced bioenergy learning (*BE+*, *BE++*) significantly reduces biofuels and biomethane costs. In particular, the impact is strong in the second half of the century. Also, under the *Reference scenario*, enhanced bioenergy learning substantially impacts reducing biofuels and biomethane costs.. However, the impact of the other learning variations is rather ambiguous.

Synfuel production costs

Substantial impact on reducing synfuel costs has enhancing learning for DAC and synfuel technologies (DACSY+, DACSY++) and hydrogen and fuel cell technologies (H2FC+, H2FC++) in both scenarios (**Figure 71.b** and **Figure 72.b**).
Moreover, highly enhanced learning for carbon capture technologies (*CC++*) results in lower synfuel costs as components of the DAC process are shared with capture technologies in POLES-JRC.

Figure 72. Impacts on energy supply costs and major components for unpaired learning variations under the *Reference scenario*.



Source: POLES-JRC model

3.3 Synergies in technology learning

This section builds on the analysis of unpaired enhanced learning presented in the previous section, taking it a step further by examining the impacts of combining enhanced learning across multiple technology groups. The analysis aims to identify favourable combinations that can create synergies across technology groups.

3.3.1 Renewable electrification learning strategies

Renewable electrification [57]–[59] plays a crucial role in the decarbonisation of energy systems, as it enables a dual transition: fossil fuel-based energy demand technologies are increasingly substituted with more efficient electric alternatives, while renewable power generating technologies simultaneously decarbonise through the power mix. This section analyses synergies of enhanced learning strategies related to renewable supply of wind and solar and electrified demand technologies.

3.3.1.1 2°C scenario learning variants

Wind combinations

With regard to reducing energy-related emissions, combining highly enhanced wind learning and battery learning (W++_*BA++*) creates merely slight synergies until 2050 (**Figure 73.a**). This limited impact is because battery costs in the transport sector, which is the primary application for batteries, are no longer influenced by enhanced learning after 2050 due to reaching the floor costs (**Figure 22** in Section 2.3.1.1).
However, combining highly enhanced learning for wind and heat pumps (W++_*HP++*, W++_BA++_*HP++*) has a substantial and long-lasting impact on reducing emissions as learning has a sustained impact on costs and efficiencies until the end of the century (**Figure 59** in 2.8.1).

Investment needs (**Figure 73.b**) and energy supply costs (**Figure 73.c**) are substantially reduced when combining highly enhanced learning for wind and battery (combinations: *W++_BA++*, *W++_BA++_HP++*). This effect is most pronounced until 2075 as batteries for transport reach floor cost by 2050 (**Figure 23.a** in Section 2.3.1), and the cost of batteries comes close to floor cost by 2075 (**Figure 25.a** in Section 2.3.2.1).

Solar combinations

Combining highly enhanced solar learning (*S++*) with enhanced learning for batteries (S++_*BA++*) and heat pumps (S++_*HP++*) creates positive synergies regarding emissions reduction (**Figure 73.a**). In the case of the solar and battery combination (S++_*BA++*), lower battery costs favour using batteries to balance intermittent solar power instead of fossil power. Moreover, lower costs of solar power (**Figure 18** in Section 2.2.2) make it more attractive to use battery electric vehicles. Similarly, for the combinations of solar and heat pump learning (S++_*HP++*), cheaper solar power favours the use of heat pumps. However, for reducing cumulative emissions by the end of the century, combinations with battery and wind enhanced learning have more impact than combinations of battery and solar.

The cumulative investments (**Figure 73.b**) are significantly lowered throughout the century when solar and battery learning are combined (*S++_BA++*). This is primarily driven by the significant impact of battery cost reductions, which are most pronounced until 2050 but have a lasting effect on cumulative investments until the end of the century (**Figure 22** in Section 2.3.1.1). However, when considering annual energy supply costs (**Figure 73.c**)., the effectiveness of this combination (S++_BA++) appears to be limited to the first half of the century as batteries reach floor cost level in the second half of the century. Combining highly enhanced learning for solar with the two demand technologies (*S++_BA++_HP++*), creates additional synergies resulting, in further improvements for all three indicators for most of the yearly snapshots show.

Wind and solar combinations

Moderate synergies in cumulative energy-related emission reductions (**Figure 73.a**) are created at the end of the century when combining highly enhanced learning for wind and solar (*W++_S++*). However, the emission impacts are rather small in the first half of the century. Adding highly enhanced battery learning

(*W++_S++_BA++*) creates additional synergies in reducing cumulative emissions by 2050 and by 2100 as lower battery costs improve the balancing of renewables and lower cost for renewable power and batteries, make driving electric vehicles cheaper.

For combinations of highly enhanced learning for wind and solar (*W++_S++*), cumulative investments (**Figure 73.b**) decrease significantly below their unpaired levels (*W++*, *S++*) until 2075. This is because most cost reductions from enhanced learning occur during this period. Adding highly enhanced battery learning (*BA++*) to the wind and solar combination (*W++_S++*) yields substantial and long-lasting synergies, resulting in further reductions in cumulative investments (*W++_S++_BA++*, *W++_S++_BA++_HP++*).

Regarding energy supply costs (**Figure 73.c**), the wind and solar combination (*W++_S++*) reduces costs substantially below its unpaired levels (*W++*, *S++*) throughout the century. Adding to this combination enhanced battery learning (*W++_S++_BA++*) positively affects energy supply cost, while the effects are rather ambiguous for adding enhanced heat pump learning (*W++_S++_HP++*).

Best-performing combination

The combination considering highly enhanced learning for both renewable supply technologies (wind and solar) and both demand side technologies (batteries and heat pumps), *W++_S++_BA++_HP++*, emerges as the top performer across all indicators throughout the century. By 2100, this combination yields significant benefits, including almost a 4% reduction in cumulative energy-related CO_2 emissions, a 6% decrease in cumulative investments, and a 5% decrease in energy supply costs. The synergies created by this combination are substantial, driven by the complementary effects of each technology. Specifically, the combination achieves benefits through three key channels: (i) solar and wind enhanced learning significantly reduce emissions and costs; (ii) battery enhanced learning has a profound impact on reducing investment needs and energy supply costs; and (iii) heat pump enhanced learning affects the economic indicators by reducing costs for heat pumps, but also by lower renewable investment needs as electricity demand decreases due to improved efficiencies.

Preliminary conclusion

Under a stringent decarbonisation path according to the *2°C scenario*, all combinations containing enhanced wind learning for *W++* have a very substantial impact on reducing cumulative energy-related CO_2 emissions until the end of the century. Moreover, all combinations with enhanced battery learning tremendously impact cumulative investments. To reduce, energy supply costs, combining enhanced wind and solar learning and additionally enhanced learning on the demand side is an effective strategy.

3.3.1.2 Reference scenario learning variants

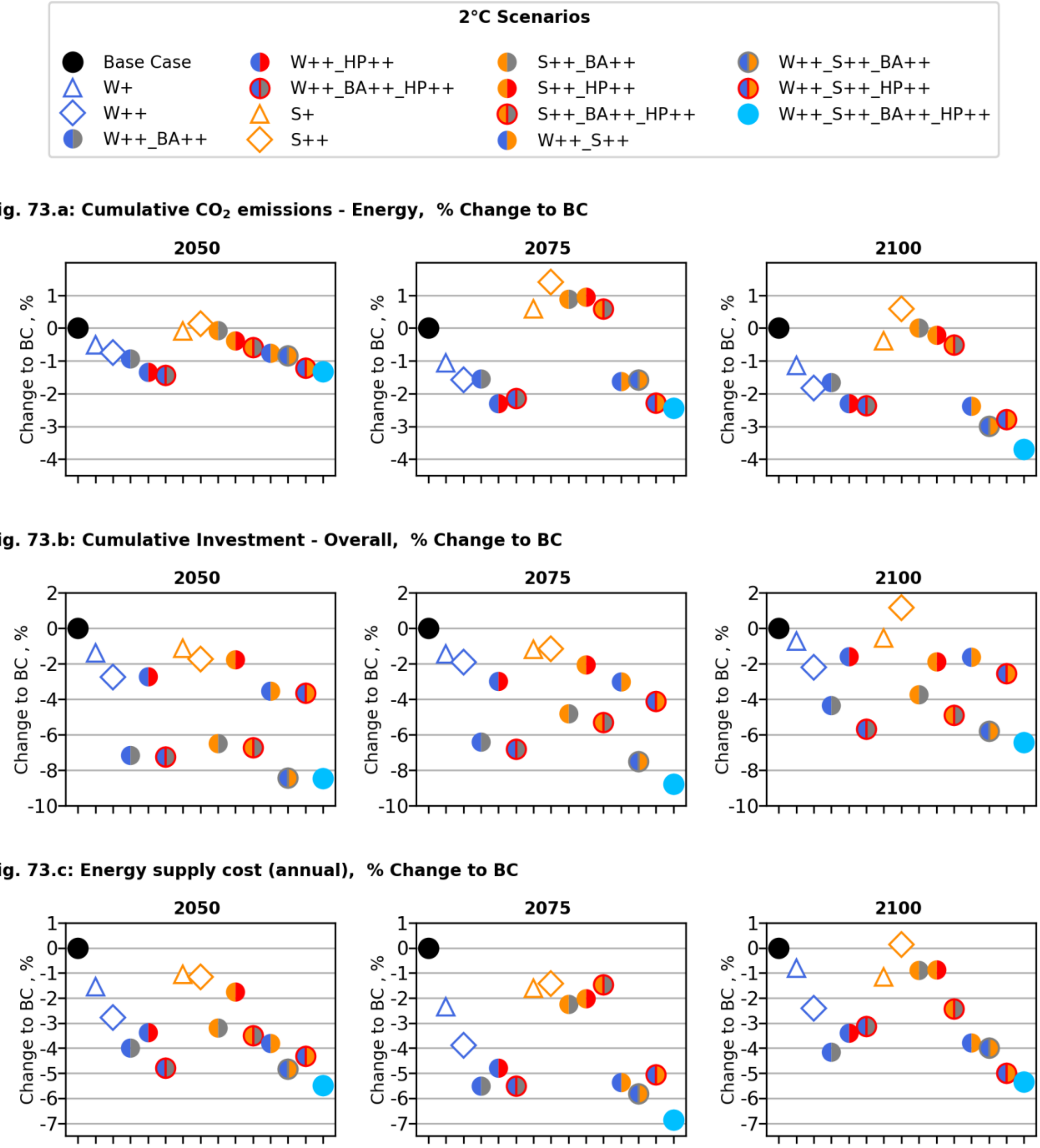
Similarly to the *2°C scenario*, combinations with enhanced wind learning have a substantial impact on reducing emissions over the entire century under the *Reference scenario*. Also, combinations with enhanced battery learning substantially reduce investment needs and energy supply costs.

The relative reductions in cumulative emissions under the combinations of the *Reference scenario* (**Figure 74.a**) are in general, higher compared to *2°C scenario* (**Figure 73.a**). The best-performing combination of the Reference scenario (*W++_S++_HP++*) reduces cumulative energy-related emissions by 7% compared to 4% for the best-performing combination under the *2°C scenario*.

On cumulative investments, the combinations under the *Reference scenario* (**Figure 74.c**) have similar effects as in f the *2°C scenario* (**Figure 73.c**).

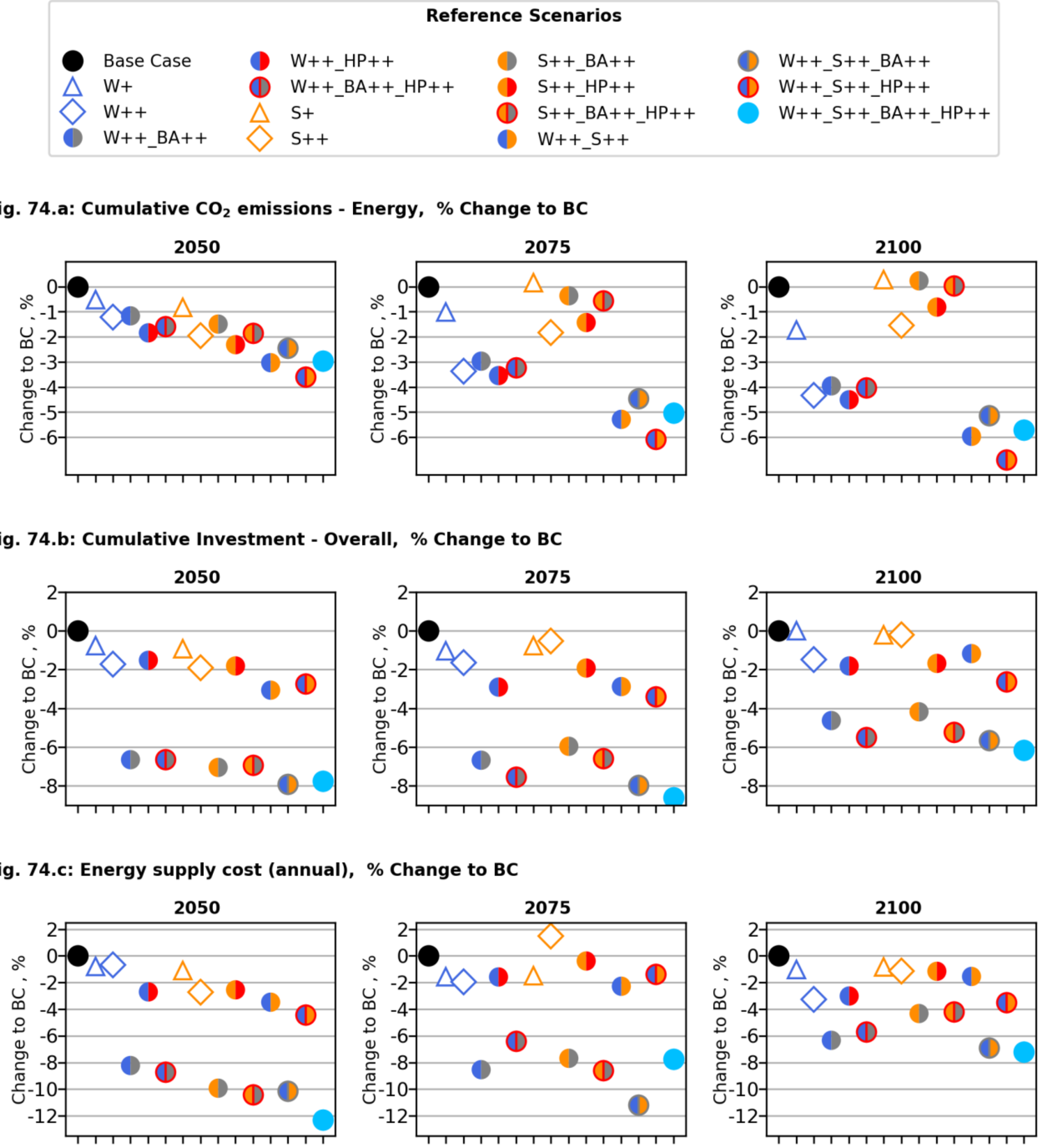
Regarding energy supply costs, enhanced battery learning has a predominant impact *o* on reducing costs within the combinations under the *Reference scenari*. Whereas under the *2°C scenario* variations, enhanced learning for wind and heat pump technologies also have a pronounced impact (**Figure 73.d**).

Figure 73. Impacts for enhanced learning combinations related to renewable electrification learning strategies under the *2°C scenario*.



Source: POLES-JRC model

Figure 74. Impacts for enhanced learning combinations related to renewable electrification learning strategies under the *Reference scenario*.



Source: POLES-JRC model

3.3.2 Carbon capture learning strategies

This section examines synergetic effects that can be achieved by combining enhanced learning across technology groups related to carbon capture, as illustrated in **Figure 75** and **Figure 76**. Learning interactions between these groups can be expected due to shared components related to carbon capture. Specifically, the carbon capture group (*CC*) shares components with the groups of direct air capture and synfuels (*DACSY*), bioenergy group (*BE*), and hydrogen and fuel cell group (*H2FC*) (see Tables in Annex 5). Additionally, the evolution of synfuel production from direct air capture is closely tied to learning within the hydrogen and fuel cell group (*H2FC*).

3.3.2.1 2°C scenario learning variants

Combining *CC++* with *DACSY++*
Combining highly enhanced learning for carbon capture (*CC*) and *direct air capture and synfuels (*DACSY) (CC++_DACSY++) creates minor positive synergies in reducing energy-related CO_2 emissions in the second half of the century (**Figure 75.a**, 2050 & 2100). However, in terms of investment needs and energy supply cost, the *CC++_DACSY++* combination leads to lower expenditures compared to the unpaired *DACSY++* learning, but it does not decrease expenditures below the level of unpaired *CC++* learning.

Combining *BE++* with *CC++* and *DACSY++*
Positive synergies are created for reducing emissions in the second half of the century (**Figure 75.a**) by combining highly enhanced learning of the bioenergy group either with the carbon capture group (*CC++_BE++*) or with the DACSY group (*DACSY++_BE++*). However, combining learning for these three technology groups (CC++_*DACSY++_BE++*) is more effective than the aforementioned paired learning combinations. Regarding economic indicators, only the combination of enhanced capture technologies and bioenergy learning (*CC++_BE++*) exhibits positive synergies, leading to reduced cumulative investments until 2100 and lower energy supply costs until 2050.

Combinations with *H2FC++*
Regarding reducing energy-related emissions, the combination of highly enhanced learning for direct air capture and synfuels and hydrogen and fuel cells (DACSY++_H2FC++) creates substantial synergies in the second half of the century (**Figure 75.a**, 2050 & 2100) as the production of synfuels benefits from improvements in hydrogen production. Moreover, the triple combination of carbon capture, bioenergy and hydrogen and fuel cells (*CC++_BE++_H2FC++*) achieves similar emission reduction synergies in the latter half of the century as improvements in shared carbon capture components positively affect power generation and hydrogen production using bioenergy and hydrogen technologies. However, the combinations of highly enhanced learning for carbon capture paired with hydrogen and fuel cells (CC++_*H2FC++*) and CC++_DACSY++_*H2FC++* triple are less effective in reducing emissions.

Regarding cumulative investments (**Figure 75.b**), positive synergies are realised in the last quarter of the century when learning for hydrogen and fuel cells is combined with other technologies, such as carbon capture (*CC++_H2FC++*), direct air capture and synthesis (*DACSY++_H2FC++*), and integrated carbon capture and direct air capture and synthesis (*CC++_DACSY++_H2FC++*), beyond the effects of unpaired learning (*H2FC++*). Synergies for annual energy supply seem to appear merely in the first half of the century for combinations with hydrogen and fuel cells enhanced learning.

Most effective combinations for reducing CO_2
The most effective combination for reducing cumulative emissions throughout the century is the triple combination (*DACSY++_BE++_H2FC+*) or the combination with all four capture relevant technologies (*CC++_DACSY++_BE++_H2FC++*), which reduce cumulative emissions until 2100 by about -3% and -3.7%, respectively.

Preliminary conclusion

Although enhanced technology learning is applied from 2025 to 2050, the main impact in reducing emissions materialises in the second half of the century. Combining learning across CO_2 capture technologies is an effective way to reduce emissions. Enhanced learning for DAC and synfuels (*DACSY++*) is predominant among the best-performing capture-related combinations. Regarding investment needs and energy supply cost, capture-related combinations do not achieve cumulated investment reductions of more than 2% which is much less than the renewable and demand combinations (Section 3.3.1.1).

3.3.2.2 Reference scenario learning variants

Combining enhanced learning across capture-related technology groups shows similar synergies for reducing energy-related CO_2 emissions (**Figure 76.a**) as in the 2°C scenario learning variations. However, the relative impact on emissions by 2100 is substantially smaller under the Reference scenario (**Figure 76.a**, 2100) compared to the 2°C scenario variations (**Figure 75.a**, 2100).

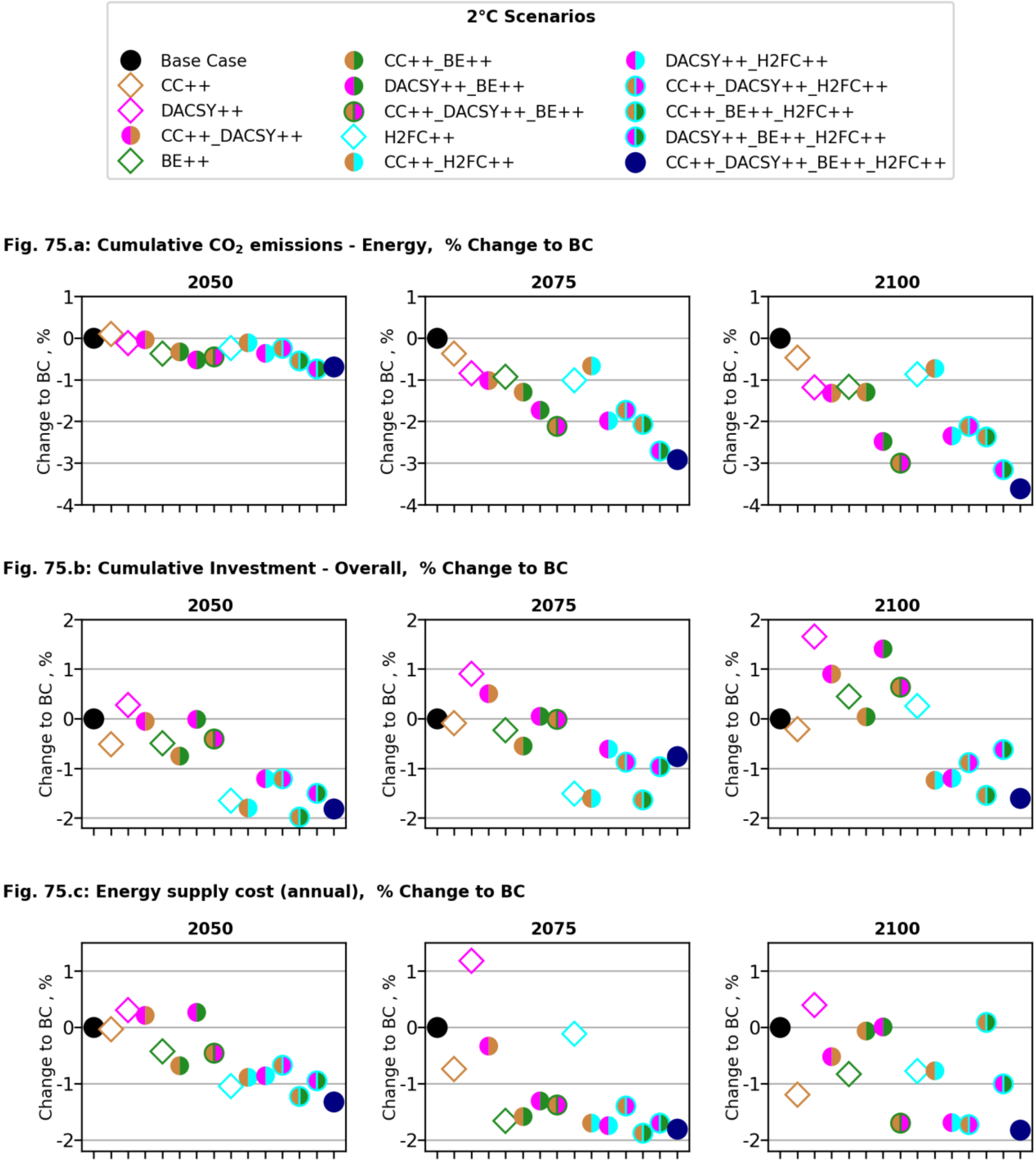
In terms of investment needs, the impact of enhanced learning for hydrogen and fuel cells is very pronounced (**Figure 76.b**). Overall, the relative impact of the best-performing learning combinations under the *Reference scenario* (**Figure 76.b**) is slightly higher compared to the *2°C scenario* variations (**Figure 75.b**).

Regarding energy supply cost, the impact under the *Reference scenario* (**Figure 76.c**) is also small but more ambiguous than under the *2°C* scenario (**Figure 75.c**).

Preliminary conclusion

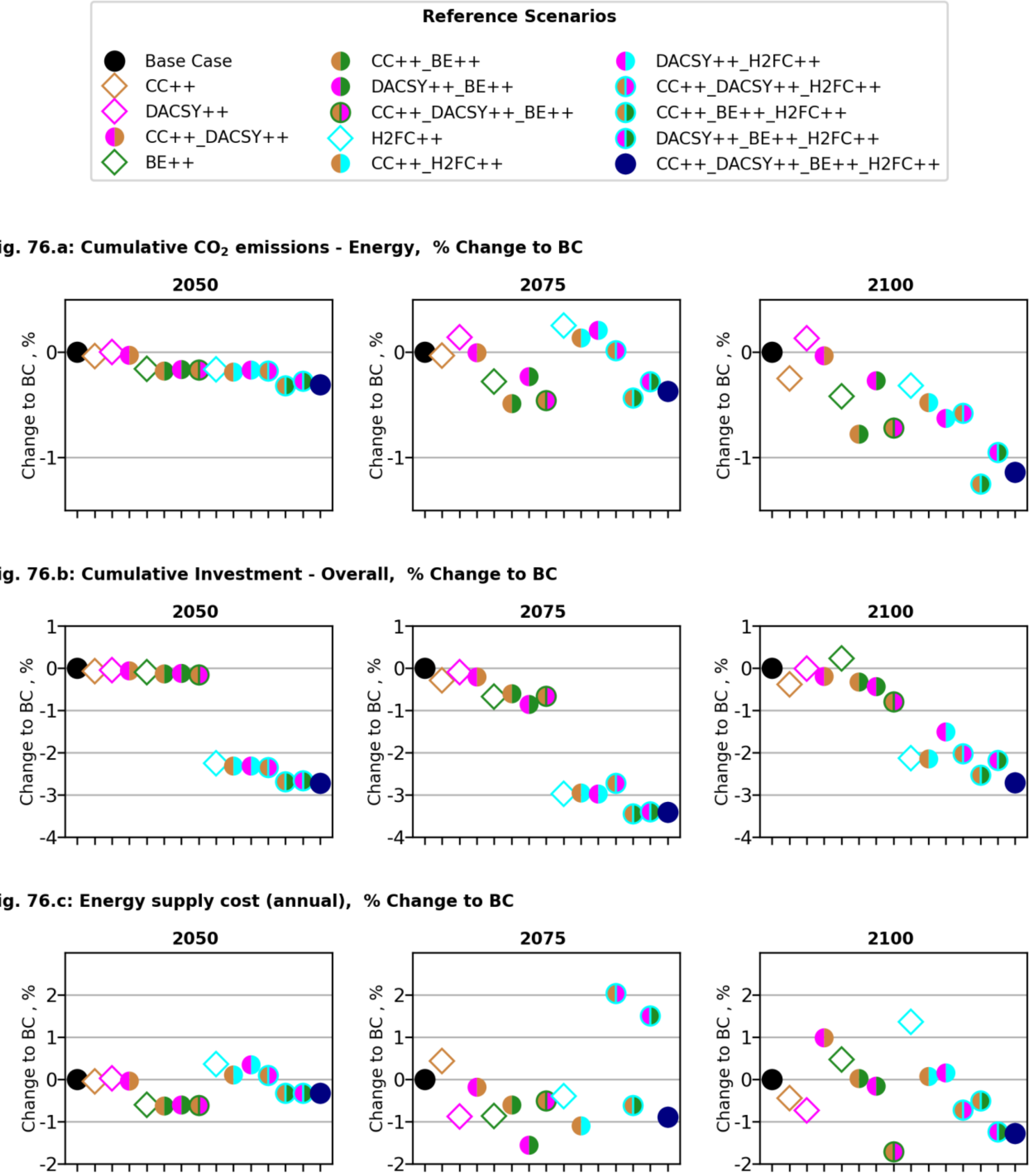
Enhanced learning for carbon capture-related technologies requires a stringent climate policy (e.g., *2°C scenario*) to unfold its full potential for reducing emissions; however without climate policies (i.e., *Reference scenario*), the impact remains quite limited.

Figure 75. Impacts for enhanced learning combinations related to carbon capture learning strategies under the *2°C scenario*.



Source: POLES-JRC model

Figure 76. Impacts for enhanced learning combinations related to carbon capture learning strategies under the *Reference scenario*.



Source: POLES-JRC model

3.3.3 Comprehensive learning strategies

This section analyses synergies of comprehensive learning strategies by combining enhanced learning across manifold technology groups. As a starting point, this section examines learning synergies associated with clean fuel-related technologies, focusing on the three technology groups: biofuels (BE group), hydrogen-based fuels (H2FC group), and synfuels (DACSY group). Additionally, learning synergies with solar and wind power are analysed as these technologies are linked to electrolysis-based hydrogen production. Moreover, to provide a comprehensive understanding of learning synergies, this section considers demand-related technologies, such as heat pumps and batteries, in addition to the aforementioned technologies.

3.3.3.1 2°C scenario learning variants

Clean fuel-related combinations
Significant emission reductions in the second half of the century originate from pairing enhanced learning across clean fuel-related technologies (*H2FC++_DACSY++*, *H2FC++_BE++*, *DACSY++_BE++*) compared to their unpaired variants (*H2FC++*, *DACSY++*, *H2FC+*) as illustrated in **Figure 77**.a. The observed emission reductions result largely from additive effects. Additional emission reductions can be achieved by combining enhanced learning from the three clean fuel-related technologies (*H2FC++_ DACSY++_BE++*), reducing of more than 3% cumulative energy-related emissions by 2100.

The investment needs and energy supply costs (**Figure 77.b and c**) decrease merely slightly for the aforementioned enhanced learning combinations due to the small share of clean-fuel-related costs in the cumulative investments (**Figure 62**) and energy supply costs (**Figure 65**).

Adding wind and solar enhanced learning
Combining enhanced learning for wind and solar (*W++_S++*) is identified in Section 3.3.1 as an effective strategy for decreasing emissions. By building on this approach and integrating enhanced learning for fuel-related technology groups, additional emission reductions can be realised, further optimising the pure renewable strategy.

Notably, combinations that include enhanced learning for DAC, synfuels, and bioenergy (*DACSY++_W++_S++*, BE*++_W++_S++*) demonstrate significant emission reductions, particularly in the second half of the century (**Figure 77.a**). This is mainly due to the lasting cost decreases and capacity increases of enhanced learning of these technologies. The lasting effects on cost and capacity of these technologies are illustrated in the respective sections in Chapter 2: (i) for DAC and synfuel technologies in **Figure 43** and **Figure 45** (DACSY in Section 2.6), (ii) for biofuels technologies in **Figure 52** (Section 2.7.1) and (iii) for biomass-based production of electricity and hydrogen in **Figure 54** and **Figure 56** (Sections 0 and 2.7.3.1).

Combining enhanced learning of the hydrogen and fuel cell group with renewables appears to be very effective until about 2075 (**Figure 77.a**, 2050 & 2075) but less effective in the second half of the century (**Figure 77.a**, 2100). This can be attributed primarily to the fact that the costs of electrolysers (**Figure 30** in Section 2.4.2.3) and PV (**Figure 17** in Section 2.2.2) have converged closely to their respective floor costs.

Notably, the economic indicators exhibit a significant decline when enhanced learning for wind and solar technologies is incorporated into the combinations of clean fuel-related technologies. This effect is particularly pronounced until 2075, as enhanced learning results in substantial wind and solar capacity expansions and cost decline during this period (**Figure 11** in Section 2.1.2 and **Figure 17** in Section 2.2.2). In general, the impact of wind and solar learning is substantial due to its large shares of cumulative investments and energy supply cost. The impact of adding wind and solar enhanced learning to the combinations is most visible for energy supply cost and slightly less apparent for cumulative investments.

Comprehensive learning strategies
Comprehensive learning strategies aim to leverage synergies by combining enhanced learning across manifold technology groups. For instance, involving all those above five fuel-related technologies (*W++_S++_H2FC++_DACSY++_BE++*) is a very effective approach for reducing cumulative energy-related emissions throughout the century as several synergetic effects apply. Adding to this fuel-related combination,

the demand-related technology groups of heat pumps and batteries allow to reduce emissions even further throughout the century (*W++_S++_BA++_H2FC++_DACSY++_BE++_HP++*).

Further cumulative emission reductions by the end of the century (**Figure 77.a**, 2100) could be achieved through two alternative 7-fold combinations:

- *W++_S++_BA++_CC++_DACSY++_BE++_HP++*: This combination substitutes enhanced learning for hydrogen and fuel cells (*H2FC++*) with carbon capture (*CC++*) in the previously mentioned combination.
- *W++_BA++_H2FC++_CC++_DACSY++_BE++_HP++*: In this scenario, enhanced learning for solar (*S++*) is replaced with carbon capture (*CC+*).

However, adding more combinations does not always result in better performance, as can be seen from figures in Section 3.3. The reason for this behaviour is that enhanced learning in a certain technology may crowd out the expansion of technologies in another technology group. In particular, the uniform combination of involving enhanced learning of *all eight* technology groups (*W++_S++_BA++_H2FC++_CC++_DACSY++_BE++_HP++*) is outperformed by the aforementioned combinations of six and seven technology groups.

Focused technology learning

Some combinations concentrating technology learning on four or fewer technologies achieve high-performing results for the economic indicators (e.g., *W++_S++_BA++_H2FC++* in **Figure 77.b** for 2050 – 2100 and **Figure 77.c** for 2050 & 2075). The strong economic performance of these focused combinations can be attributed primarily to the substantial cost-reduction effects of enhanced battery learning. The high economic performance of these focused combinations results largely from the high impact of enhanced battery learning on reducing costs. However, in terms of emission reductions, focused learning strategies seem inferior compared to comprehensive learning strategies involving six or more technology groups.

3.3.3.2 Reference scenario learning variants

Emission reduction

Without a stringent carbon policy, enhanced learning for clean fuel-related technology groups and their combinations has little impact on reducing emissions (**Figure 78.a**). However, adding enhanced wind and solar learning substantially increases the impact on reducing emissions and creates synergies among the technologies (right group of combinations in **Figure 78.a**).

Investment needs and energy supply cost

Similarly to the *2°C scenario*, adding enhanced wind and solar learning to clean fuel-related combinations substantially decreases cumulative investments and energy supply costs.

The impact of enhanced learning combinations for reducing energy supply cost is more pronounced under the *2°C scenario* (**Figure 77.c**) compared to the *Reference scenario* (**Figure 78.c**). Therefore, enhanced learning can contribute substantially to mitigating the elevated energy supply cost of stringent carbon policies.

Figure 77. Impacts for enhanced learning combinations related to comprehensive learning strategies under the *2°C scenario*.

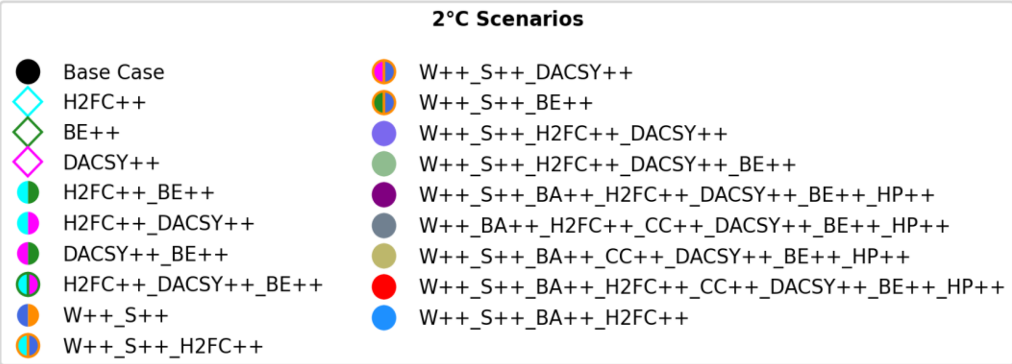


Fig. 77.a: Cumulative CO_2 emissions - Energy, % Change to BC

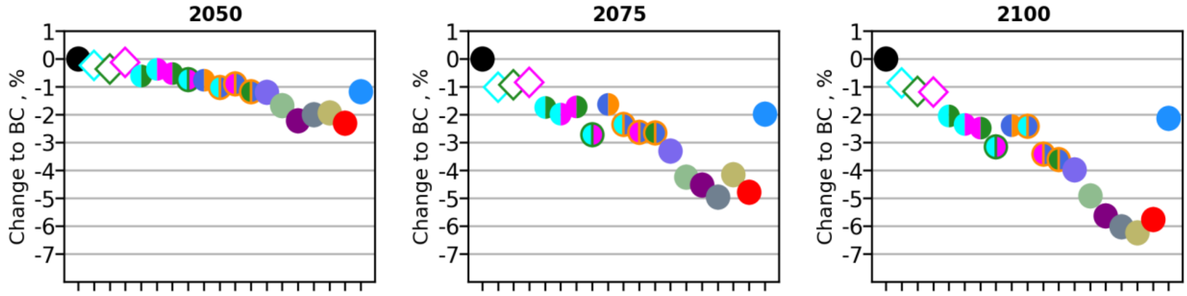


Fig. 77.b: Cumulative Investment - Overall, % Change to BC

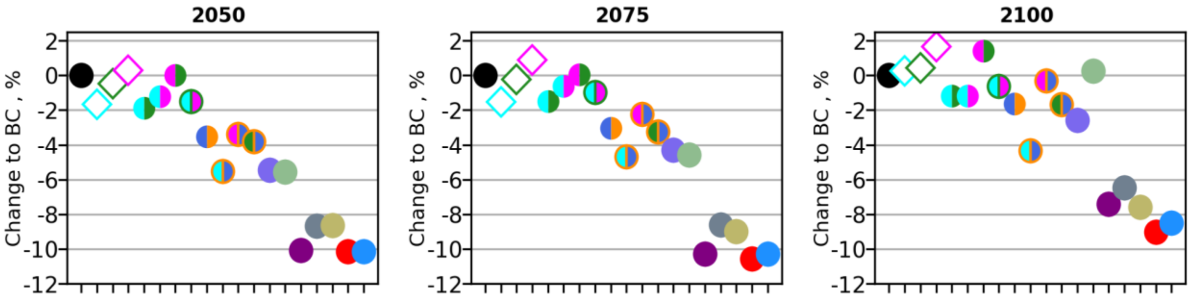
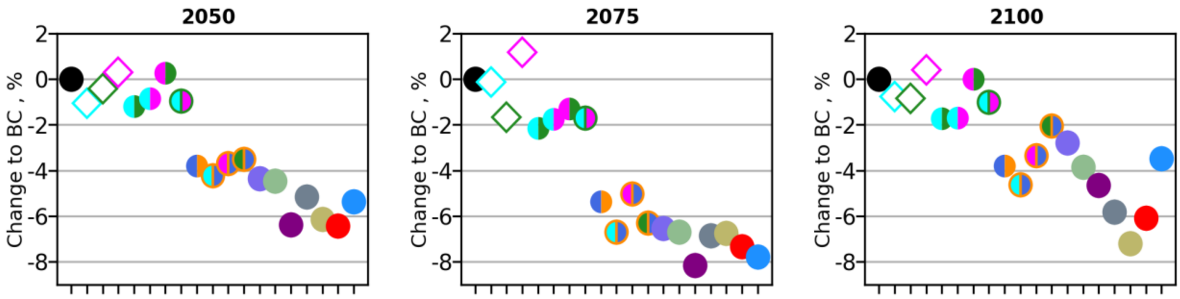
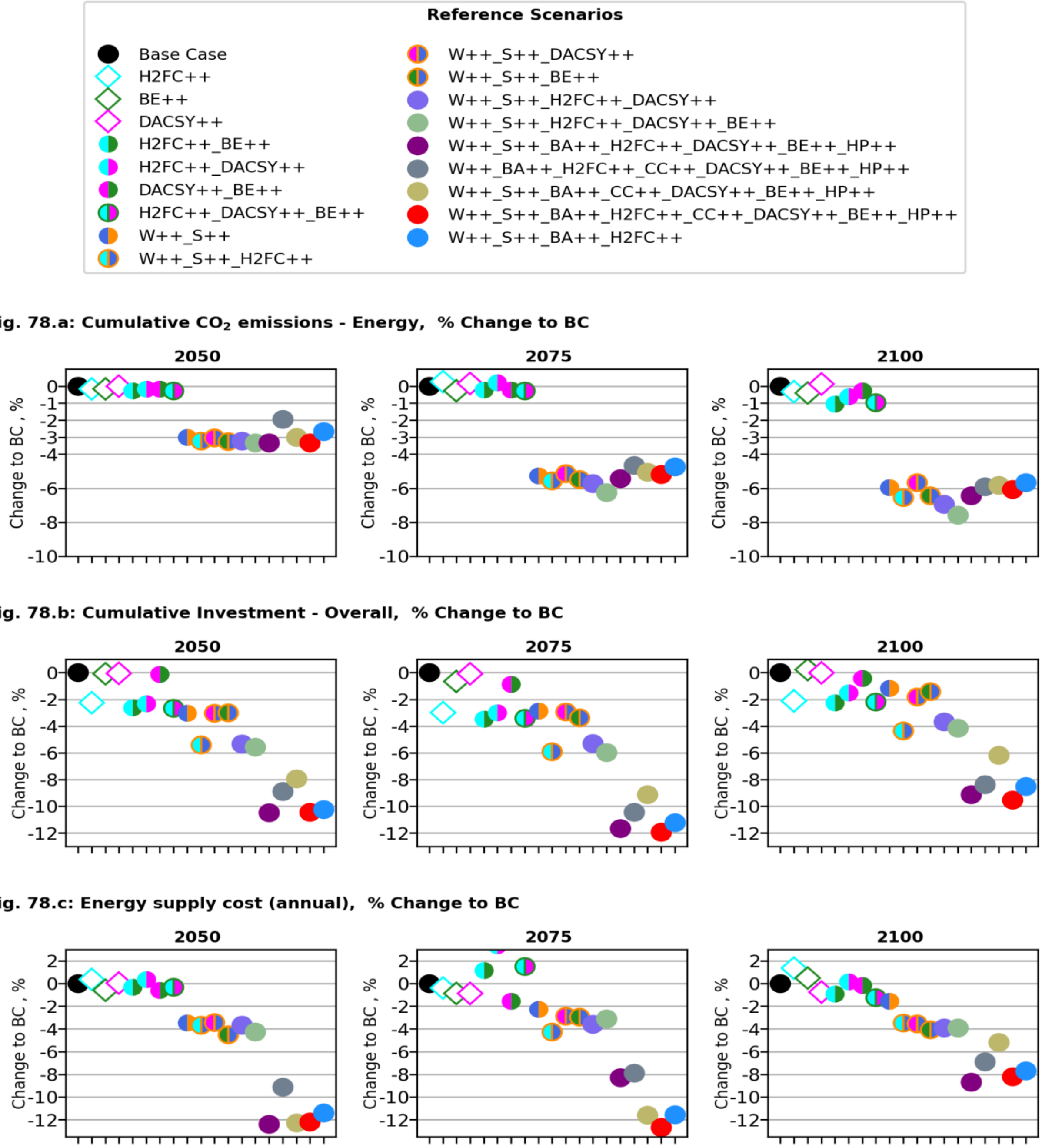


Fig. 77.c: Energy supply cost (annual), % Change to BC



Source: POLES-JRC model

Figure 78. Impacts for enhanced learning combinations related to comprehensive learning strategies under the *Reference scenario*.



Source: POLES-JRC model

3.4 Sensitivity analysis

This section presents a systematic analysis of enhanced learning combinations from the eight technology groups. A large number of possible combinations are analysed to assess their overall impacts and corresponding technology composition.

3.4.1 Methodology and analysis

3.4.1.1 Combinations and scenario variants

Combinations of enhanced learning under both the *2°C scenario* and the *Reference scenario* are analysed in this section. For each of the scenarios, two complete ensembles of enhanced learning combinations are analysed which contain uniformly either moderately enhanced learning (*+*) or highly enhanced learning (*++*).

Several possibilities exist to combine a subset of *k* technology groups out of the eight technology groups. **Table 4** provides an overview of the number of possible combinations (central column) for combining a subset of *k* technology groups (left column). For each learning level (*+* or *++*) exist a complete ensemble of in total 255 combinations. As a result, four complete ensembles of combinations with in total 1020 scenario variants are considered.

Mixing of learning levels (*+* or *++*) within the combinations were not considered for this sensitivity analysis as the number of possible combinations (6561 combinations per scenario case) would have exceeded the available computation resources while not contributing to the understanding of enhanced learning consequences.

Table 4. Number of combinations: base case and scenario variants.

k-subsets (number *k* of technology groups)	**Number of combinations** (learning level *+* or *++*)	**Scenario variations** (2°C and Reference scenario for learning level *+* or *++*)
0 (base case)	1	2 (base cases Ref. & 2°C)
1	8	32
2	28	112
3	56	224
4	70	280
5	56	224
6	28	112
7	8	32
8	1	4
Total	**256**	**1022**

3.4.1.2 Graphical analysis

In the following sections a special graphical representation is used to analyse the impacts of an ensemble of enhanced learning combinations. This graph is divided into two sections: the *upper section* displays the impact of enhanced learning combinations, while the *lower section* illustrates the corresponding technology composition.

Technically, the *upper section* is a histogram showing the frequency distribution of combinations by relative change to the base case, binned within intervals which are subdivided by the k-subsets (1 to 8) of technology groups. While the *lower section* illustrates technology composition (as percentage) of a technology being part of the corresponding k-subsets (1 to 8) of technology groups in the *upper section*.

This graphical representation aims to provide a clear and intuitive link between the impacts and its underlying technology composition.

3.4.2 CO_2 emissions

3.4.2.1 Cumulative energy-related CO_2 emissions

Highly enhanced learning combinations
The relative impact of all the combinations for *highly* enhanced learning on cumulative energy-related CO_2 emissions until 2050 and 2100 is illustrated in **Figure 79** and **Figure 80**, respectively.

<u>2°C scenario</u>
Under the *2°C scenario*, by 2050 the best-performing combinations of highly enhanced learning achieve reductions of cumulative energy-related CO_2 of slightly more than 2% (**Figure 79.a**, top). By 2100 the best-performing combinations achieve more than 5% energy-related emission reductions (**Figure 80.a**, top, two upper intervals).

The technology composition comprises at least five technology groups for the best-performing technology combinations by 2050 and 2100 under the 2°C scenario (**Figure 79.a** and **Figure 80.a**, bottom). Moreover, the technology composition is rather balanced throughout the eight technology groups. Conversely, the low-performing technology combinations tend to contain a small number of technology groups.

However, combining many technologies does not result necessarily in the best results. For instance, **Figure 80.a** (top) reveals that by 2100 the combination applying uniformly enhanced learning from all technology groups (*W++_S++_BA++_H2FC++_CC++_DACSY++_BE++_HP++, k=8* in the -6% to -5% interval) is outperformed by some combinations consisting of merely seven technology groups (see **Figure 80.a**, top).

Notably, second-best performances can be achieved by concentrating on four or fewer technology groups. For instance, by 2100 several combinations reducing energy-related CO_2 emissions by 4-5% consist of merely two to four technology groups. Among these technologies, wind power stands out, followed by Direct Air Capture (DAC) and synfuels, as well as bioenergy, albeit to a lesser extent.

Highly enhanced wind learning (*W++*) plays an important role in reducing emissions throughout the century as it is predominantly represented in the better performing intervals, and absent or sparely represented in the two lowest performing intervals (**Figure 79.a** and **Figure 80.a**, bottom). Highly enhanced learning for DAC and synfuels (*DACSY++*) becomes more important in the second half of the century for reducing emissions as it is absent in the two lowest performing intervals.

<u>Reference scenario</u>
Under the *Reference scenario* (**Figure 79.b** and **Figure 80.b**), the relative emission reductions for the best-performing combinations of highly enhanced learning are more pronounced compared to the *2°C scenario*. The

best-performing combinations achieve under the *Reference scenario* reductions of 3-4% by 2050 (**Figure 79.b**, top). By 2100, best-performing combinations under the *Reference scenario* achieve eductions of 6-7%, but for substantially more combinations than under the *2°C scenario*.

Under the best performing combinations of highly enhanced learning for the *Reference scenario* wind and solar are predominantly represented.

Moderately enhanced learning
Evidently, emission reductions are substantially smaller for moderately enhanced learning for both, the *2°C scenario* and the *Reference scenario* (**Figure 99** and **Figure 100** in AN 4.1).

Under the best-performing combinations of the *2°C scenario* until 2050 wind, bioenergies and heat pumps are influential (**Figure 99.a**, bottom). Whereas by 2100 the technology composition of the best-performing combinations is rather balanced (**Figure 100.a**, bottom).

Under the best-performing combinations of the *Reference scenario* until 2050 wind, solar and, to a lesser extent, heat pumps are prominently represented (**Figure 99.b**, bottom). Whereas by 2100 wind, solar, bioenergies, and hydrogen and fuels are influential, but not heat pumps anymore (**Figure 100.b**, bottom).

Preliminary conclusion
The most effective learning strategies for reducing energy-related CO_2 emissions in the long term is to boost learning across a broad range of clean energy technologies. This approach leverages additive effects from progress in multiple technologies and creates synergies between them, leading to significantly greater overall impact.

In the coming decades, boosting learning of established and dynamic technologies with high learning rates can yield significant additional emission reductions. Wind power, in particular, stands out in this category. Solar, hydrogen, and fuel cell technologies also fall into this category, although their impact is somewhat limited.

However, for emerging technologies with high long-term potential, such as Direct Air Capture (DAC) and synfuels, boosting learning in the coming decades is crucial to unlocking substantial additional impact in the longer term.

Figure 79. Relative impacts on **cumulative energy-related CO_2 emissions by 2050** of **highly** enhanced learning (**++**) variations under the *2°C* and *Reference scenario*.

Fig. 79.a: Cumulative energy-related CO_2 emissions - 2°C scenario - 2050 - ++

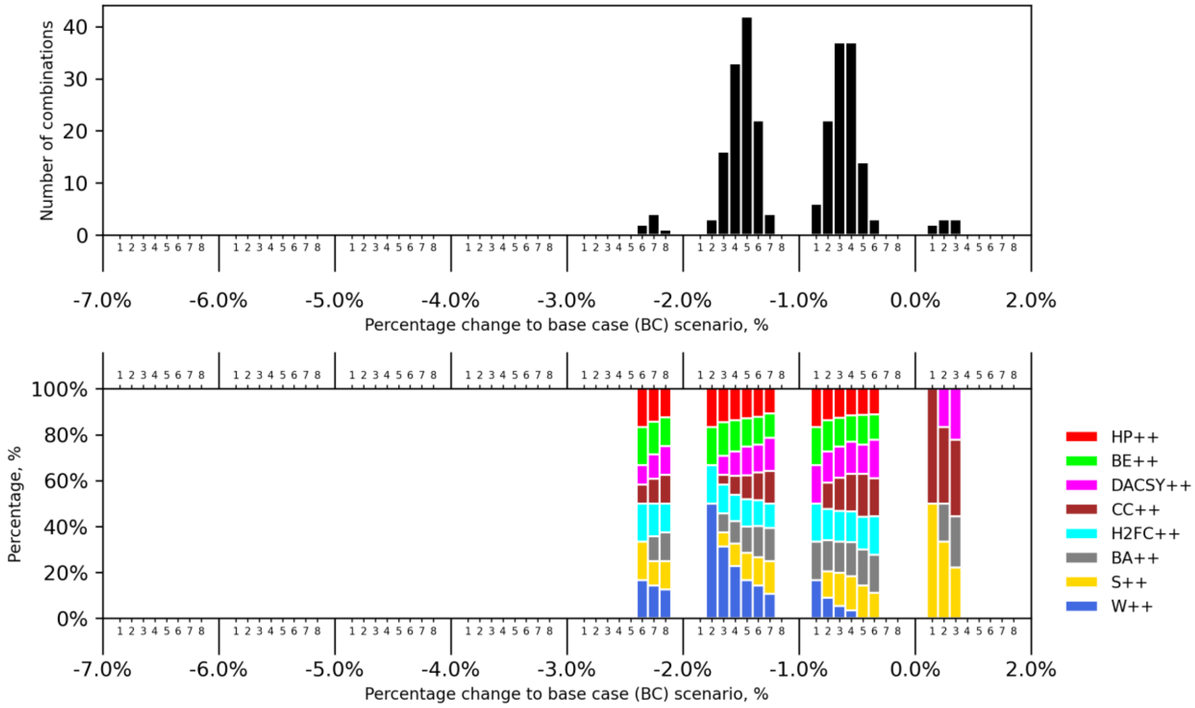
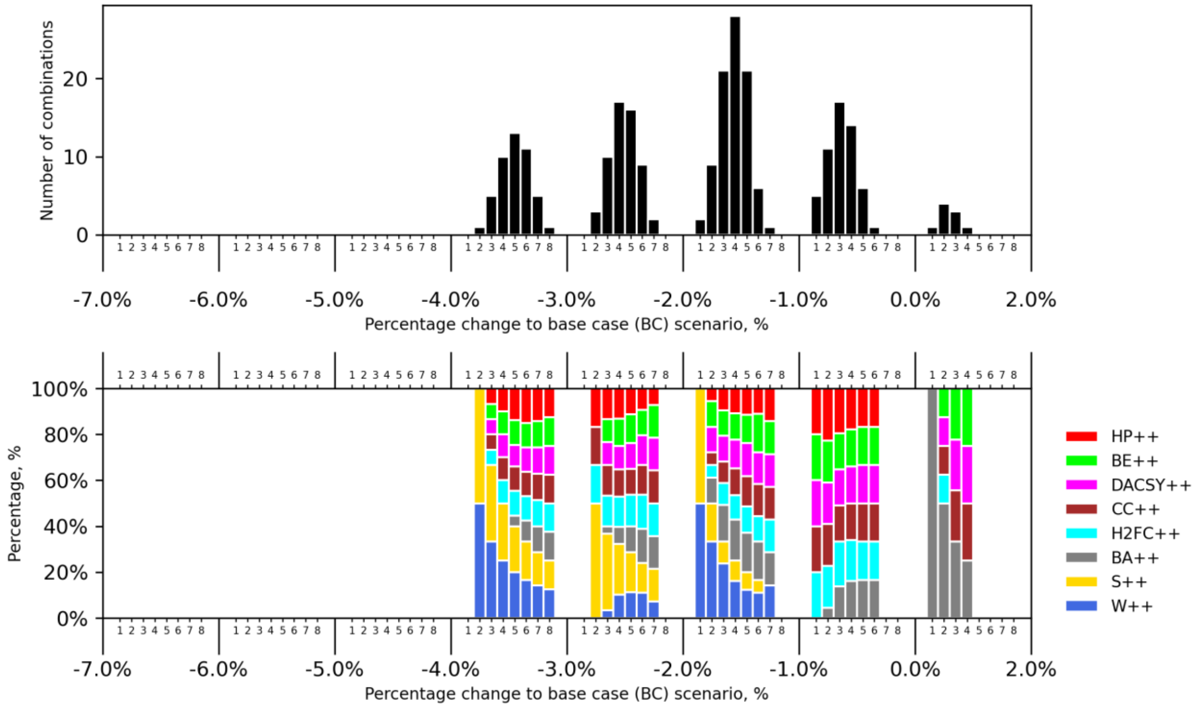
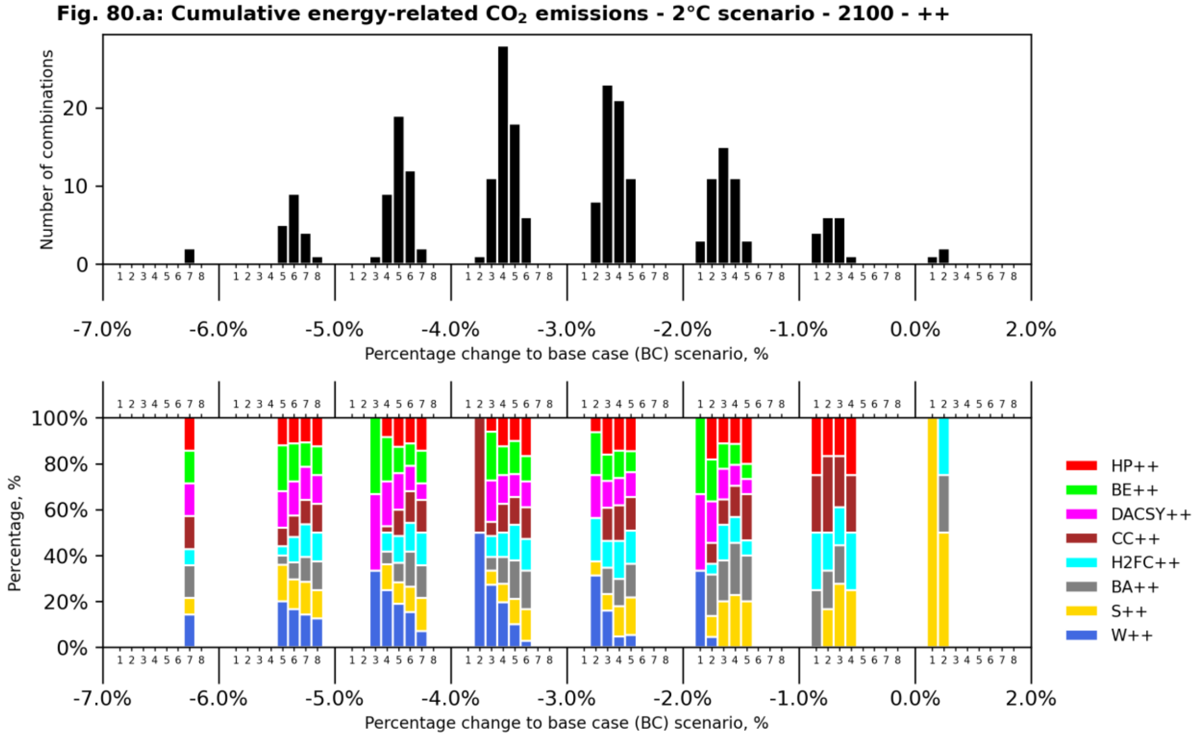


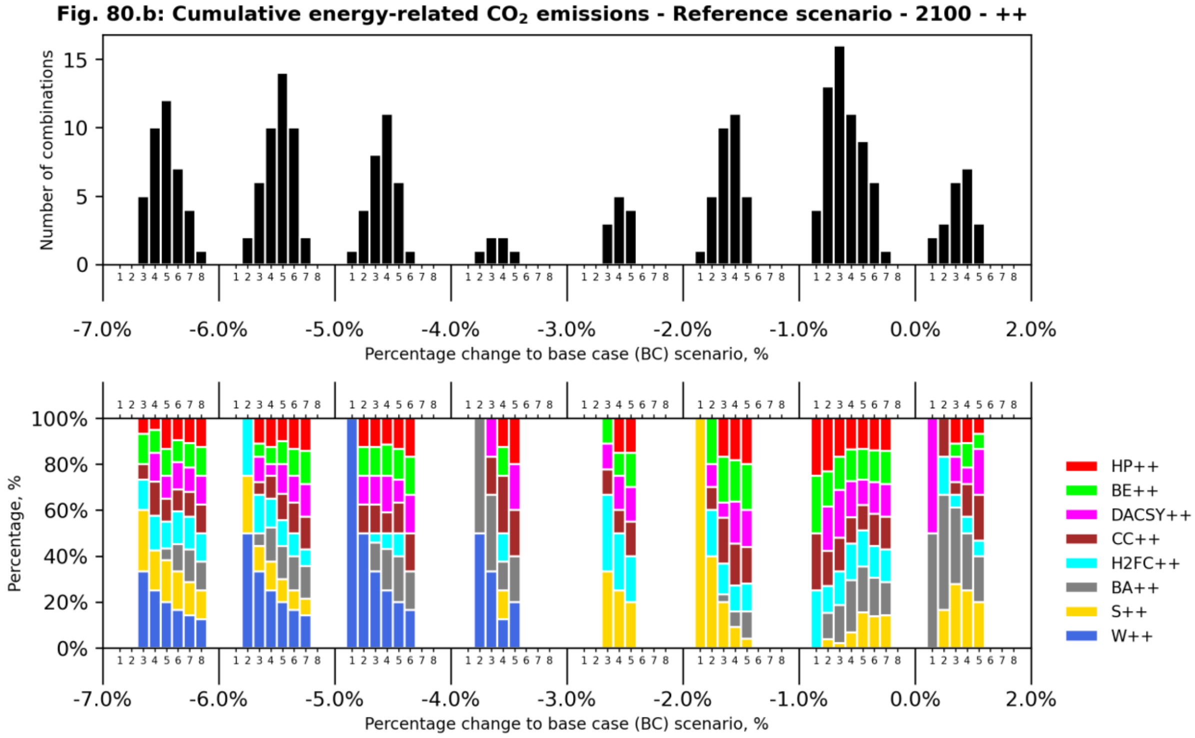
Fig. 79.b: Cumulative energy-related CO_2 emissions - Reference scenario - 2050 - ++



Source: POLES-JRC model

Figure 80. Relative impacts on **cumulative energy-related CO_2 emissions by 2100** of **highly** enhanced learning (**++**) variations under the *2°C* and *Reference scenario*.





Source: POLES-JRC model

3.4.2.2 *Cumulative CO_2 emissions*

The underlying research question of this study is to which extent enhanced learning of clean energy technologies could reduce emissions and contribute to closing the gap to the *2°C* and *1.5°C* objectives.

The cumulative CO_2 emissions for the *Reference scenario* and the *2°C scenario* correspond to the carbon budgets in 2100 as illustrated in **Figure 61.d**. For the base cases of the *Reference scenario* the cumulative CO_2 emissions amou*nt* to 2700 Gt_{CO2} and for the *2°C scenario* to 1170 Gt_{CO2} (Section 3.1.1.2). Verified with MAGICC these scenarios are below 3°C and likely below 2°C, respectively. The indicator cumulative energy-related emissions, which is used in the previous sections, accounts for the vast majority of overall CO_2 emissions. Consequently, the impacts of enhanced learning rates on overall cumulative CO_2 emissions is smaller than its impact on cumulative energy-related CO_2 emissions.

Reference Scenario

The best-performing combinations of highly enhanced learning can achieve about 6-7% reduction in cumulative CO_2 emissions by 2100 under the *Reference scenario* (**Figure 81.b**) Whereas for moderately enhanced learning, the best-performing combinations can yield reductions of 3-4% in cumulative CO_2 emissions by 2100 (**Figure 82.b**). In absolute terms, the best-performing combination for highly enhanced learning can achieve a reduction of around 163-190 Gt_{CO2} by 2100.

However, this reduction represents only a small fraction of the overall emissions gap: the *Reference scenario*'s cumulative CO_2 emissions exceed those of the *2°C scenario* by around 1530 Gt_{CO2}. As a result, even in the best case, enhanced learning can only account for about 12% of the required emissions reductions to meet the 2°C objective under the Reference scenario.

2°C scenario

From the perspective of the *2°C scenario*, an additional reduction of around 930 Gt_{CO2} is needed to reach the 1.5°C objective (corresponding to 240 Gt_{CO2}, Section 3.1.1.2).

The best-performing combinations can achieve a maximum decrease in cumulative CO_2 emissions of 5-6% with highly enhanced learning (**Figure 81.a**) and 3-4% with moderately enhanced learning (**Figure 82.a**) by 2100 under the 2°C scenario. The best performing combination achieves an absolute reduction of approximately 65 Gt_{CO2} of cumulative CO_2 emissions by 2100. Consequently, enhanced learning can contribute in the best case, to about 7% of the emission reductions required to bridge the gap between the *2°C* and the *1.5°C* objective.

Preliminary conclusion

Under the 2°C scenario, enhanced learning within the scope of this study could contribute, in the best case, to approximately 7% of the emission reductions required to align with the 1.5°C objective.

In the scenario without stringent climate policies (*Reference scenario*), merely about 12% of the emission reductions required to reach the 2°C target can be achieved by enhanced learning within the study's scope.

Figure 81. Relative impacts on **cumulative CO_2 emissions by 2050** of **highly** enhanced learning (**++**) variations under the *2°C* and *Reference scenario*.

Fig. 81.a: Cumulative CO_2 emissions - 2°C scenario - 2050 - ++

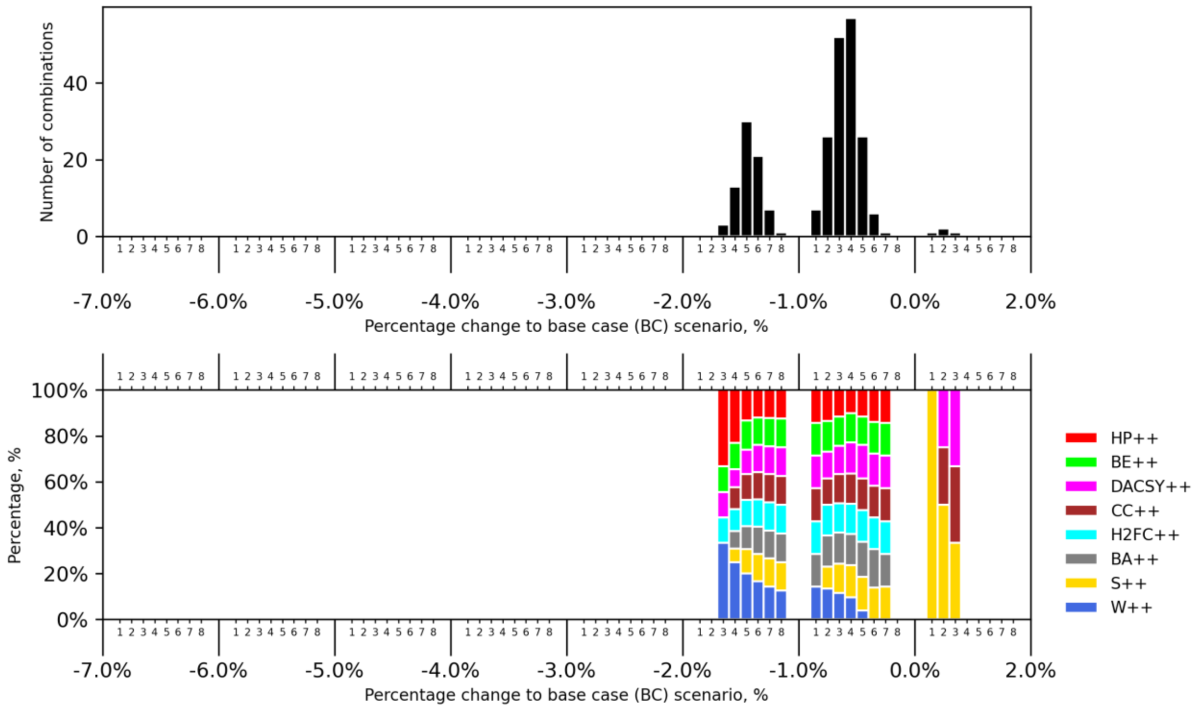
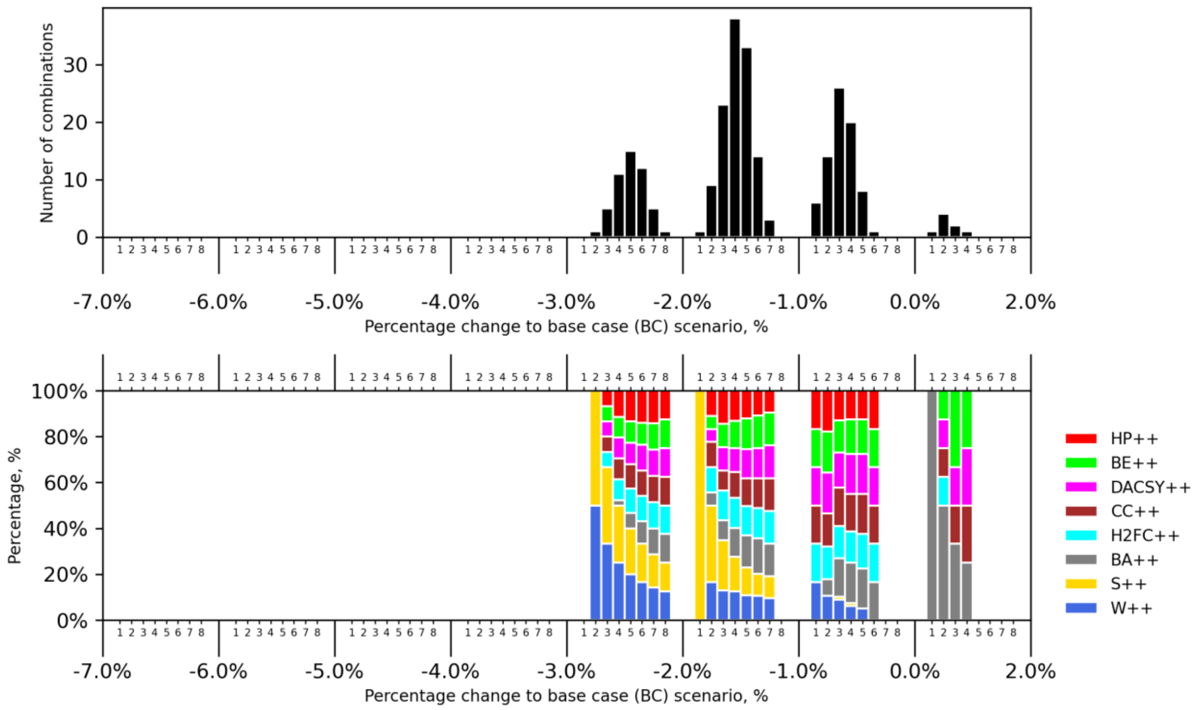


Fig. 81.b: Cumulative CO_2 emissions - Reference scenario - 2050 - ++



Source: POLES-JRC model

Figure 82. Relative impacts on **cumulative CO_2 emissions by 2100 (i.e., carbon budget)** of **highly** enhanced learning (**++**) variations under the *2°C* and *Reference scenario*.

Fig. 82.a: Cumulative CO_2 emissions - 2°C scenario - 2100 - ++

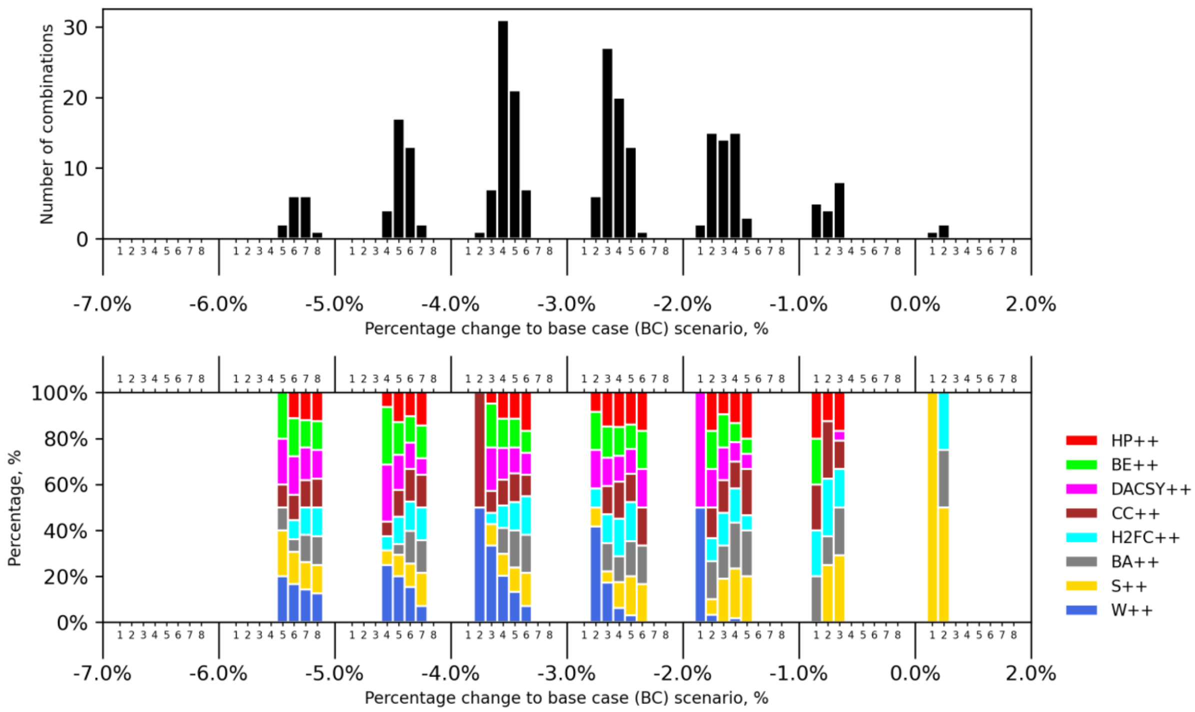
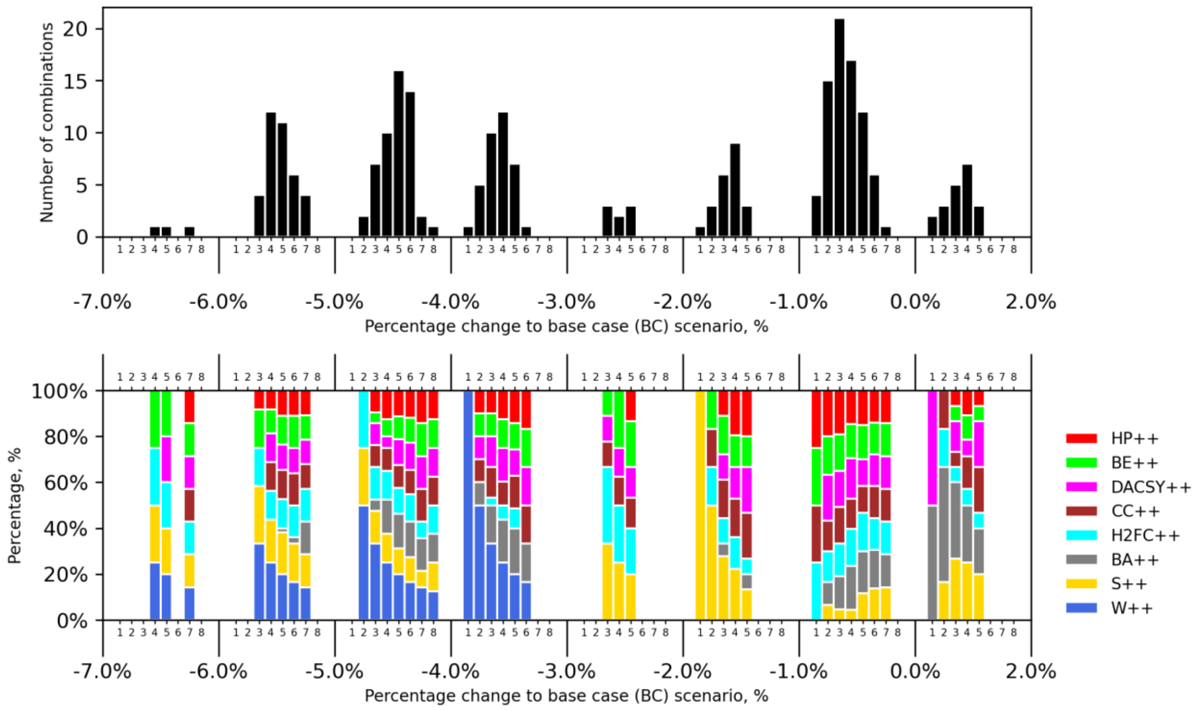


Fig. 82.b: Cumulative CO_2 emissions - Reference scenario - 2100 - ++



Source: POLES-JRC model

3.4.3 Energy-related investment needs

Highly enhanced learning combinations

The relative impact of all the combinations for highly enhanced learning on cumulative investments under the *2°C* and *Reference scenario* until 2050 and 2100 is illustrated in **Figure 83** and **Figure 84**, respectively.

By 2050, the best-performing highly enhanced learning combinations decrease cumulative investments by 10-12.5% under both, the *2°C* and *Reference scenario* (**Figure 83.a and b**). Noticeably, for both scenarios, the distributions in terms of frequency and technology combination patterns appear highly similar. In particular, the technology combination patterns of the three best-performing intervals are almost identical.

By 2100, the relative reductions in investments for the best-performing combinations for both scenarios (**Figure 84**) are smaller, merely 8-10%, as floor cost levels have been reached with highly enhanced learning for several technologies such as PV, batteries and electrolysers.

Moderately enhanced learning combinations

Under the *2°C scenario*, the best-performing combinations of moderately enhanced learning decrease investments 6-8% by 2050 (**Figure 101.a** in Section AN 4.2) but merely by 4-6% by 2100 (**Figure 102.a** in Section AN 4.2) as floor cost levels are approached.

Under the *Reference scenario*, the best-performing combinations of moderately enhanced learning decrease investment needs of the same range (6-8%) by 2050 and 2100 (**Figure 101.b** and **Figure 102.b** in Section AN 4.2) as investment costs for the main technologies have not yet approached floor cost levels.

Performance of technology combinations

Battery learning appears significantly impact reducing cumulative investments as the vast majority of its combinations fall into the three best performing intervals.

Combinations containing enhanced learning for wind, solar, battery, and hydrogen and fuel cells seem to have a significant effect on reducing cumulative investments as these combinations are predominantly represented within the two best-performing intervals.

Remarkably, combinations of *four* or even *three* technologies qualify consistently for the best-performing intervals for the afore-examined cases. Therefore, to achieve substantial reductions in investments, it can be a sufficient strategy to concentrate on merely several technologies instead of combining a broad range of technologies.

Preliminary conclusion

A notable outcome of enhanced learning is that it can overcome the economic disadvantage of higher investment needs under the *2°C scenario* compared to the *Reference scenario* (**Figure 64** in Section 3.1.2). With the best-performing highly enhanced learning combinations, investments required under the *2°C scenario* could be diminished to a level 3% below the investment needs of the base case *Reference scenario*. This finding has significant implications for the green transition. By combining highly enhanced learning in dynamic key technologies such as batteries, wind, solar, and hydrogen and fuel cells, it is possible to mitigate the substantial investment needs associated with this transition.

Moreover, the results indicate that the benefits of enhanced learning are most pronounced in the period leading up to 2050. This suggests that benefits from boosting learning between 2025 and 2050 could be harvested promptly, allowing for faster and more cost-effective progress towards a low-carbon economy.

Figure 83. Relative impacts on **cumulative investments** by **2050** of **moderately** enhanced learning (**++**) variations under the *2°C* and *Reference scenario*.

Fig. 83.a: Cumulative investments - 2°C scenario - 2050 - ++

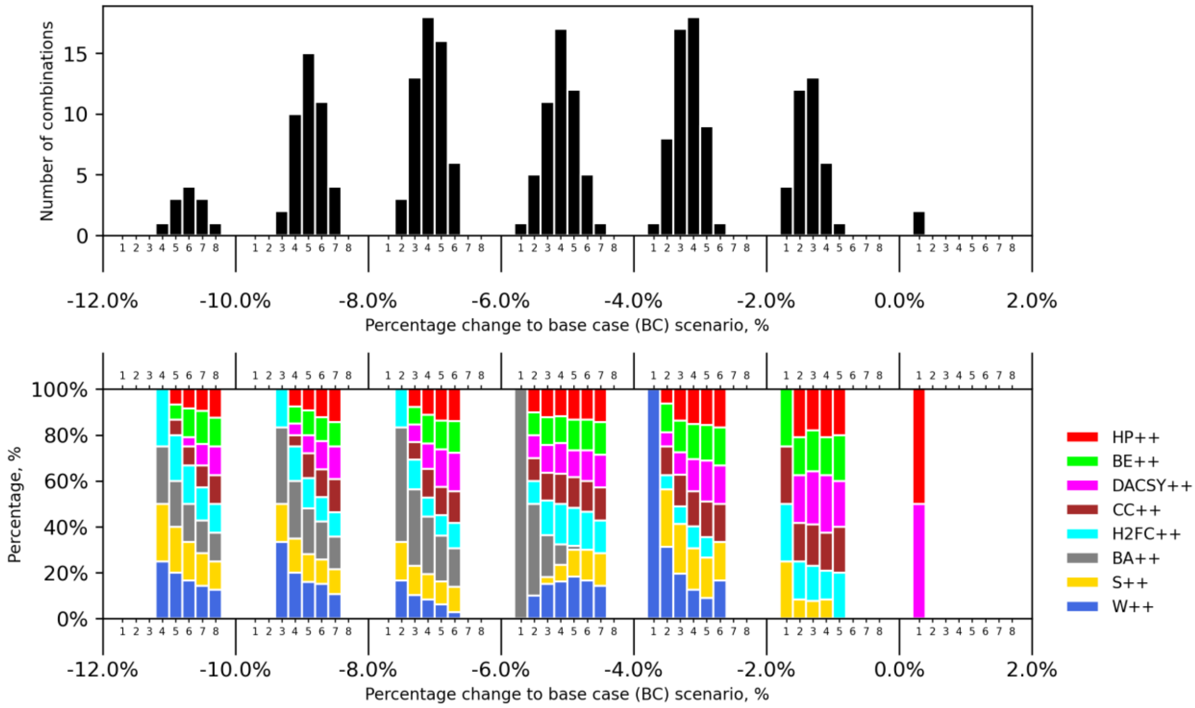
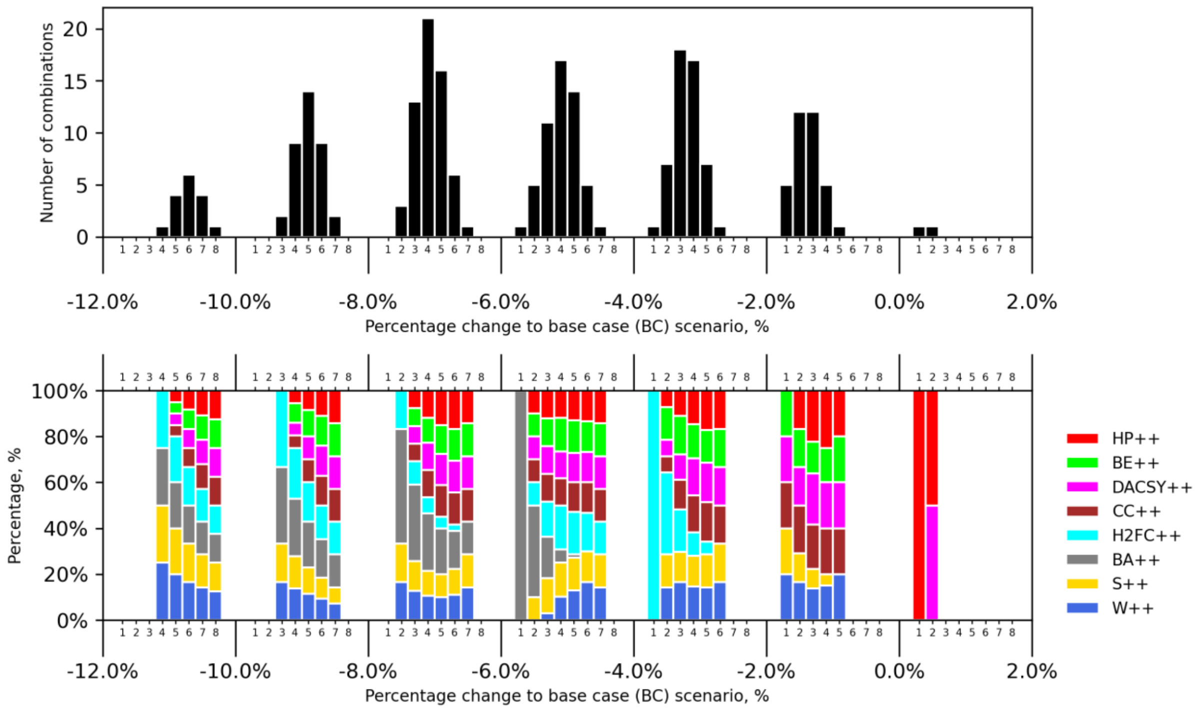


Fig. 83.b: Cumulative investments - Reference scenario - 2050 - ++



Source: POLES-JRC model

Figure 84. Relative impacts on **cumulative investments** by **2100** of **moderately** enhanced learning (**++**) variations under the *2°C* and *Reference scenario*.

Fig. 84.a: Cumulative investments - 2°C scenario - 2100 - ++

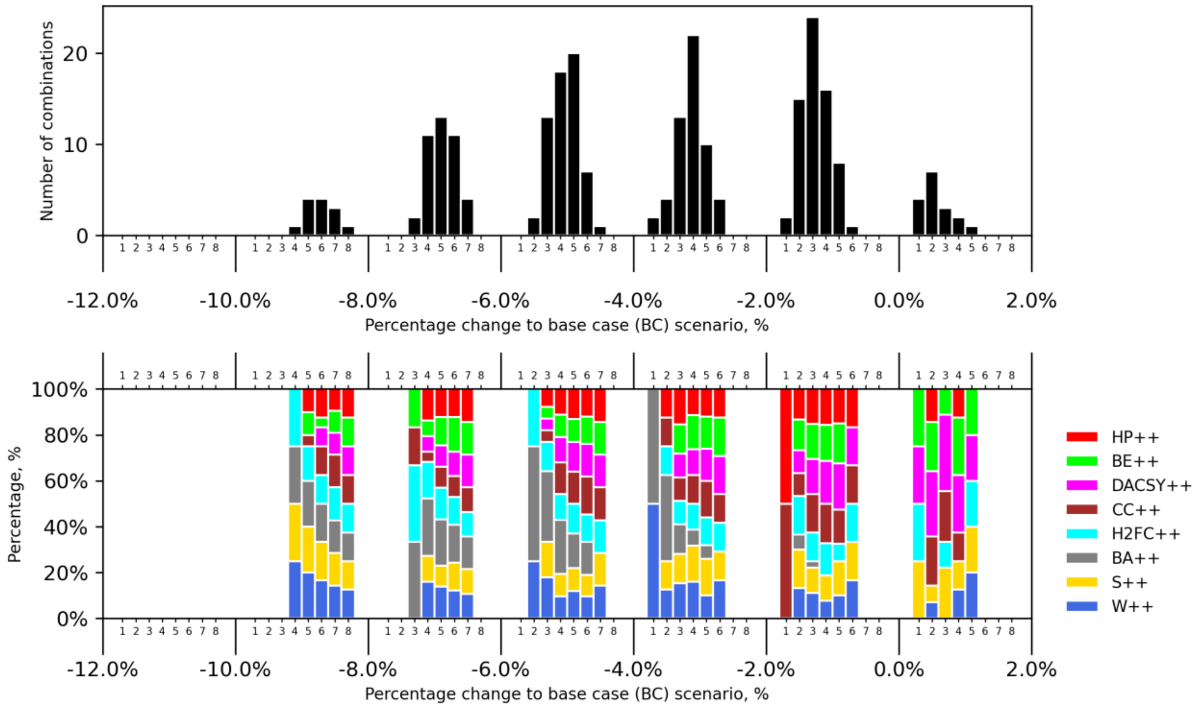
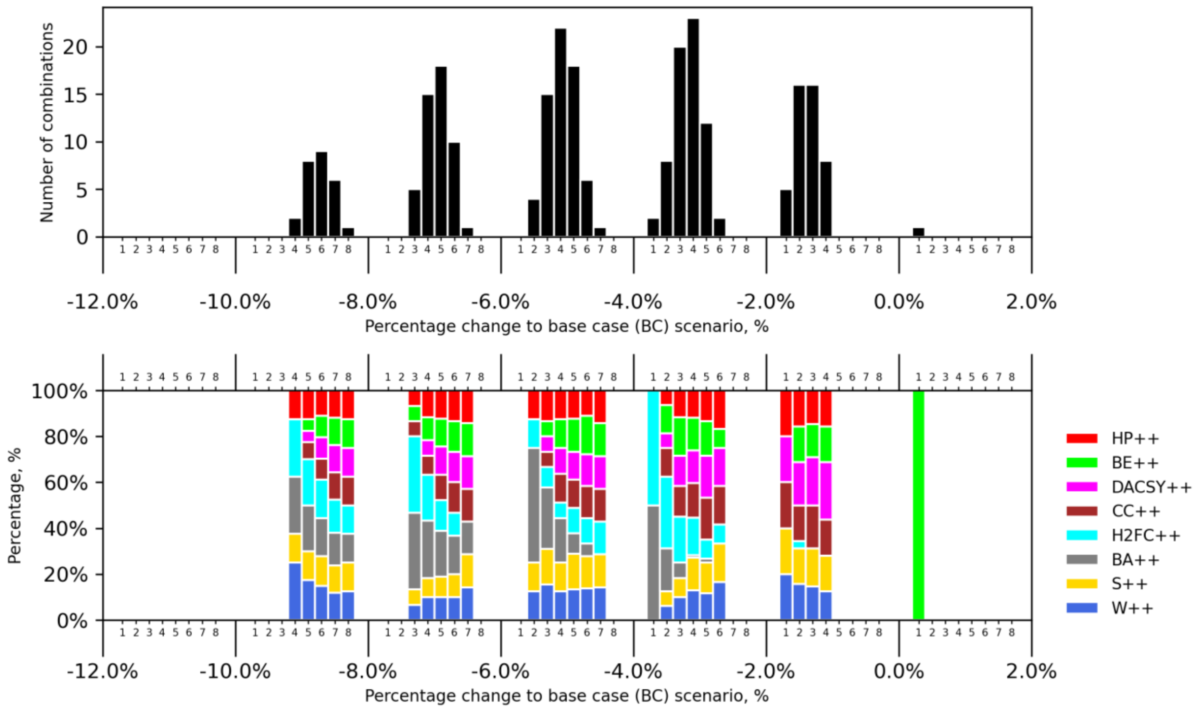


Fig. 84.b: Cumulative investments - Reference scenario - 2100 - ++



Source: POLES-JRC model

3.4.4 Energy supply costs

Highly enhanced learning combinations

The relative impact of all the combinations for highly enhanced learning on annual energy supply costs under the *2°C* and *Reference scenario* until 2050 and 2100 is illustrated in **Figure 85** and **Figure 86**, respectively.

2°C scenario vs. Reference scenario

Under the *2°C scenario*, the best-performing combinations of highly enhanced learning could reduce energy supply costs by 6-8% by 2050 and 2100 (**Figure 85**.a and **Figure 86.a**). Whereas for the *Reference scenario* the best-performing combinations have a higher impact on reducing energy supply costs, achieving reductions of 10-12.5% by 2050 (**Figure 85.b**) and still 8-10% by 2100 (**Figure 86.b**).

In relative terms, the impact of enhancing learning on energy supply cost under the *2°C scenario* is smaller than under the *Reference scenario* as the cost decreasing by learning in the *2°C scenario* has to compensate for the additional cost for the global carbon value.

Moderately enhanced learning combinations

Similarly, under the *Reference scenario*, the reduction of energy supply costs is stronger than under the *2°C scenario* for the best-performing combinations of moderately enhanced learning (**Figure 103** and **Figure 104**, Section AN 4.3). By 2100, the best-performing moderately enhanced learning combinations (**Figure 104**, Section AN 4.3) reduce energy supply costs under the *2°C scenario* by 4-6% and under the *Reference scenario* higher reductions in the range of 6-8% are achieved.

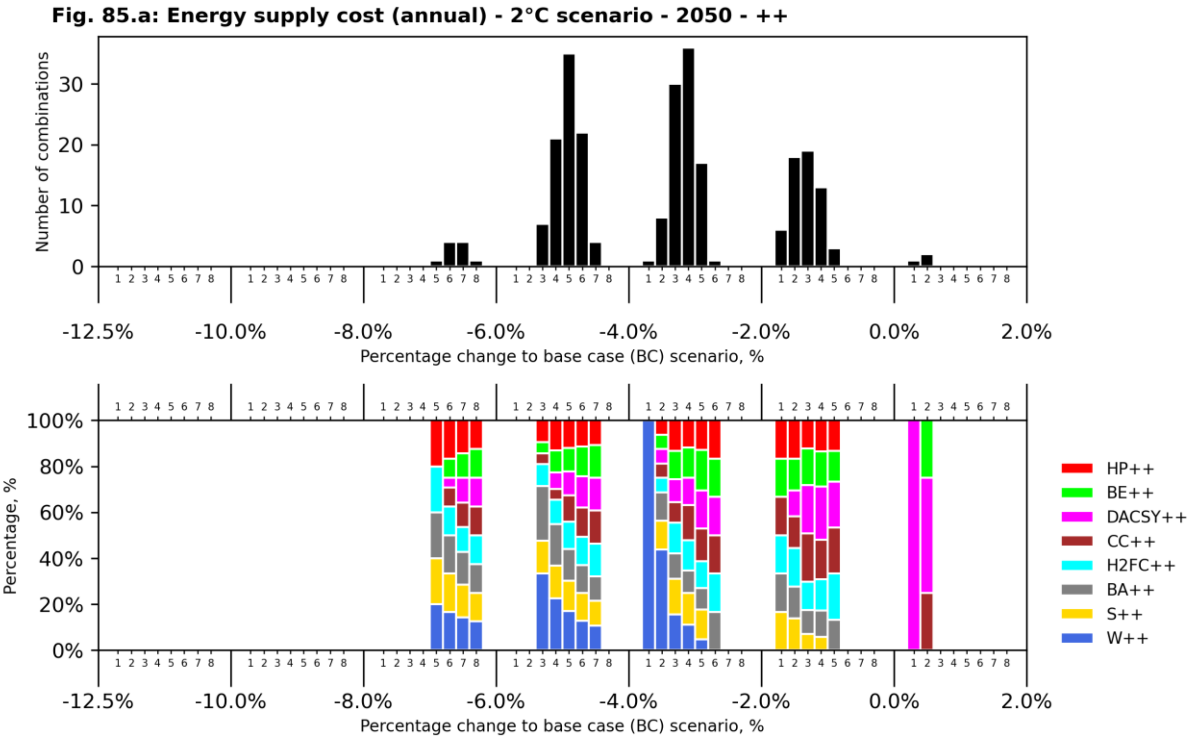
Technology composition

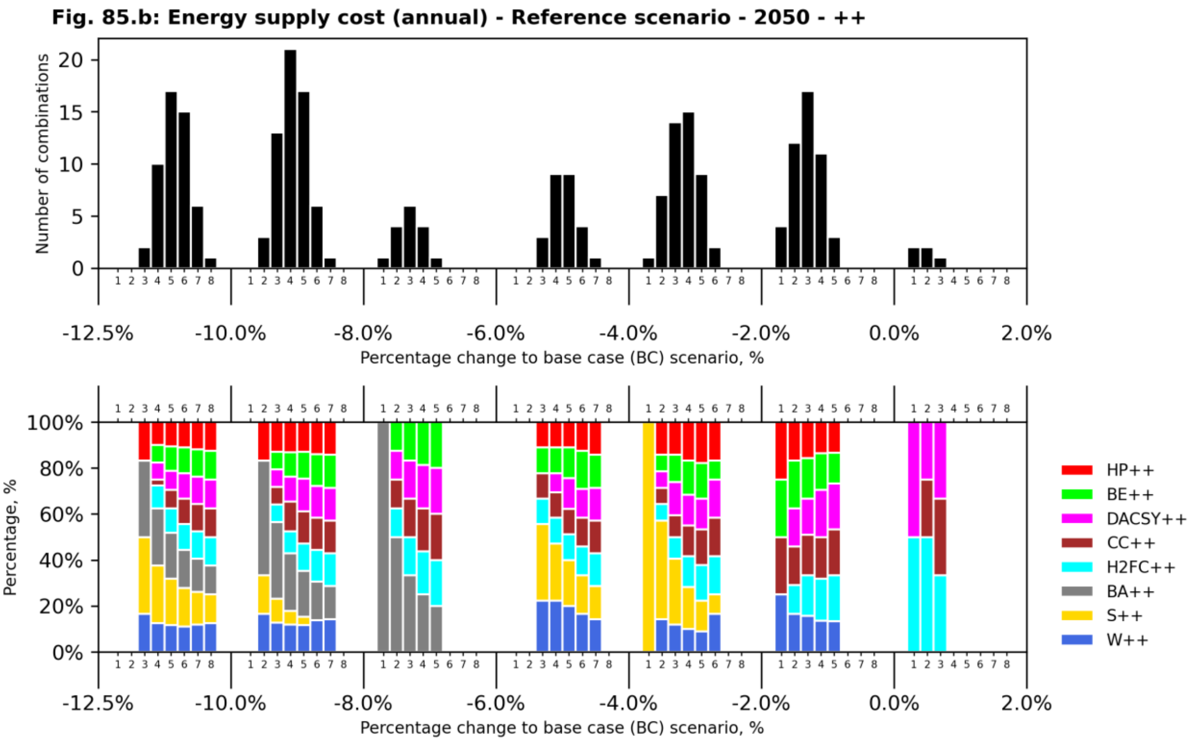
The technology compositions reveal that enhanced learning for batteries for batteries (*BA+*, *BA++*), wind (*W+*, *W++*) and solar (*S+*, *S++*) has a profound impact on reducing energy supply costs throughout the century. This finding holds for both enhanced learning levels and across both scenarios. Furthermore, under the *2°C scenario*, particularly in the first half of the century, enhanced learning for heat pumps (*HP+*, *HP++*), and hydrogen and fuel cells (*H2FC+*, *H2FC++*) also play a significant role in driving down energy supply costs.

Concluding remark

A significant benefit of enhanced learning is its potential to mitigate higher energy supply costs in the *2°C scenario*. As illustrated in **Figure 66**, the base case scenarios reveal that energy supply costs under the *2°C scenario* are approximately 10% higher than those in the *Reference scenario*. However, with the best-performing combinations of enhanced learning, more than half of this cost difference can be eliminated, significantly reducing the costs in a scenario with stringent carbon policies (*2°C scenario*).

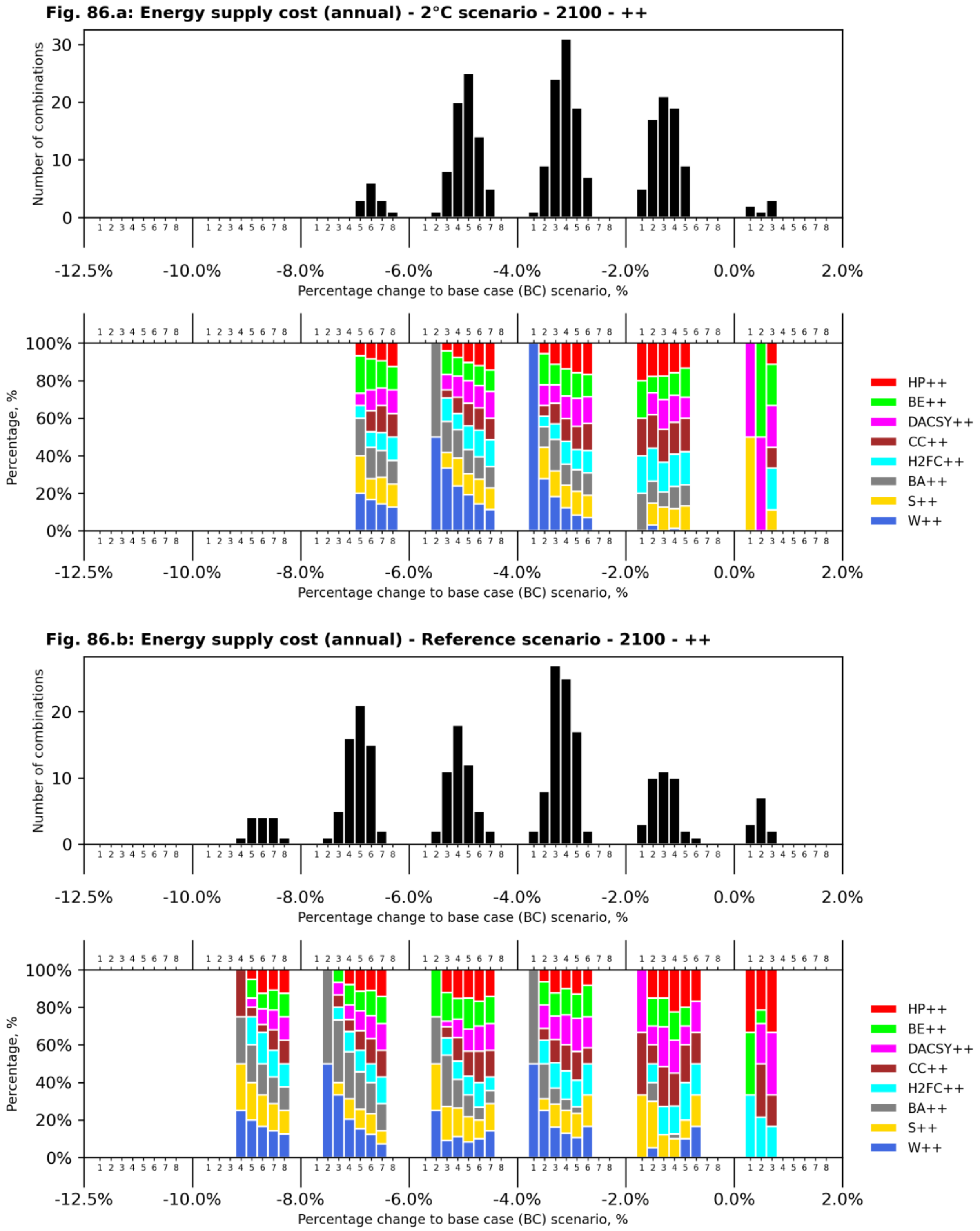
Figure 85. Relative impacts on annual **energy supply costs** by **2050** of **highly** enhanced learning (**++**) variations under the *2°C* and *Reference scenario*.





Source: POLES-JRC model

Figure 86. Relative impacts on annual **energy supply costs** by **2100** of **highly** enhanced learning (**++**) variations under the *2°C* and *Reference scenario*.



Source: POLES-JRC model

3.5 Conclusions on the overall impacts of enhanced technology learning

This chapter examined the overall impacts of enhanced learning rates on the global energy system. To this end, a range of key indicators was introduced to assess the effectiveness of enhanced learning. The elements of the analysis *unpaired technology learning*, *combination of learning strategies* and a *sensitivity analysis* were used to analyse the overall impacts.

The analysis using *unpaired technology learning* (i.e., solely within a thematic technology group) illustrated that enhanced learning for wind (*W+*, *W++*) – followed by hydrogen and fuel cell group (*H2FC+*, *H2FC++*) - have the most significant positive impact on cumulative CO_2 emissions in 2100 under both, the *2°C scenario* and the *Reference scenario*. Regarding investment needs, enhanced learning in the most dynamic technologies, such as batteries, wind, PV, and hydrogen and fuel cells, leads to significant additional reductions in cumulative overall investments compared to the base case. This is because the cost savings resulting from enhanced learning outweigh the quantity effect of expanding capacities, ultimately driving down investment needs even further.

The analysis of *combination of learning strategies* across different technology groups illustrated that the combination considering highly enhanced learning for both renewable supply technologies (wind and solar) and both demand side technologies (batteries and heat pumps), *W++_S++_BA++_HP++*, emerges as the top performer across all indicators throughout the century. By 2100, this combination yields significant benefits, including almost 4% reduction in cumulative energy-related CO_2 emissions, a 6% decrease in cumulative investments, and a 5% decrease in energy supply costs.

A combination of enhanced learning for DAC and synfuels (*DACSY++*) combined with bioenergy and hydrogen and fuel cells (*CC++_BE++_H2FC++)* achieves similar emission reduction like the renewable electrification strategy, in which enhanced learning leads to lower costs of renewable supply and demand technologies (*W++_S++_BA++*). In the case of this DAC combination, synergies emerge in the latter half of the century. These synergies emerge as enhanced learning in DAC improves the cost and efficiencies of carbon capture components, which at the same time positively affect power generation and hydrogen production using bioenergy and hydrogen technologies. Regarding investment needs and energy supply cost, capture-related combinations do not achieve cumulative investment reductions of more than 2% which is much less compared to the renewable and demand combinations.

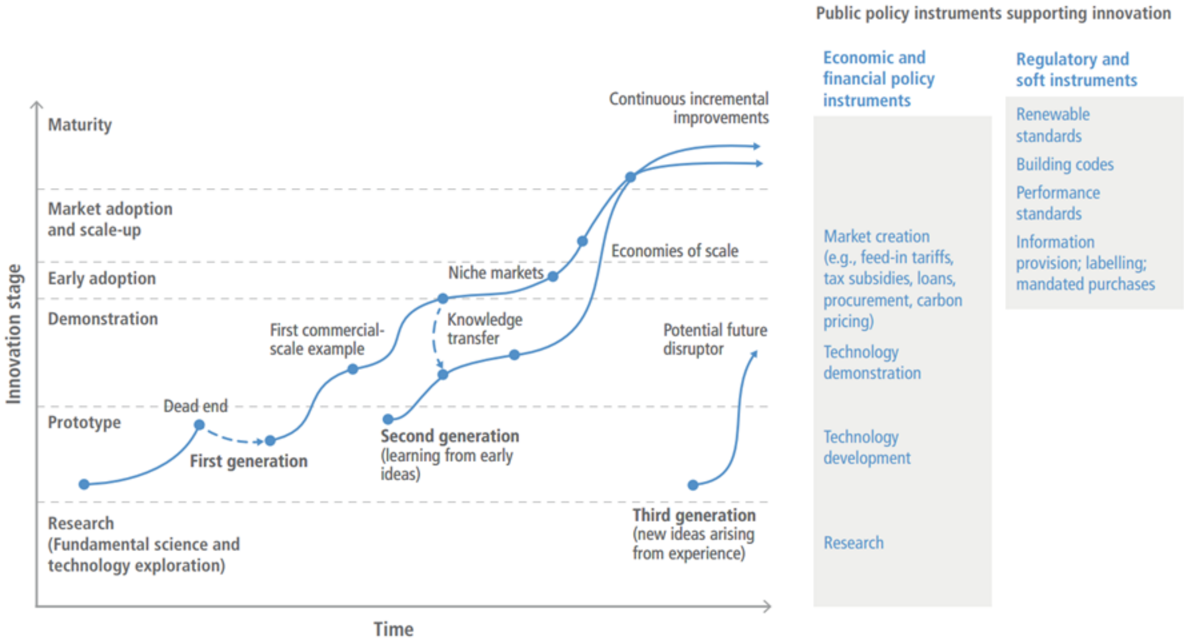
The *sensitivity analysis* of combining enhanced learning from the eight technology groups illustrates that the most effective learning strategies for reducing energy-related CO_2 emissions in the long term is to boost learning across a broad range of clean energy technologies instead of focusing on a silver bullet. This approach leverages additive effects from progress in multiple technologies and creates synergies between them, leading to significantly greater overall impact. In the *Reference scenario*, some technology groups like bioenergy, DAC, synfuels and heat pumps appear to have a lower impact on the key indicators. Main reason for this is that the global carbon value is supportive to overcome their lack of competitiveness. Overall, enhanced learning in the reference scenario has significant impacts by lowering CO_2 emissions and will deliver 12% of the gap between a 3*°C and 2°C scenario*. In the scenario with stringent climate policies (*2°C scenario*), merely about 7% of the emission reductions required to reach the 1.5°C target can be achieved by enhanced learning within the study's scope.

4 Socio-economic analysis

Energy supply investments, particularly in renewables, have been growing exponentially over the last years, anticipating an upcoming shift in the energy mix [60] and avoiding the lock-in on emissions-intensive technologies [61]. Policy support, technological development and shifting investor preferences appear to align with a strengthened ambition to deploy new technologies and effectively reduce emissions, while promoting economic activity (Keramidas et al., 2023).

Learning typically improves productivity as firms and workers become more experienced in the production process. A vast literature explores how learning affects the cost of technologies and their economic implications. Nordhaus [62] notes the growing interest in modelling of learning effects in the assessment of energy and climate policies. The learning curve is the most common framework for investigating changes in technology costs due to technological learning. Albeit the learning rates and functional forms that determine the shape of the learning curves are uncertain and sensitive to technological change rates, learning curves are able to capture the complex relationships between investments in R&D and technology adoption [63]. Learning curves have been often used in energy system models [64], and as a justification for public spending on R&D and innovation procurement to foster technology adoption [65], particularly as a support to firms in the case of technologies (e.g., CCUS, DACs) that have not yet reached full maturity. **Figure 87** illustrates the technology innovation process over time, from prototype stage until market adoption, and the roles of different public policy instruments (e.g., feed-in tariffs, subsidies, technology standards, codes) in support of innovation.

Figure 87. Technology innovation process and the illustrative roles of different public policy instruments (on the right-hand side).



Source: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [66].

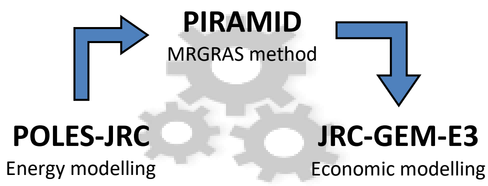
A number of studies have assessed how technological progress influences future electricity generation [11], [15], [67]–[69]. For instance, [70] conducted a comprehensive meta-analysis examining learning rates for wind power and found a large variance in the results, ranging from over 30 per cent to negative numbers. Recently, Castrejon-Campos et al. [71] investigated wind and solar PV cost developments in the US and estimated learning-by-doing rates ranging from 2.9% to 31.4% for wind onshore and from 28.3% to 40.4% for solar PV. [72] assesses the impacts of technology shocks under different policy instruments, with technology shocks modelled as a deviation from the expected learning rate, where higher learning rates reduce the cost of technology and can shift the technology mix of a certain sector e.g., from fossil-based to renewable power generation. In [72], learning rates increase from 15 % to 18.7% for wind and from 19% to 22.8% for solar under the policy shock scenario.

Given that several technologies are still in their early stages of deployment, precise estimates of learning curves become challenging due to the absence of data. In this chapter, we therefore examine the learning effects on well-established renewable power generation technologies, namely wind and solar. We use the aggregate sectors of a macroeconomic computable general equilibrium (CGE) model, JRC-GEM-E3[4] [4], to assess the effects of global energy investments throughout the supply chains over the next decades under a 2°C cost-efficient global temperature stabilisation scenario. The analysis takes a macro- and socio-economic perspective, with a specific focus on the associated supply chain effects in capital and labour, including the impacts on employment.

4.1 Modelling toolbox

This section builds on the most updated version of the modelling toolbox used in the European Commission's energy and climate policy assessments [73], covering the impacts on the energy system and over multiple sectors, and the corresponding macro-economic effects, including employment. **Figure 88** presents the modelling toolbox, portraying the connection between the bottom-up energy system and top-down global economic modelling through the PIRAMID tool [74].

Figure 88. Modelling toolbox. Bottom-up energy system and top-down global economic modelling combined.



Source: JRC-GEM-E3 model.

As described in Section 1.1, the POLES-JRC model is a global partial equilibrium simulation model of the energy sector, covering a wide range of activities from upstream production to final user demand [75]. The model describes how multiple energy resources are put into production, resulting in trade flows from producers to consumers (for oil, gas, coal, bioenergy, hydrogen), and providing full energy and emission balances for 66 countries and regions worldwide.

JRC-GEM-E3 is a multi-regional, multi-sectoral, recursive dynamic CGE model [4]. The model has been extensively used for climate and energy policy analysis and impact assessment, being particularly valuable in capturing the effects of the transformation of the energy system and of climate-related policies over the macroeconomic aggregates, including the effects on employment [73], [76]–[78].

The PIRAMID tool [74] links the POLES-JRC and JRC-GEM-E3 models, reconciling the economic structure derived from the Global Trade Analysis Project (GTAP) 10 Power database [79], [80] with the energy balances provided by POLES-JRC. The PIRAMID tool is based on the multi-regional generalised RAS method [81], which ensures that the JRC-GEM-E3 is aligned with the energy use and GHG emissions as projected in POLES-JRC, so that the projected input-output tables provide a fully consistent baseline scenario.

The starting point of the analysis is to construct the *Reference scenario* (**REF**). To this end, we use the PIRAMID/CGE combination and input-output tables based on GTAP's initial base year (2014). The *REF scenario* is constructed by projecting multiregional input-output tables forward in time and calculate indicators covering the entire value chain of a good or service for future years. The projections for economic activities, energy use and emissions are harmonised with POLES-JRC, so that the economic starting point for the analysis closely resembles that of the base case *Reference scenario* of POLES-JRC as presented in section 1.2.

[4] For more details about the JRC-GEM-E3 model, such as publications and documentation, please refer to: https://joint-research-centre.ec.europa.eu/scientific-tools-and-databases/jrc-gem-e3-model_en

Because the JRC-GEM-E3 represents sectors with a lower level of technology detail than POLES-JRC, we use it to simulate two policy scenarios:

- **2°C BASE CASE**: This policy scenario refers to the base case *2°C scenario* (POLES-JRC) as presented in Section 1.2 but as interpreted in JRC-GEM-E3 (the soft-link approach is described below).
- **2°C RES**: This policy scenario refers to the variant of the *2°C scenario* (POLES-JRC) as interpreted in JRC-GEM-E3 with highly enhanced learning for wind and solar technologies (*W++_S++*). The overall impacts of this learning combination are analysed in Section 3.3.1.1 and illustrated in **Figure 73** in terms of cumulative CO_2 emissions, cumulative energy-related investment costs and energy supply costs according to the results from the POLES-JRC model.

In the scenarios, we use a soft-link approach to impose transitions projected in POLES-JRC to the JRC-GEM-E3 model. In this approach, we adjust the parameters that describe the decarbonisation of key energy sectors (e.g., electricity, transport, buildings), taking into account additional costs (e.g., from higher capital expenses). By doing so, we consistently reflect the technological shift and energy efficiency gains from POLES-JRC, as well as policy instruments implemented in POLES-JRC (e.g., technology standards, energy efficiency labels, codes) across these sectors. We did several improvements in the soft-link with the POLES-JRC model to better represent additional investment needs in the JRC-GEM-E3 model. For the power generation technologies, this is captured through the capital expenditures on the additional installed capacities required to reach the 2°C target. We also harmonise investments in other sectors (e.g., buildings, transport) using the capital cost from the POLES-JRC model. The technological detail from POLES-JRC differs from JRC-GEM-E3, hence as a final step to achieve the same level of CO_2 emissions from POLES-JRC in the policy scenarios, we implement a global (uniform) carbon value in JRC-GEM-E3 to capture the costs to mitigate CO_2 emissions. We use the same carbon value in both policy scenarios, allowing for a maximum difference of 1% in the total GHG emissions. Regarding employment, we project the number of workers in the energy sectors, including power generation technologies, based on employment factors (number of direct jobs per energy unit produced) from [5]. We multiply the total output of the energy sectors to calculate and project the total number of direct jobs in those sectors.

4.1.1 Modelling of learning effects in JRC-GEM-E3

The costs of power generation technologies are reduced over 2025-2050 through the learning-by-doing effects implemented in POLES-JRC. Similarly to [72], [82], in JRC-GEM-E3 we apply the learning effect on costs to the new capital stock (i.e., additions to the installed capacity of wind and solar), thus informing the JRC-GEM-E3 model that the investment decisions are based on the current productivity of a given technology.

We project the REF scenario until 2050 to further assess the socio-economic effects of reaching the 2°C target and of higher learning in power generation technologies. We compare the results of the 2°C BASE CASE scenario with a 2°C scenario in which increased learning takes effect from 2025 onwards, the 2 °C RES scenario. These policy scenarios are implemented as counterfactual to the REF scenario, resulting in an end-of-century temperature rise of below 3.0°C with a more than 66% probability.
Learning rates central values are obtained from POLES-JRC (see Annex 4) and implemented in the JRC-GEM-E3. Under the 2°C RES scenario, the rates are increased by 6.5 and 11 percentage points, respectively, to reflect the enhanced learning in JRC-GEM-E3. Although we assume that there are no deviations from the expected value of learning rates across all regions, differences in the costs of these technologies may still have an impact due to the different renewable potential across regions.

4.2 Macroeconomic impacts

Figure 89 shows the macroeconomic impacts of the policy scenarios compared to the REF scenario. Relative changes in global GDP in both scenarios are not greater than -1%, reaching -0.9% and -0.7% in the 2°C BASE CASE and 2°C RES, respectively, in 2050. In both scenarios, the decrease in GDP is driven by the reduction in private consumption, which outweighs the increase in economy-wide investment. The decrease in consumption reflects the mitigation costs needed to reduce GHG emissions and achieve a temperature increase of 2°C above pre-industrial levels by the end of the century. In both scenarios, the relative increase of economy-wide investment is driven by the expansion of renewable power generation and electricity supply. Nonetheless, as technology costs decline over time due to the learning effects (recall **Figure 15** in Section 2.1.4), the increase in investment is lower in the 2°C RES than in 2°C BASE CASE. Therefore, by design, these effects are more pronounced in the long run when the difference between the two scenarios results in a difference of 0.2 percentage points (0.8% versus 0.6%) of additional investment compared to the REF scenario in 2050.

Figure 89. Changes in global GDP and its components (investment and private consumption) in the 2°C BASE CASE (top) and 2°C RES (bottom) scenarios compared to the REF scenario over 2025-50.

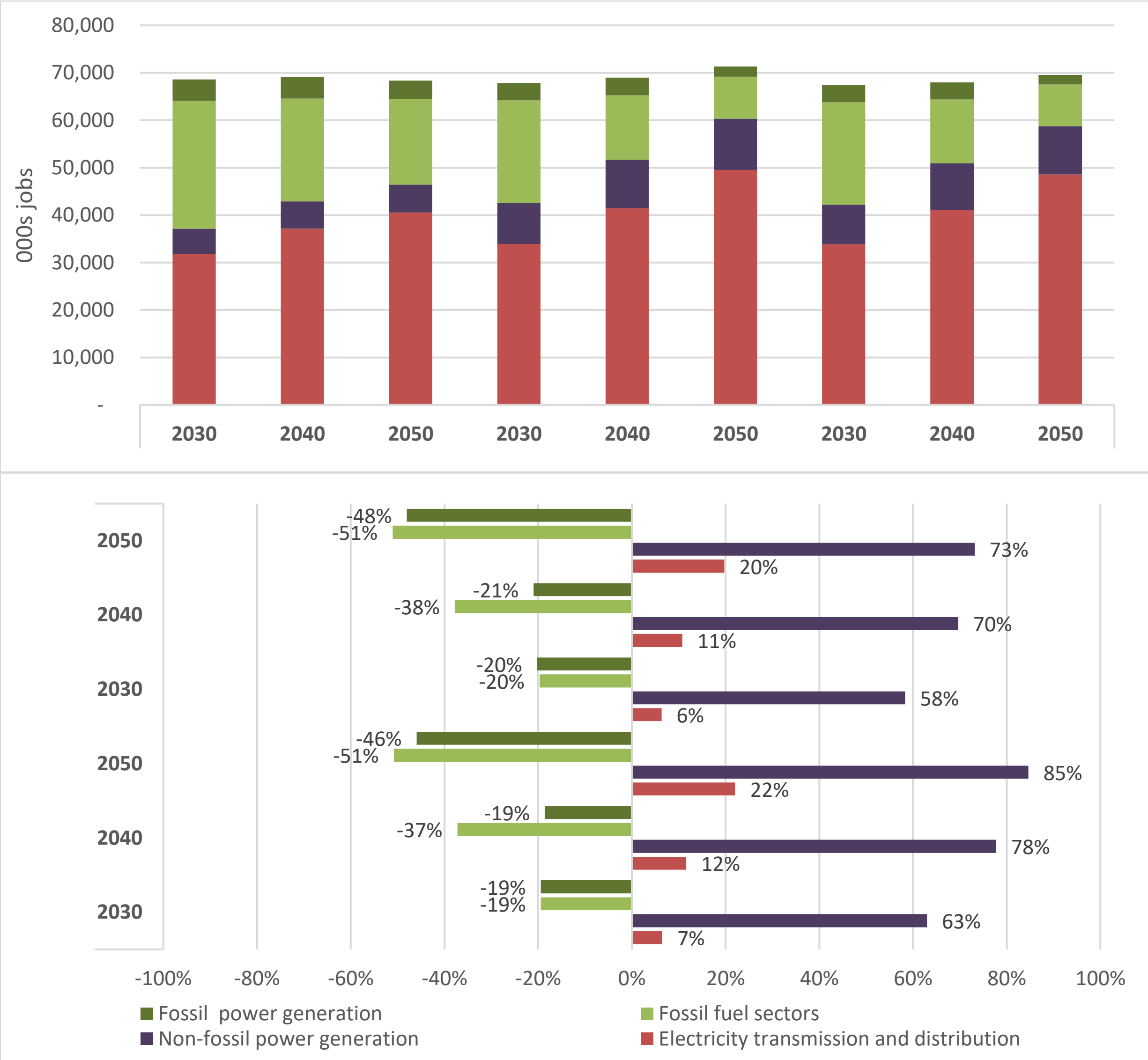
Source: JRC-GEM-E3 model.

4.2.1 Impacts on employment – electrification creates job opportunities

Figure 90 shows the evolution of employment globally in the *energy sectors* under the REF, 2°C BASE CASE and 2°C RES scenarios over 2025-50. The higher electrification rate in the 2°C BASE CASE and 2°C RES scenarios creates job opportunities in the electricity transmission and distribution sector, reaching 34 million jobs already in 2030 (compared to 31.8 million in the REF scenario) and about 49 million jobs in 2050 (compared to 40 million in the REF scenario, corresponding to 20-22% increase in 2050). Although increased electrification is already perceived in the REF scenario, under the 2 °C scenarios the additional 9 million jobs in the electricity transmission and distribution sector over 2030-50 contribute more substantially to reducing job losses in fossil fuel sectors (about 9.2 million jobs compared to the REF scenario, corresponding to a 51% decrease in 2050).

When looking solely at power generation sectors, the decarbonisation under the 2°C RES contributes to adding about 4.2 million jobs in non-fossil power generation compared to the REF scenario in 2050. This corresponds to an increase of 73% compared to the REF scenario, while under the 2°C BASE CASE this increase reaches 85% in 2050. The increase in the number of jobs in non-fossil power generation helps absorbing losses of about 1.8 million jobs in fossil fuel power generation in 2050 under the 2 °C scenarios, which correspond to a decrease of 46% and 48% in the scenarios of the 2°C BASE CASE and 2°C RES compared to the REF scenario.

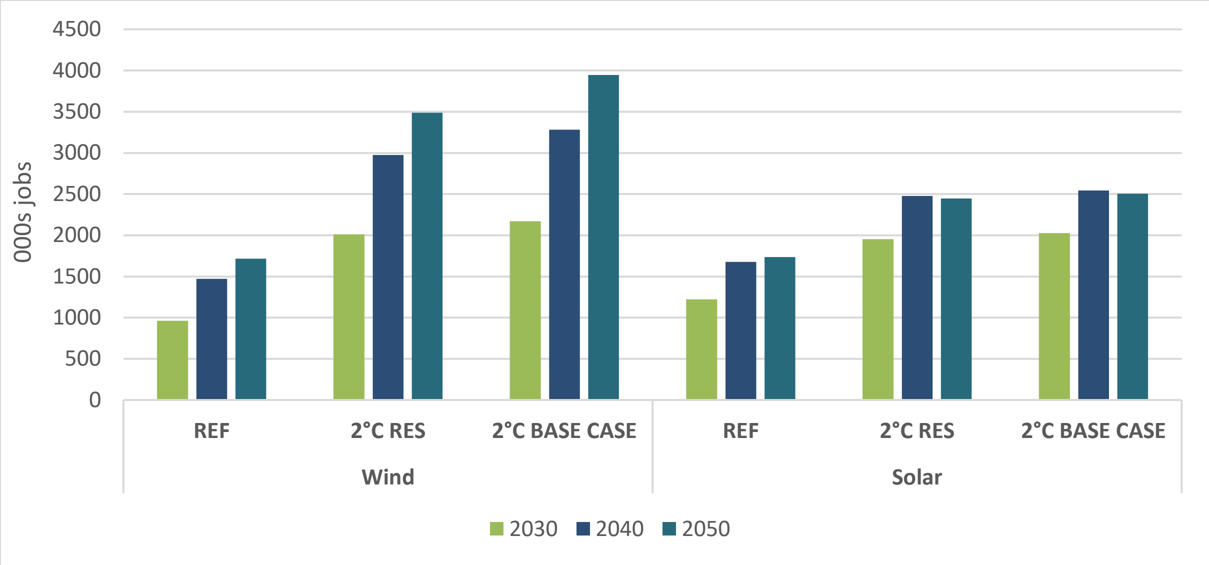
Figure 90. Absolute employment in thousand jobs (top) and relative change to Reference (bottom) in energy sectors. REF scenario, 2 °C BASE CASE and 2 °C RES scenarios over 2030-50.



Source: JRC-GEM-E3 model.

Figure 91 shows the evolution in the number of direct jobs globally in wind and solar PV power generation under the 2°C scenarios. Here, the direct jobs are those of workers involved in the operation and maintenance (O&M) of wind and solar PV power generation. Among the different renewable energy technologies, wind power generation is the one that creates the largest number of direct jobs, with an additional 2.2 million jobs in the 2° BASE CASE and 1.8 million jobs in the 2°C RES globally compared to the REF scenario in 2050. In the case of solar, there are an additional 0.8 million jobs in the 2°C BASE CASE and 0.7 million jobs in the 2°C RES globally compared to the REF scenario in 2050. The higher learning rates under the 2°C RES imply greater efficiency compared to the 2°C BASE CASE for the new (or re-powered) installed capacities of wind and solar – because the technologies are more efficient, fewer jobs per installed capacity are needed in the 2°C RES. This effect is more noticeable over time in wind power generation, with fewer workers needed – for example, less operation and maintenance (O&M) workers in a wind farm with 80 turbines versus one with 10 turbines, but with the same installed capacity. Regardless of potential shifts in the labour market that the greater efficiency of technologies may trigger, there are more jobs in the energy sectors under the 2°C scenarios compared to the REF scenario.

Figure 91. Direct jobs (in thousand workers) in wind and solar power generation in the 2°C BASE CASE and 2°C RES scenarios over 2030-50.

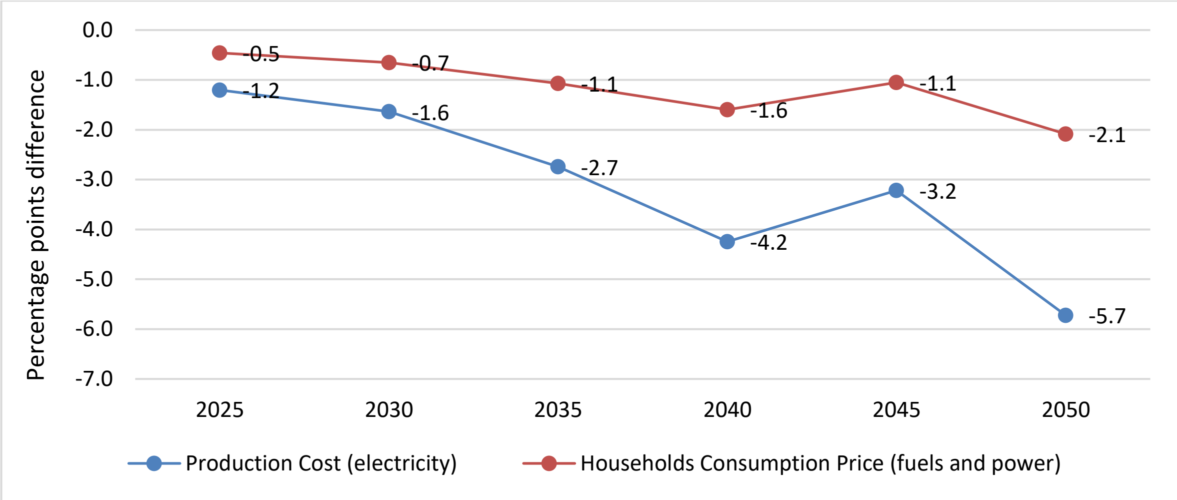


Source: JRC-GEM-E3 model.

4.2.2 Impacts in the electricity sector – the role of floor costs

Although consumers are faced with costs to mitigate GHG emissions to reach a 2°C target, the transition to an energy system with more renewables also has benefits. **Figure 92** presents the evolution of the production cost of electricity and the consumer price index for fuels and power, showing the difference in percentage points between the two scenarios (2°C RES and 2°C BASE CASE) over 2025-50. Due to the impacts of enhanced learning rates (see Sections 2.1.3 and 2.2.3), the production cost of electricity in the 2 °C RES decreases faster than in 2°C BASE CASE, reaching a floor level already by 2050. The difference in the production cost of electricity between 2°C RES and 2°C BASE CASE reaches 5.7 percentage points in 2050. The electricity consumption by households is relatively inelastic to price changes. Hence, they are positively affected by the greater reduction of the electricity price in the 2°C RES scenario. This leads to a difference in the household consumption price index for 'fuels and power' of 2.1 percentage points in 2050 between 2 °C RES and 2 °C BASE CASE. Such a difference is not negligible, particularly for the lower-income households that typically spend a greater share of their income in 'fuels and power' compared to the mid- and high-income households. This also means that, because consumers face lower electricity prices under the 2°C RES scenario, the overall cost of mitigation to reach a 2°C target is reduced (recall changes in GDP in **Figure 89**). Notably, the co-benefits associated with fossil fuels phase-out, such as air quality improvements, are not quantified in this analysis as they go beyond the scope, but can be substantial as detailed in previous analysis [83].
The lower production cost of electricity (5.7%, 2050) and the household consumption prices (2.1%, 2050) of the macroeconomic modelling with JRC-GEM-E3 are in good accordance with the lower energy supply costs (3.8%, 2050) for the corresponding energy scenarios of POLES-JRC (see Figure 73.c, 2050 in Section 3.3.3.1, scenarios: difference of the base case (BC) to highly enhanced learning for wind and solar, *W++_S++*, under the *2°C scenario*). This reflects the soft-link approach used to impose transitions projected in POLES-JRC to the JRC-GEM-E3 model, which consistently reflects the technological shift and energy efficiency gains from POLES-JRC.

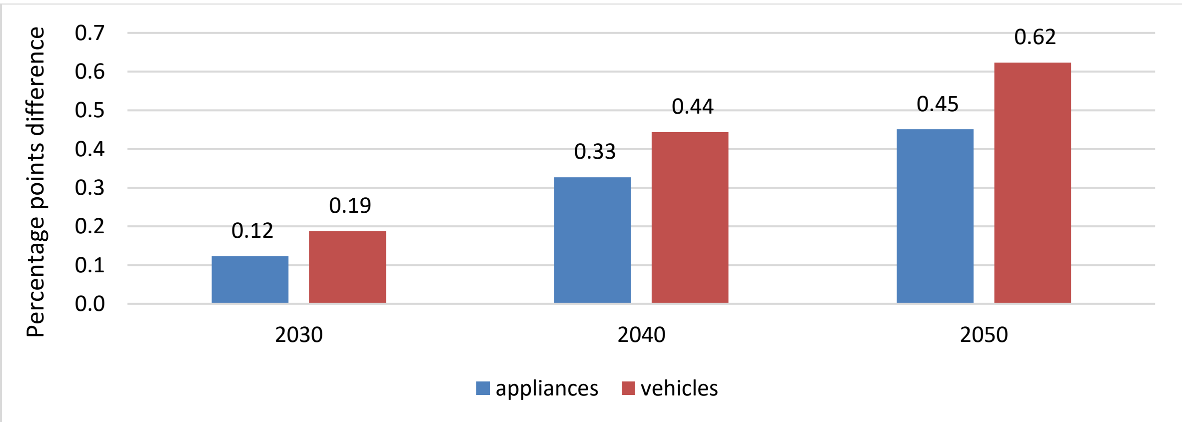
Figure 92. Production cost of electricity and Consumer price. Percentage points difference between 2°C RES and 2°C BASE CASE scenarios over 2025-2050.



Source: JRC-GEM-E3 model.

The lower electricity cost of for consumers also has additional effects on household expenditure. Overall, because R&D investments imply a faster reduction in the costs of crucial technologies for the decarbonisation of the power system (i.e., floor costs of wind and solar), the cost reduction ends-up working indirectly as an incentive for faster adoption by households of goods that use electricity. This effect is especially observed in the consumption of durable goods, such as household appliances and vehicles, as they use energy (electricity or fuels) to operate. Amongst 14 consumption categories, the JRC-GEM-E3 model captures changes in the consumption of two categories of durable goods linked to their energy consumption, namely: 'heating and cooking appliances' and 'purchase of vehicles'. The results suggest that, because consumers spend a lower share of their income on electricity, they have more disposable income to use in the consumption of other goods, which leads to a greater consumption of durable goods over time in the 2°C RES compared to the 2°C BASE CASE.

Figure 93. Consumption of durable goods (household appliances and vehicles). Percentage points difference between 2 °C RES and 2 °C BASE CASE scenarios over 2030-2050.



Source: JRC-GEM-E3 model.

Figure 93 shows the percentage point difference between the two scenarios (2°C RES and 2°C BASE CASE) for the consumption of 'heating and cooking appliances' and 'purchase of vehicles' over 2030-50. The difference in the consumption of 'heating and cooking appliances' between 2°C RES and 2°C BASE CASE reaches 0.62 percentage points (p.p.) in 2050, while achieving 0.45p.p. for 'purchase of vehicles'. On the one hand, this suggests that households perceive lower operational costs and move faster towards the electrification of end-uses faster in their consumption choices under the 2°C RES. On the other hand, after the general equilibrium effects, the small increase of 0.9% electricity consumption from the 2°C BASE CASE to the 2°C RES scenario suggests potential rebound effects, with consumers slightly increasing their consumption in the face of lower electricity prices.

5 Conclusions

This analysis of the long-term impacts of boosting technology progress of clean energy technologies offers several key findings for an effective climate policy. Major insights concern the impact on reducing GHG emissions and economic implications. Moreover, the analysis provides guidance for which technologies the progress needs to be accelerated to maximise benefits. Furthermore, the study sheds light on the technology impacts over time.

Analytical framework and methodology

This analysis builds on the well-established energy scenario model POLES-JRC, which considers detailed multi-regional energy systems in its global coverage. The technology scope is comprehensive, encompassing *eight thematic technology groups* that cover the most relevant clean energy technologies for energy supply and consumption. The technology boost is modelled through enhanced learning rates between 2025 and 2050, which aim to simulate additional R&D expenditures. The resulting impacts and synergies are analysed by combining enhanced learning across the aforementioned *eight thematic technology groups*.

The enhanced learning rates combinations are analysed for *two scenarios*, which start from the current energy system and take into account already legislated energy policies:

- a *2°C scenario* considering stringent carbon policies simulated by a single global carbon value trajectory;
- a *Reference scenario* describing a business-as-usual scenario which is solely driven by market forces.

The single global carbon value trajectory is intended to simulate the combination of a range of decarbonisation policy measures, such as actual carbon pricing schemes, but also other measures, such as regulatory standards (e.g., emission standards), restrictions (e.g., phase-outs, bans), incentives and subsidies for clean technologies (e.g., feed-in tariffs, tax incentives).

Emission Reduction: Accelerating clean technology supports climate policies

This study shows that, under a scenario with stringent carbon policies (*2°C scenario*), the boost in technology progress can, at best, reduce cumulative CO_2 emissions by an additional 1-2% by 2050 and by 2100 by 5-6% (56-67 Gt_{CO2}). The reduction in cumulative emissions at the end of the century is small compared to the 930 Gt_{CO2} emission reduction required for achieving the *1.5°C objective* (compare Section 3.4.2.2).
Under a scenario primarily driven by market forces (*Reference scenario*), the boost in technology progress can, at best, reduce cumulative CO_2 emissions by an additional 2-3% by 2050 and by 2100 by 6-7% (163-190 Gt_{CO2}). However, reaching the *2°C objective* would require a reduction of 1530 Gt_{CO2} (compare Section 3.4.2.2).

To conclude, boosting the progress of clean energy technologies reduces emissions significantly but falls short of achieving climate objectives. Therefore, it is essential to note that boosting technology progress is not a substitute for stringent climate policies. However, the analysis suggests that technology progress can reinforce the impacts of carbon policies. This conclusion is in line with existing literature. For instance, a recent multi-model framework analysis, which examined the impact of R&D expenditures on emissions by means of several energy models, concluded that R&D merely plays a supporting role for climate policies [84]. Similarly, other studies examining the impact of R&D and learning on clean energy technologies have found a significant but limited impact on reducing greenhouse gas emissions [85], [86].

Economic impacts: Increasing economic efficiency of green transition

Decarbonisation policies, while crucial for achieving a low-carbon economy, can impose significant costs. However, this analysis finds that boosting technology progress can substantially alleviate the economic burden. For policymakers, this insight is important, as boosting technology progress presents an opportunity to balance environmental goals with economic concerns.

<u>Investment needs and energy supply costs</u>

This study shows that boosting progress in clean energy technologies can significantly reduce investment needs and energy supply costs.
A key finding is that the required investments of the *2°C scenario* can be diminished below the level of the base case *Reference scenario* for the best-performing combinations of highly enhanced learning.
Moreover, the difference in energy supply costs between the base cases of the *2°C scenario* and the *Reference scenario* can be diminished by more than half with the best-performing combinations of enhanced learning.
These findings are supported by previous studies that, using different methodologies, have shown how R&D investments under deep decarbonisation scenarios can substantially reduce investment needs [84] and abatement costs [85].

<u>Macroeconomic impacts</u>
The macroeconomic impacts of combining highly enhanced learning for wind and solar technologies (*W++_S++*) were investigated in detail under the *2°C scenario*.
The results reveal that GDP losses under the *2°C scenario* compared to the *Reference scenario* could be reduced by about 20% (0.7% compared to 0.9% loss of GDP) by 2050.
The underlying drivers of this development are significantly lower electricity generation costs, as the enhanced learning for wind and solar has a substantial impact on reducing electricity generation costs. For final consumers, this results in lower electricity prices under the *2°C scenario* compared to the *Reference scenario*. In particular, households benefit from lower electricity prices and perceive a relatively higher disposable income. Consequently, this eventually leads to more consumption of durable goods, such as household appliances and electric vehicles.

Job opportunities in non-fossil power generation and the general electricity sector compensate for job losses in the fossil energy industry globally. This aligns well with the transition towards renewable electrification of demand and renewable power supply. Notably, the enhanced learning variant of the *2°C scenario* results in slightly fewer jobs in non-fossil power generation, as the enhanced learning implies improvements in labour efficiency. This effect is more pronounced for employment in wind power due to beneficial economies of scale and less noticeable for solar power.

<u>Cost-benefits analysis:</u> R&I expenditures vs. energy investments
To benefit from the aforementioned significant economic advantages of enhanced learning requires additional R&I expenditures. This study estimated the additional R&I expenditures corresponding to moderately and highly enhanced learning for wind (*W+*, *W++*) and solar technologies (*S+*, *S++*) under the *2°C scenario*.
The results show that the cost savings from reduced investment needs are several multiples higher than the additional R&I expenditures. This study estimates that the cumulative additional R&I expenditures for highly enhanced learning in wind technologies (*W++*) from 2025 to 2050 amount to approximately 122 B$, while the corresponding savings in cumulative investments are around 1000 B$. For highly enhanced learning in solar technologies (*S++*), the additional cumulative R&I expenditures are estimated at around 92 B$, whereas the corresponding savings in cumulative investments are approximately 700 B$ over the same period.

<u>Concluding remarks</u>
Boosting technology progress appears as an effective strategy for policymakers to mitigate economic risks and cost increases of decarbonisation policies.

Technology composition and impact over time
This analysis highlights key technologies that should be prioritised when boosting technology progress to achieve superior emissions reductions and economic benefits.

Boosting learning of a wide range of established and dynamic technologies can achieve substantial additional emission reductions. Wind power, in particular, stands out in this category. Solar, hydrogen, and fuel cell technologies also fall into this category, although their impact is less than in wind.
However, for emerging technologies with high long-term emission reduction potential, such as Direct Air Capture (DAC) and synfuels, boosting learning in the coming decades is crucial to unlocking substantial additional impact in the longer term.

To reduce investment needs, boosting progress for wind, solar, battery, and hydrogen and fuel cells is key. In particular, enhancing battery learning significantly reduces investment needs due to the very large manufacturing capacities that are required for the electrification of transport.

For mitigating energy supply costs, boosting progress for batteries, wind and solar has substantial impact throughout the century in both scenarios. Moreover, boosting progress for heat pumps, and hydrogen and fuel cells can reduce energy supply costs substantially in the first half of the century under the *2°C scenario*.

Notably, the impacts of boosting technology progress for clean energy technologies persist over time, with significant emissions reductions and economic benefits achievable in the long term. This analysis shows that additional R&I efforts simulated as enhanced learning in the period 2025 to 2050 unlock substantial impacts not only within this period but also in the second half of the century.

Limitations and outlook

This study focuses on modelling the evolution of existing technologies, including well-established ones (e.g., solar, wind, and batteries), and emerging technologies with potential for future commercial viability (e.g., carbon capture, DAC, and synfuels). However, this study does not consider emerging technologies with a low technology readiness level (TRL). It is possible that some of these technologies may be widely deployed in future or even become game-changers, such as nuclear fusion.

Instead, this study deliberately avoids technology forecasting and concentrates on the known technologies within its scope. As a result, the technology-related findings are strictly limited to these existing technologies and do not imply anything for emerging technologies.

To leverage the potential of breakthrough technologies, it is essential to sustain and intensify research and innovation (R&I) efforts. The authors emphasise the crucial importance of maintaining a broad scope and open-minded approach to R&I, recognising its vital role in driving progress and advancement.

To further enhance the relevance and robustness of this analysis for policymakers, several aspects could be explored in future research:

- **Expanding the technology scope**: Widening the analysis to include a broader range of energy technologies could provide more comprehensive insights into the impact of learning on the energy sector. Currently, the study focuses on eight major clean energy technology groups, leaving out several important areas, such as nuclear technologies, industrial processes (incl. heating and cooling in industry), power transmission and distribution networks (incl. smart grids), and demand-side technologies in the residential and service sectors (e.g., insulation, appliances, other heating and cooling technologies, smart control technologies).
- **Refining the relationship between R&I expenditures and impact modelling**: To provide more concrete guidance for policymakers, improving the availability and technology detail of historic R&I expenditure data is essential. This would enable a more accurate modelling of the impacts of R&I investments, allowing policymakers to make more informed decisions.
- **Examining the interplay between investments and learning**: Investigating the interaction between investments and learning could offer valuable insights into how to optimise the interplay between push policies (aimed at stimulating innovation and technology development) and pull policies (focused on driving investment). By understanding how these policies interact, policymakers can design more effective strategies to support the development and deployment of new energy technologies.

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List of abbreviations and definitions

A/C	Air Conditioning
AFOLU	Agriculture, Forestry and Other Land Use
BC	Base Case
BECCS	BioEnergy with Carbon Capture and Storage
BES	Battery Energy Storage
BEV	Battery-electric Vehicles
BOS	Balance of System
CAE	Compressed-air Energy Storage
CC	Carbon Capture
CCS	Carbon Capture and Storage
CCUS	Carbon Capture, Use and Storage
CDD	Cooling Degree Day
CETO	Clean Energy Technology Observatory
CGE	Computable General Equilibrium
CNG	Compressed Natural Gas
CSP	Concentrated Solar Power
DDGS	Distiller Dry Grain Solubles
EPV	Electric Passenger Vehicle
EV	Electric Vehicle
FCV	Fuel Cell Vehicles
FF	Fossil Fuel
FT	Fischer-Tropsch
GDP	Gross Domestic Product
GECO	Global Climate and Energy Outlook
GEM-E3	General Equilibrium Model for Economy-Energy-Environment
GHG	Greenhouse Gas
GLOBIOM	The Global Biosphere Management Model
HDD	Heating Degree Day
HDV	Heavy-duty Vehicles
HT	High temperature (electrolysis)
IBG	Integrated Biomass Gasification

ICE	Internal Combustion Engine
ICG	Integrated Coal Gasification
IEA	International Energy Agency
IGCC	Integrated Gasification Combined Cycle
JRC	Joint Research Centre.
LBD	Learning-by-doing
LBR	Learning-by-research
LCV	Light Commercial Vehicle
LH2	Liquid Hydrogen
LPG	Liquefied Petroleum Gas
LR	Learning Rate
LT	Low temperature (electrolysis)
LULUCF	Land use, Land-use Change, and Forestry
N/A	Not Applicable
NDCs	Nationally Determined Contributions
NG	Natural Gas
NH_3	Ammonia
OIC	Overnight Investment Cost
OM	Operation & Maintenance
PEM	Proton Exchange Membrane
PHS	Pumped Hydro Storage
POLES	Prospective Outlook for the Long-term Energy System
POME	Palm oil mill effluent
PV	Photovoltaics
RCP4.5	Representative Concentration Pathway 4.5
Ref.	Reference
RFNBO	Renewable Fuels of Non-Biological Origin
R&I	Research and Innovation
SCOP	Seasonal Coefficient of Performance
SELEXOL	Trade name for a selective acid gas removal process for hydrogen sulfide and CO_2 from the syngas produced by gasification.
SMR	Steam methane reforming
TRL	Technology Readiness Level

T&D	Transmission and Distribution
USD	U.S. dollar
V2G	Vehicle-to-grid
w/ w/o	with and without

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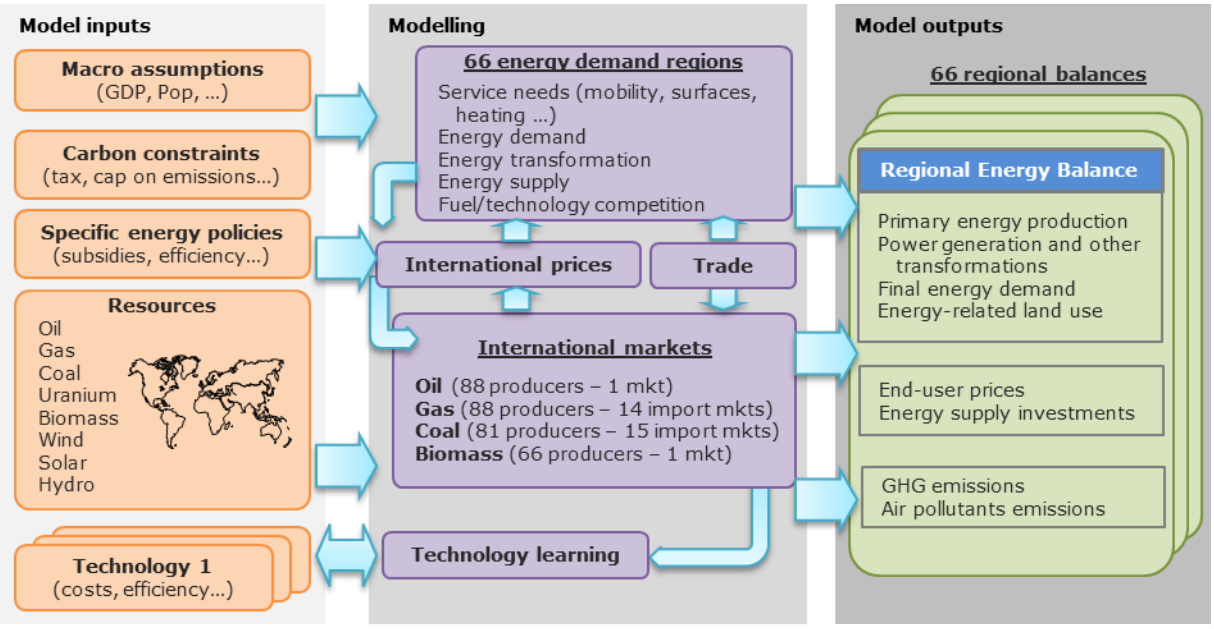
Annexes

Annex 1 Description of POLES-JRC

POLES-JRC is a world energy-economy partial equilibrium simulation model of the energy sector, with complete modelling from upstream production through to final user demand. It follows a year-by-year recursive modelling, with endogenous international energy prices and lagged adjustments of supply and demand by world region, which allows for describing full development pathways to 2050 (see general scheme **Figure 94**). The model provides full energy and emission balances for 66 countries or regions worldwide (including an explicit representation of OECD and G20 countries), 14 fuel supply branches and 15 final demand sectors.
This exercise used the POLES-JRC 2023 version as a starting point. Differences with other exercises done with the POLES-JRC model, or with exercises by other entities using the POLES model may exist.
For a more comprehensive description of the model, see [20].

Figure 94. POLES-JRC model general scheme.



Source: POLES-JRC model

Final demand

The final demand evolves with activity drivers, energy prices and technological progress. The following sectors are represented:

- industry: chemicals (energy uses and non-energy uses are differentiated), non-metallic minerals, steel, other industry;
- buildings: residential, services (detailed per end-uses: space heating, space cooling, water heating, cooking, lighting, appliances);
- transport (goods and passengers are differentiated): road (motorcycles, cars, light and heavy trucks; different engine types are considered), rail, inland water, international maritime, air (domestic and international);
- agriculture.

Power system

The power system describes the capacity planning of new plants and the operation of existing plants. The electricity demand curve is built from the sectoral distribution. The load, wind supply and solar supply are clustered into a number of representative days. The planning considers the existing structure of the power mix (vintage per technology type), the expected evolution of the load demand, the production cost of new technologies and the resource potential for renewables. The operation matches electricity demand considering the installed capacities, the variable production costs per technology type, the resource availability for renewables and the contribution of flexible means (stationary storage, vehicle-to-grid, demand-side management). The electricity price by sector depends on the evolution of the power mix, of the load curve and of energy taxes.

Other transformation
The model also describes other energy transformations sectors: liquid biofuels, coal-to-liquids, gas-to-liquids, hydrogen, centralised heat production.

Oil supply
Oil discoveries, reserves and production are simulated for producing countries and different resource types.
Investments in new capacities are influenced by production costs, which include direct energy inputs in the production process.
The international oil price depends on the evolution of the oil stocks in the short term, and on the marginal production cost and ratio of the Reserves by Production (R/P) ratio in the longer run.

Gas supply
Gas discoveries, reserves and production are simulated for individual producers and different resource types. Investments in new capacities are influenced by production costs, which include direct energy inputs in the production process. They supply regional markets through inland pipeline, offshore pipelines or LNG. The gas prices depend on the transport cost, the regional R/P ratio, the evolution of oil price and the development of LNG (integration of the different regional markets).

Coal supply
Coal production is simulated for individual producers. Production cost is influenced by short-term utilisation of existing capacities and a longer-term evolution for the development of new resources. They supply regional markets through inland transport (rail) or by maritime freight. Coal delivery price for each route depends on the production cost and the transport cost.

Biomass supply
The model differentiates various types of primary biomass: energy crops, short rotation crop (lignocellulosic) and wood (lignocellulosic). They are described through a potential and a production cost curve – information on lignocellulosic biomass (short rotation coppices, wood) is derived from look-up tables provided by the specialised model GLOBIOM-G4M (Global Biosphere Management Model). Biomass can be traded, either in solid form or as liquid biofuel.

Wind, solar and other renewables
They are associated with potentials and supply curves per country.

GHG emissions
CO_2 emissions from fossil fuel combustion are derived directly from the projected energy balance. Other GHGs from energy and industry are simulated using activity drivers identified in the model (e.g., sectoral value added, mobility per type of vehicles, fuel production, fuel consumption) and abatement cost curves. GHG from agriculture and LULUCF are derived from GLOBIOM-G4M lookup tables.

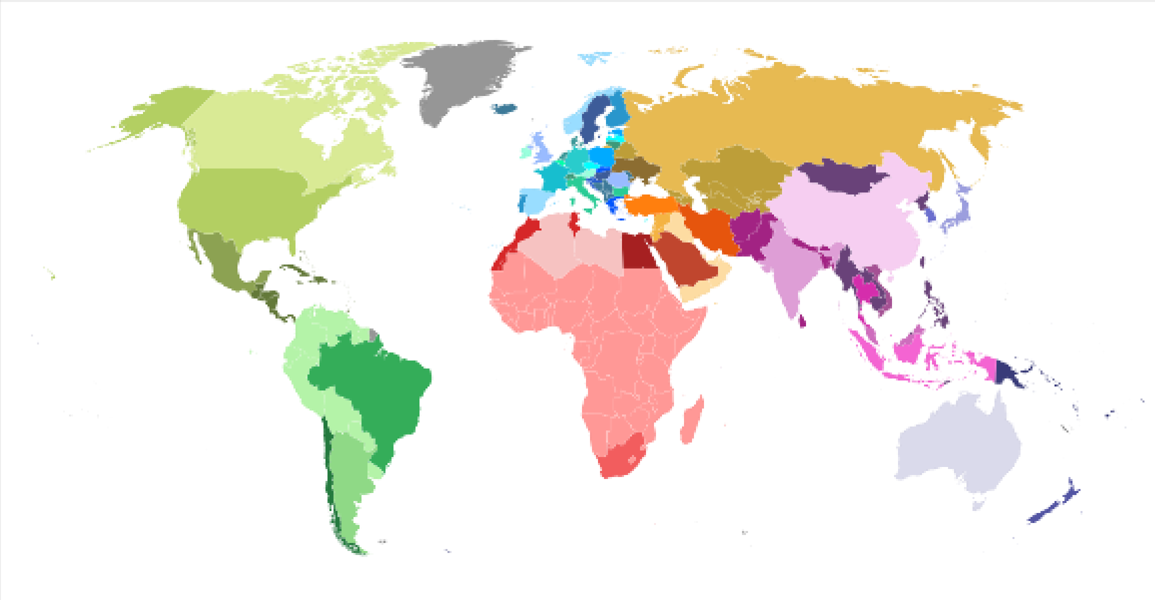
Definitions
In this report, hydrogen demand refers to hydrogen used as a fuel for energy use and non-energy applications, such as hydrogen used as feedstock for ammonia production. E-fuels refers to fuels obtained from power-to-gas and power-to-liquid processes, in which hydrogen and CO_2 are converted to gaseous or liquid hydrocarbon fuels through methanation or the Fischer-Tropsch process. In both cases the CO_2 is sourced from direct air capture powered by renewables. E-fuels are renewable fuels of non-biological origin (RFNBO). Hydrogen demand as feedstock (pure hydrogen for the production of ammonia and other industrial applications) appears in "Non-energy uses" in the balances, except for hydrogen demand in steelmaking which appears in industry energy demand. Hydrogen uses mixed with other gases (such as methanol) are not considered. Energy inputs for the production of hydrogen, for both energy and non-energy uses, appear in "Other energy transformation and losses" in the balances.
Hydrogen demand as industrial feedstock is included in total hydrogen demand (Section 4.1). Ammonia demand as an energy fuel is only included in international maritime bunkers grouped together with e-fuels. Domestic e-fuel production can be both gaseous and liquid fuels; however the international trade of e-fuels is exclusively liquid fuels.

Internationally traded e-fuels can only be produced from renewables ("green hydrogen"). Biomethane is produced from biomass and agricultural wastes, and the inputs of which are accounted for in primary energy as biomass. Biomethane is then mixed together with fossil gas for final users and appears as gas in final energy demand.

Countries and regions

The model decomposes the world energy system into 66 regional entities: 54 individual countries and 12 residual regions see **Figure 95.**, to which international bunkers (air and maritime) are added.

Figure 95. POLES-JRC model regional detail map (for energy balances).



Source: POLES-JRC model

Table 5. List of 54 individual countries represented in POLES-JRC (for energy balances).

Non-EU individual countries	EU Member States
Argentina	Austria
Australia	Belgium
Brazil	Bulgaria
Canada	Croatia
Chile	Cyprus
China	Czech Republic
Egypt	Denmark
Iceland	Estonia
India	Finland
Indonesia	France
Iran	Germany
Japan	Greece
Malaysia	Hungary
Mexico	Ireland

New Zealand	Italy
Norway	Latvia
Russia	Lithuania
Saudi Arabia	Luxembourg
South Africa	Malta
South Korea	Netherlands
Switzerland	Poland
Thailand	Portugal
Turkey	Romania
Ukraine	Slovak Republic
United Kingdom	Slovenia
United States	Spain
Vietnam	Sweden

Source: POLES-JRC model. Note: Hong-Kong and Macau are included in China.

Table 6. Country mapping for the 12 regions in POLES-JRC (for energy balances).

Rest Central America	Rest Balkans	Rest Sub-Saharan Africa (continued)	Rest South Asia
Bahamas	Albania	Burkina Faso	Afghanistan
Barbados	Bosnia-Herzegovina	Burundi	Bangladesh
Belize	Kosovo	Cameroon	Bhutan
Bermuda	Macedonia	Cape Verde	Maldives
Costa Rica	Moldova	Central African Republic	Nepal
Cuba	Montenegro	Chad	Pakistan
Dominica	Serbia	Comoros	Seychelles
Dominican Republic	Rest of Commonwealth of Independent States	Congo	Sri Lanka
El Salvador	Armenia	Congo DR	Rest South East Asia
Grenada	Azerbaijan	Cote d'Ivoire	Brunei
Guatemala	Belarus	Djibouti	Cambodia
Haiti	Georgia	Equatorial Guinea	Lao PDR
Honduras	Kazakhstan	Eritrea	Mongolia
Jamaica	Kyrgyz Rep.	Ethiopia	Myanmar
Nicaragua	Tajikistan	Gabon	North Korea
NL Antilles and Aruba	Turkmenistan	Gambia	Philippines
Panama	Uzbekistan	Ghana	Singapore
Sao Tome and Principe	Mediterranean Middle East	Guinea	Taiwan
St Lucia	Israel	Guinea-Bissau	Rest Pacific

St Vincent & Grenadines	Jordan	Kenya	Fiji Islands
Trinidad and Tobago	Lebanon	Lesotho	Kiribati
Rest South America	Syria	Liberia	Papua New Guinea
Bolivia	**Rest of Persian Gulf**	Madagascar	Samoa (Western)
Colombia	Bahrain	Malawi	Solomon Islands
Ecuador	Iraq	Mali	Tonga
Guyana	Kuwait	Mauritania	Vanuatu
Paraguay	Oman	Mauritius	
Peru	Qatar	Mozambique	
Suriname	United Arab Emirates	Namibia	
Uruguay	Yemen	Niger	
Venezuela	**Morocco & Tunisia**	Nigeria	
	Morocco	Rwanda	
	Tunisia	Senegal	
	Algeria & Libya	Sierra Leone	
	Algeria	Somalia	
	Libya	Sudan	
	Rest Sub-Saharan Africa	Swaziland	
	Angola	Tanzania	
	Benin	Togo	
	Botswana	Uganda	
		Zambia	

Source: POLES-JRC model.

Table 7. POLES-JRC model historical data and projections.

<table>
<tr><th colspan="2">Series</th><th>Historical data</th><th>GECO Projections</th></tr>
<tr><td colspan="2">Population</td><td colspan="2">[87]–[89]</td></tr>
<tr><td colspan="2">GDP, growth</td><td>(World Bank, 2023); [90]–[92]</td><td>[90], [91], [93]</td></tr>
<tr><td rowspan="2">Other activity drivers</td><td>Value added</td><td>World Bank</td><td rowspan="9">POLES-JRC model</td></tr>
<tr><td>Mobility, vehicles, households, tons of steel, …</td><td>Sectoral databases</td></tr>
<tr><td rowspan="5">Energy resources</td><td>Oil, gas, coal</td><td>BGR, USGS, WEC, Rystad, sectoral information</td></tr>
<tr><td>Uranium</td><td>NEA</td></tr>
<tr><td>Biomass</td><td>GLOBIOM-G4M model</td></tr>
<tr><td>Hydro</td><td>Enerdata</td></tr>
<tr><td>Wind, solar</td><td>NREL, DLR</td></tr>
<tr><td rowspan="3">Energy balances</td><td>Reserves, production</td><td>BP, Enerdata</td></tr>
<tr><td>Demand by sector and fuel, transformation (including. power), losses</td><td>Enerdata, IEA</td></tr>
<tr><td>Power plants</td><td>Platts</td><td></td></tr>
<tr><td>Energy prices</td><td>International prices, prices to consumer</td><td>Enerdata, IEA</td><td>POLES-JRC model</td></tr>
<tr><td rowspan="4">GHG emissions</td><td>Energy CO_2</td><td>Derived from POLES-JRC energy balances</td><td>POLES-JRC model</td></tr>
<tr><td>Other GHG Annex 1 (excl. LULUCF)</td><td>UNFCCC</td><td>POLES-JRC model, GLOBIOM-G4M model</td></tr>
<tr><td>Other GHG Non-Annex 1 (excl. LULUCF)</td><td>EDGAR</td><td>POLES-JRC model, GLOBIOM-G4M model</td></tr>
<tr><td>LULUCF</td><td>[94]</td><td>POLES-JRC model, GLOBIOM-G4M model</td></tr>
<tr><td colspan="2">Air pollutants emissions</td><td>GAINS model, EDGAR, IPCC, national sources</td><td>GAINS model, national sources</td></tr>
<tr><td colspan="2">Technology costs</td><td colspan="2">POLES-JRC learning curves based on literature, including but not limited to: EC JRC, WEC, IEA, TECHPOL database</td></tr>
</table>

Source: Own elaboration

Annex 2 JRC-GEM-E3 sectoral and regional aggregation

Table 8. Sectors in the JRC-GEM-E3 model.

Sector name	#	Sector name	#	Sector name	#
Crops	01	Non-metallic Minerals	11	Non-market Services	21
Coal	02	Electric Goods	12	Coal-fired Electricity	22
Crude Oil	03	Transport Equipment	13	Oil-fired Electricity	23
Oil	04	Other Equipment Goods	14	Gas-fired Electricity	24
Gas	05	Consumer Goods Industries	15	Nuclear Electricity	25
Electricity Supply	06	Construction	16	Biomass Electricity	26
Ferrous Metals	07	Transport (Air)	17	Hydro Electricity	27
Non-ferrous Metals	08	Transport (Land)	18	Wind Electricity	28
Chemical Products	09	Transport (Water)	19	Solar Electricity	29
Paper Products	10	Market Services	20	Livestock	30
				Forestry	31

Source: Own elaboration

Table 9. Regional aggregation of the JRC-GEM-E3 model.

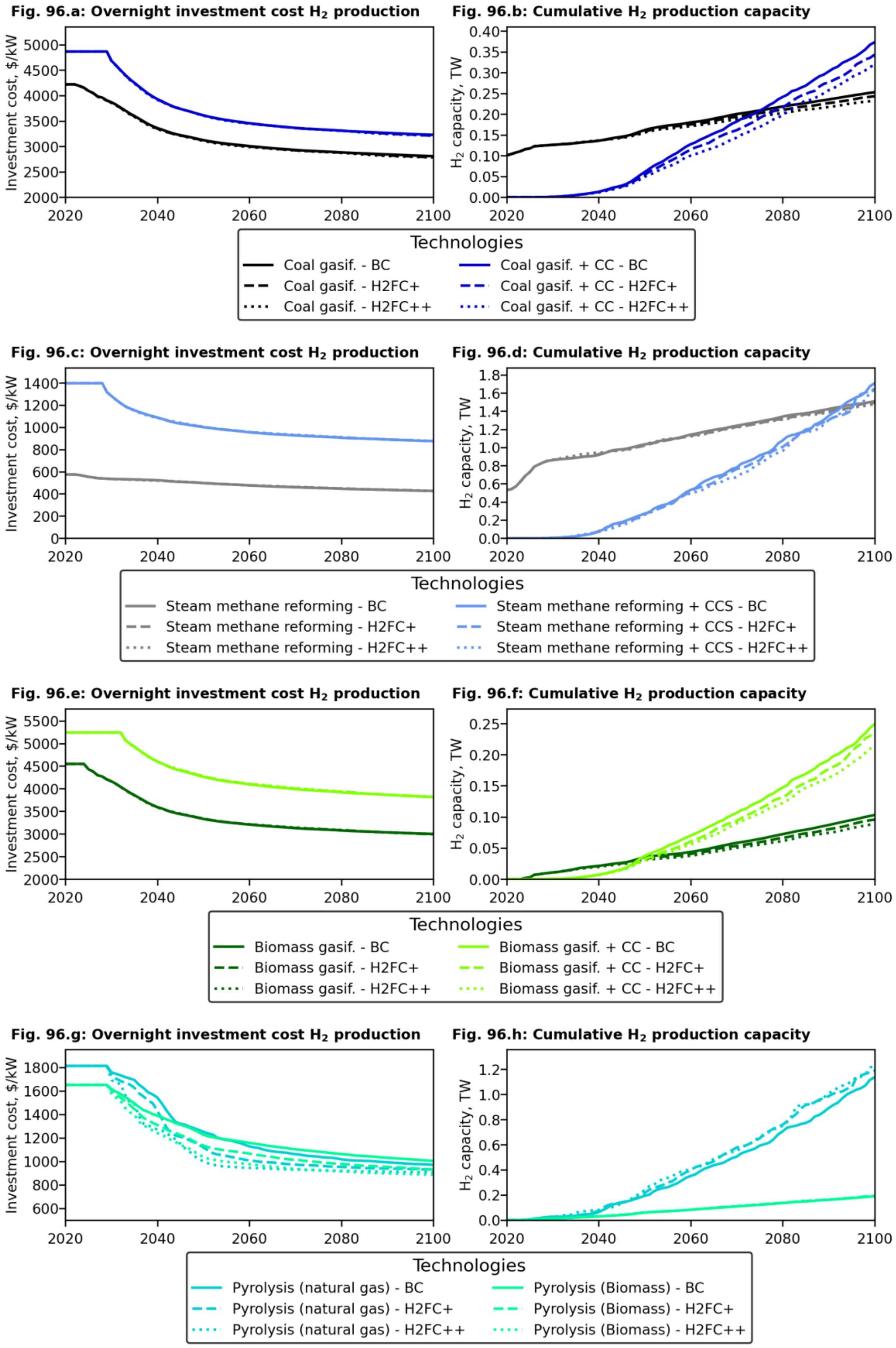
Regions in the JRC-GEM-E3 model	Abbreviation
European Union	EU27
United Kingdom	GBR
United States	USA
Japan	JPN
Canada	CAN
Australia	AUS
Russian Federation	RUS
Brazil	BRA
China	CHN
India	IND
South Korea	KOR
Saudi Arabia	SAU
Türkiye	TUR
South Africa	SAF
Mexico	MEX
Argentina	ARG
Indonesia	IDN
EFTA	EFA
Middle East	MEA
Africa	AFR
Other Americas	OAM
Other Asia	OAS
Rest of Eurasia	REA

Source: Own elaboration

Annex 3 Scenario details of technology groups

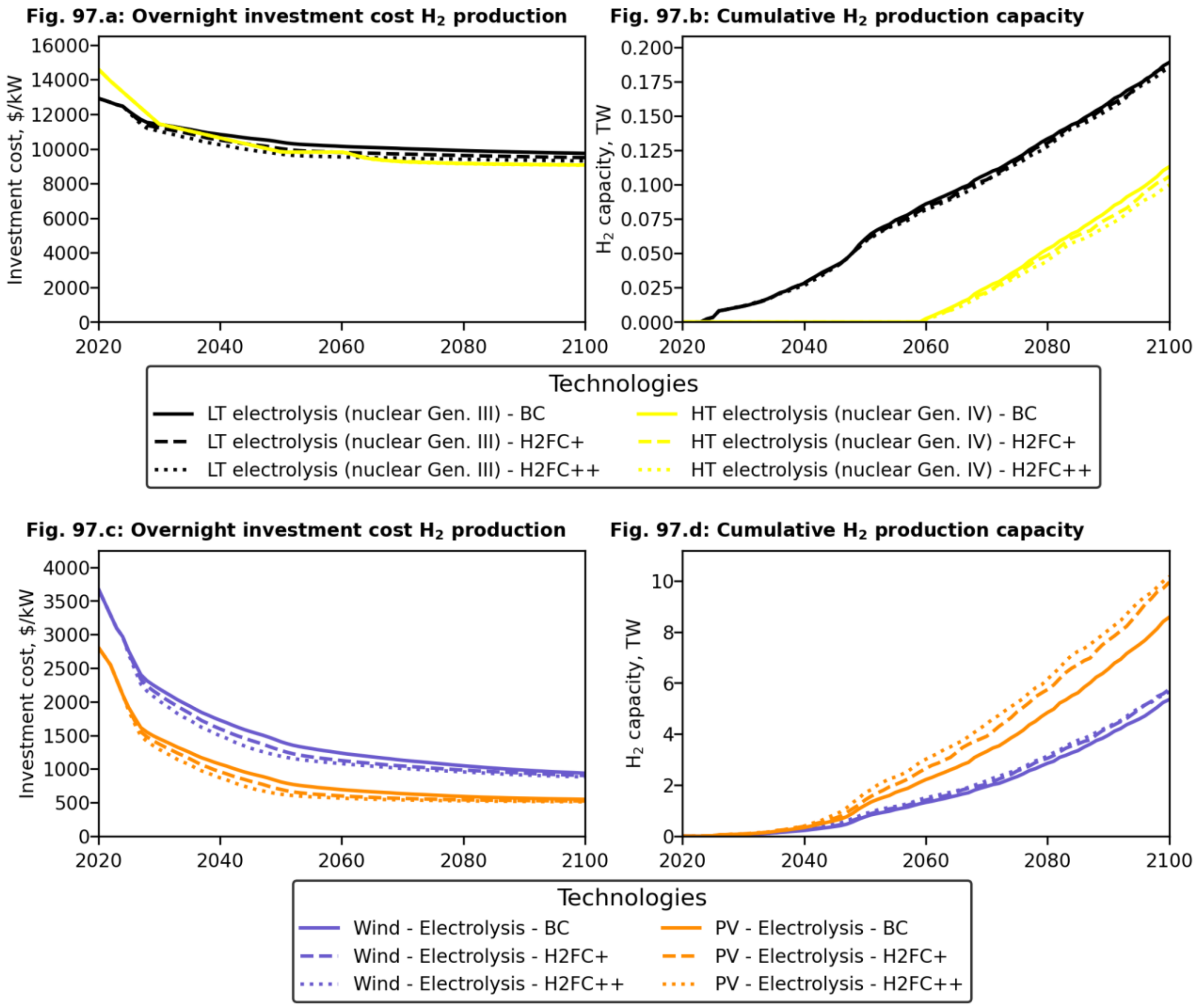
AN 3.1 Hydrogen and fuel cell technologies

Figure 96. Thermo-chemical technologies - Investment cost and cumulative capacities.



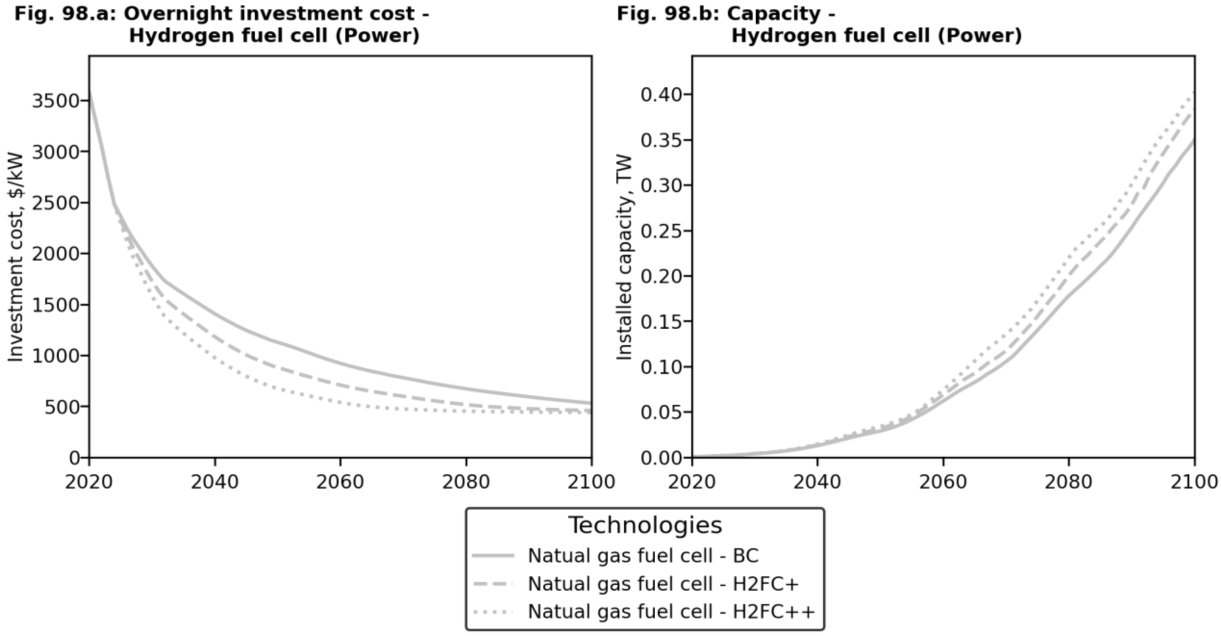
Source: POLES-JRC model

Figure 97. Nuclear and renewable electrolysis technologies - Evolution of investment cost and cumulative capacities.



Source: POLES-JRC model

Figure 98. Fuel cells using natural gas in power generation: Evolution of investment cost and cumulative capacities.

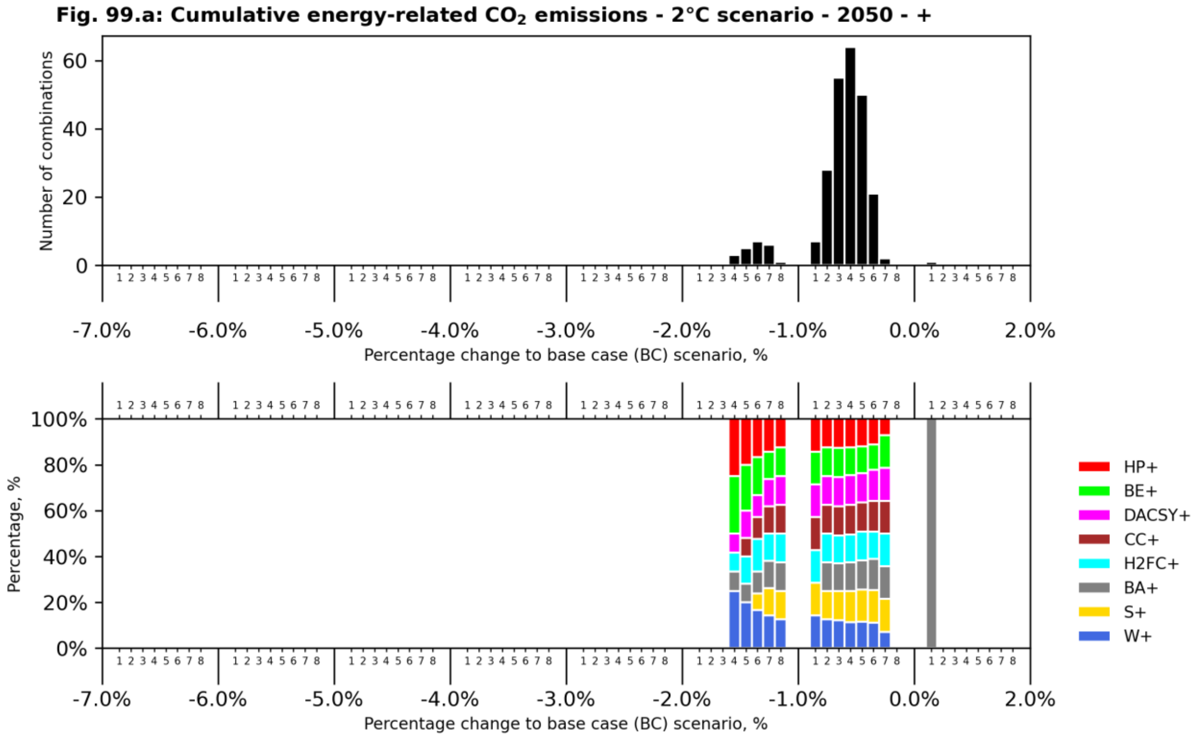


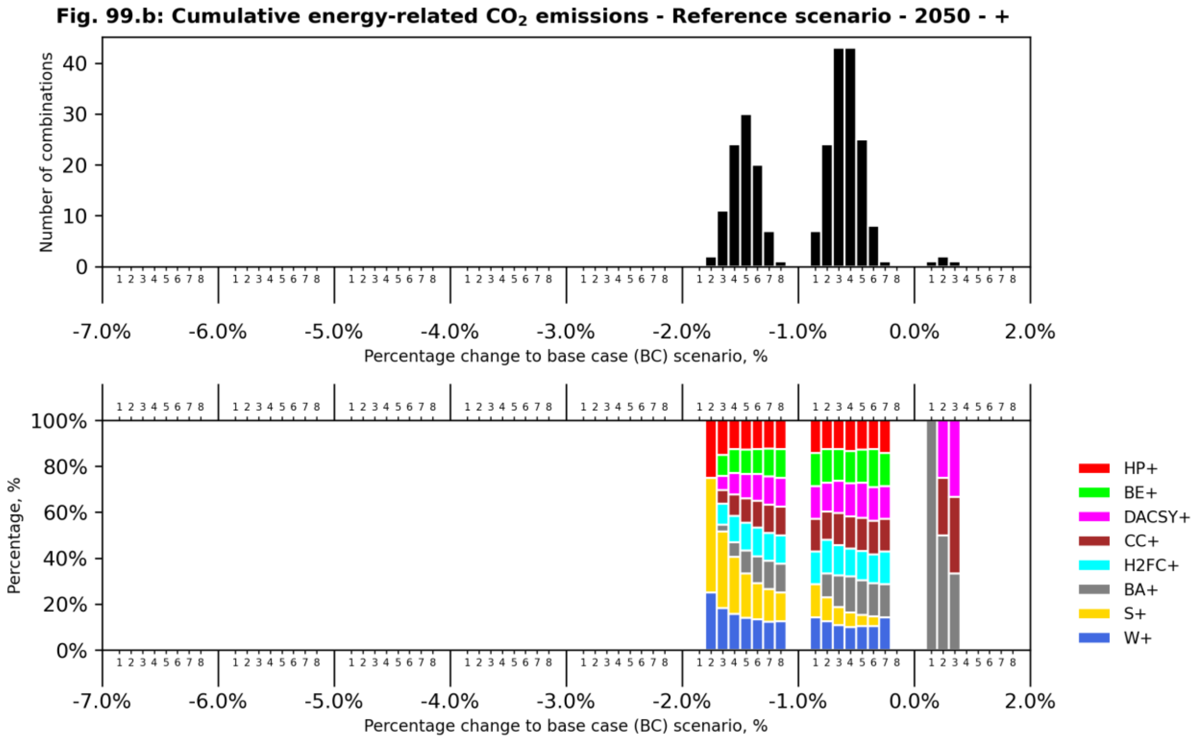
Source: POLES-JRC model

Annex 4 Results sensitivity analysis for moderately enhanced learning

AN 4.1 Cumulative energy-related CO_2 emissions

Figure 99. Relative impacts on **cumulative energy-related CO_2 emissions by 2050** of **moderately** enhanced learning (**+**) variations under the *2°C* and *Reference scenario*.





Source: POLES-JRC model

Figure 100. Relative impacts on **cumulative energy-related CO_2 emissions by 2100** of **moderately** enhanced learning (**+**) variations under the *2°C* and *Reference scenario*.

Fig. 100.a: Cumulative energy-related CO_2 emissions - 2°C scenario - 2100 - +

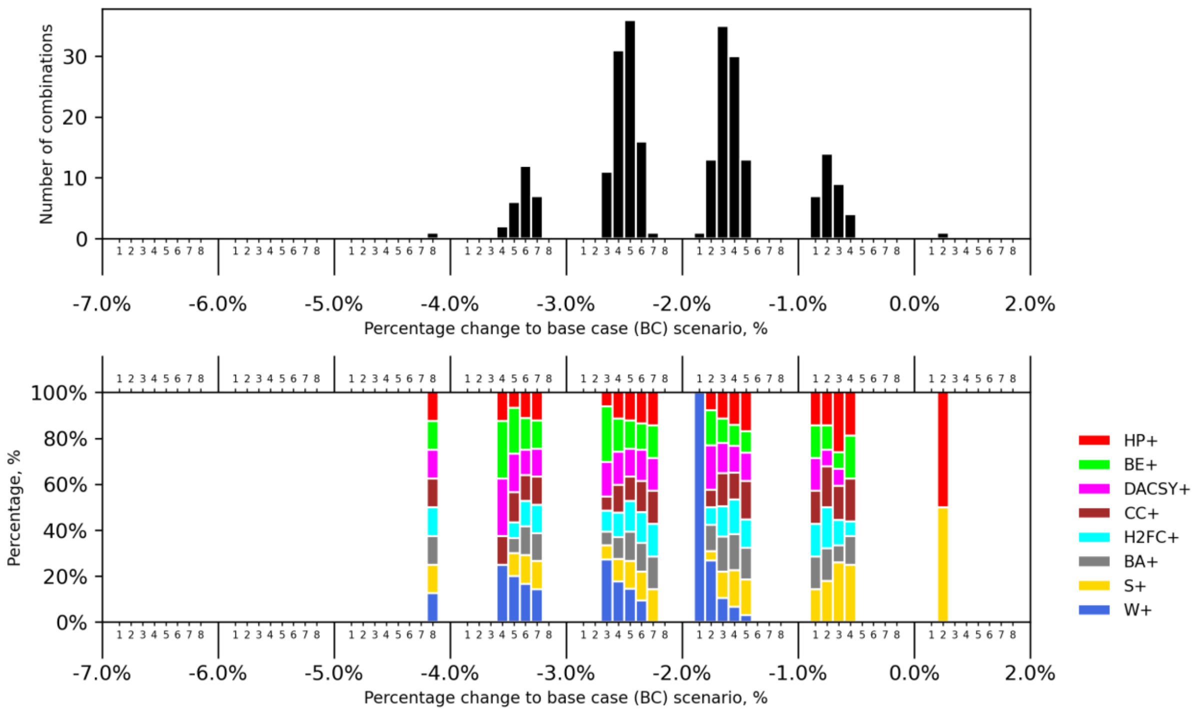
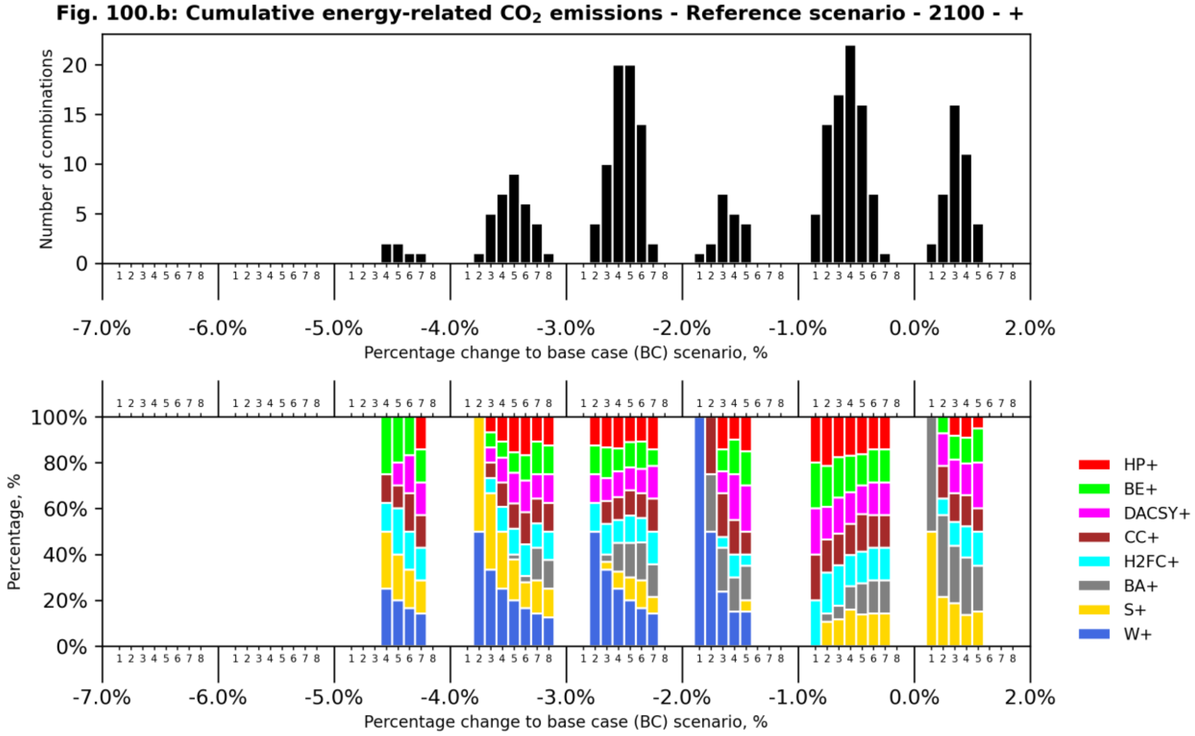


Fig. 100.b: Cumulative energy-related CO_2 emissions - Reference scenario - 2100 - +



Source: POLES-JRC model

AN 4.2 Cumulative investments

Figure 101. Relative impacts on **cumulative investments** by **2050** of **moderately** enhanced learning (**+**) variations under the *2°C* and *Reference scenario*.

Fig. 101.a: Cumulative investments - 2°C scenario - 2050 - +

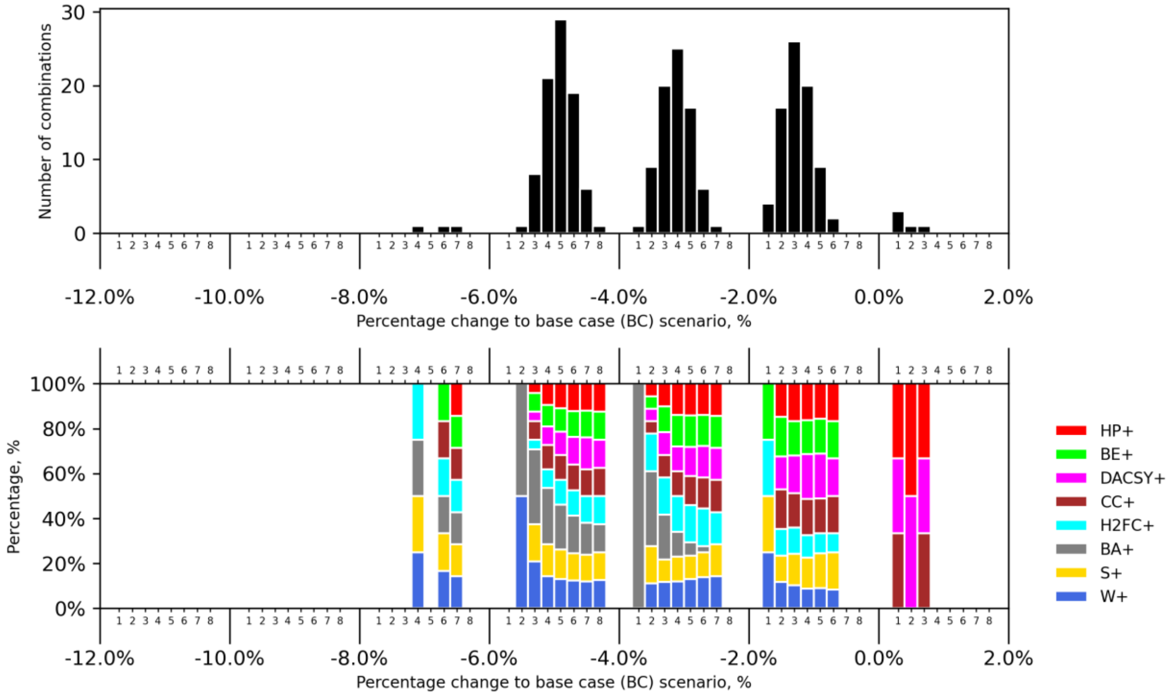
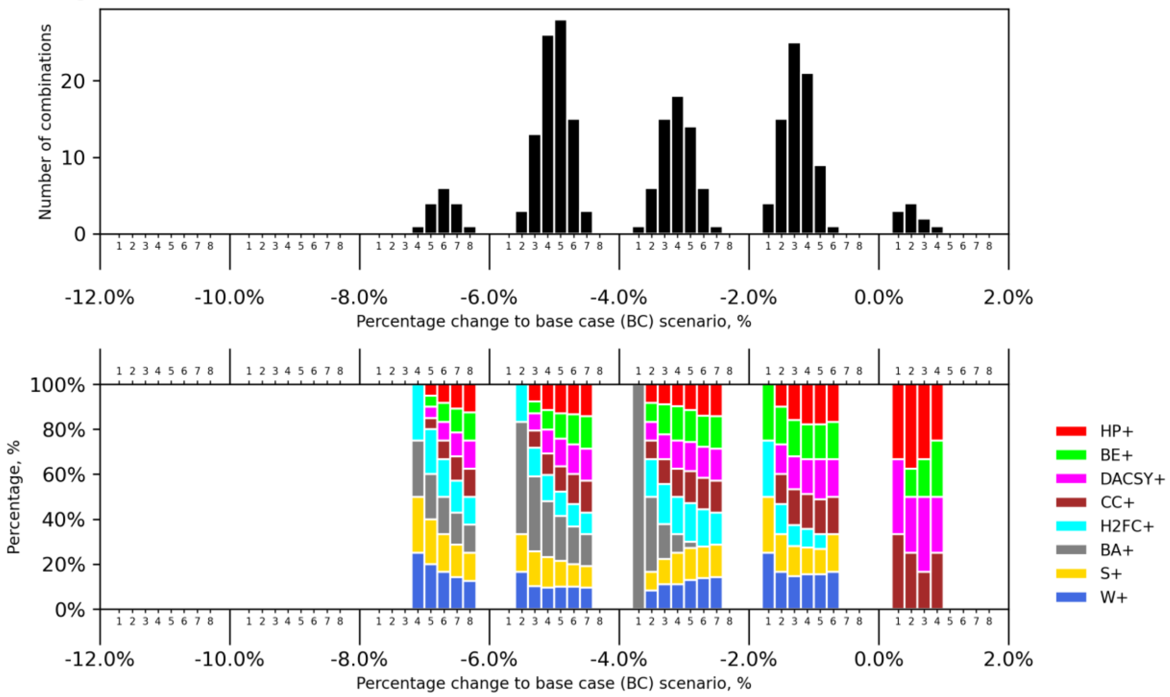
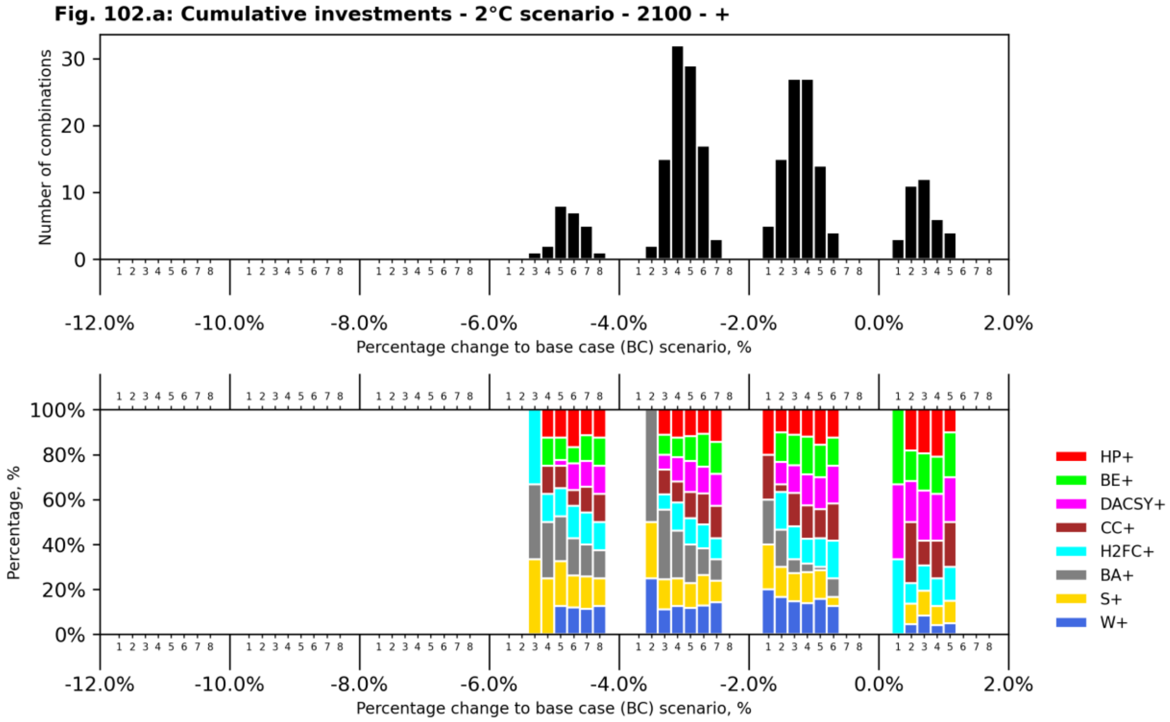


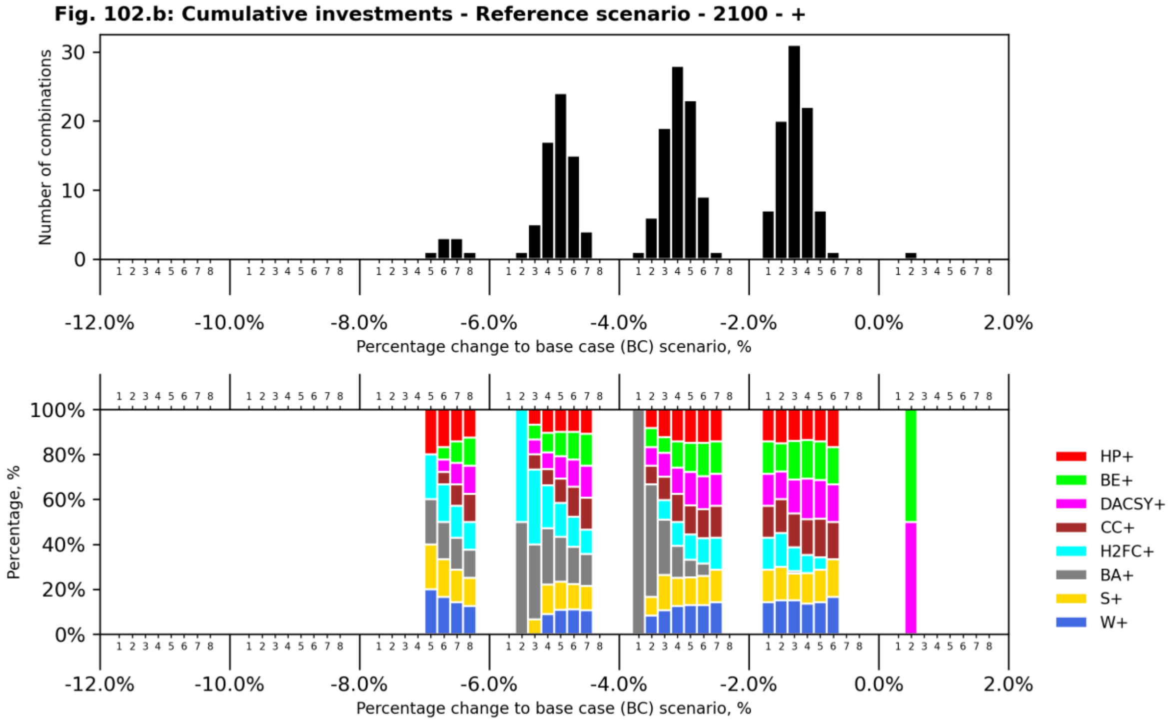
Fig. 101.b: Cumulative investments - Reference scenario - 2050 - +



Source: POLES-JRC model

Figure 102. Relative impacts on **cumulative investments** by **2100** of **moderately** enhanced learning (**+**) variations under the *2°C* and *Reference scenario*.

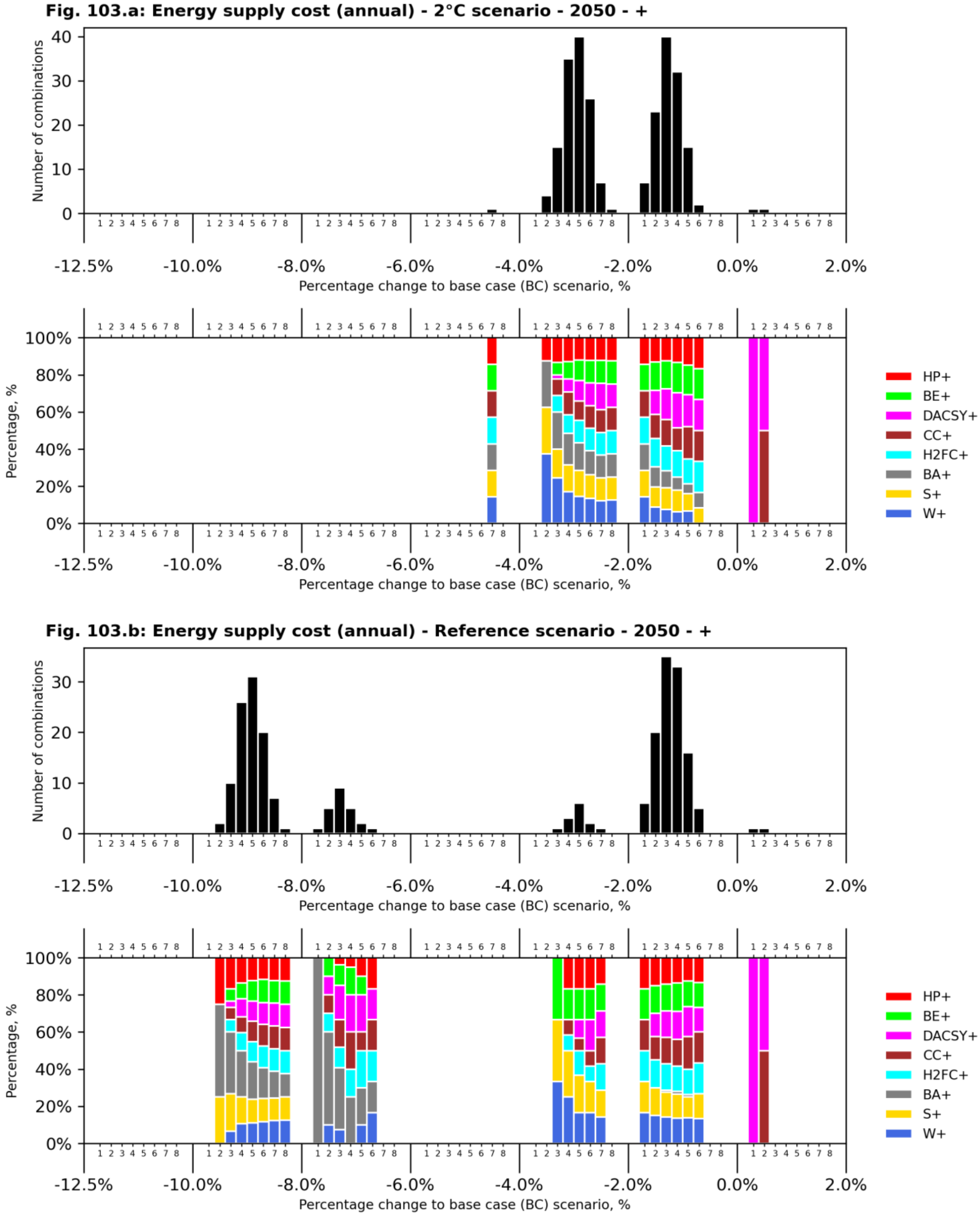




Source: POLES-JRC model

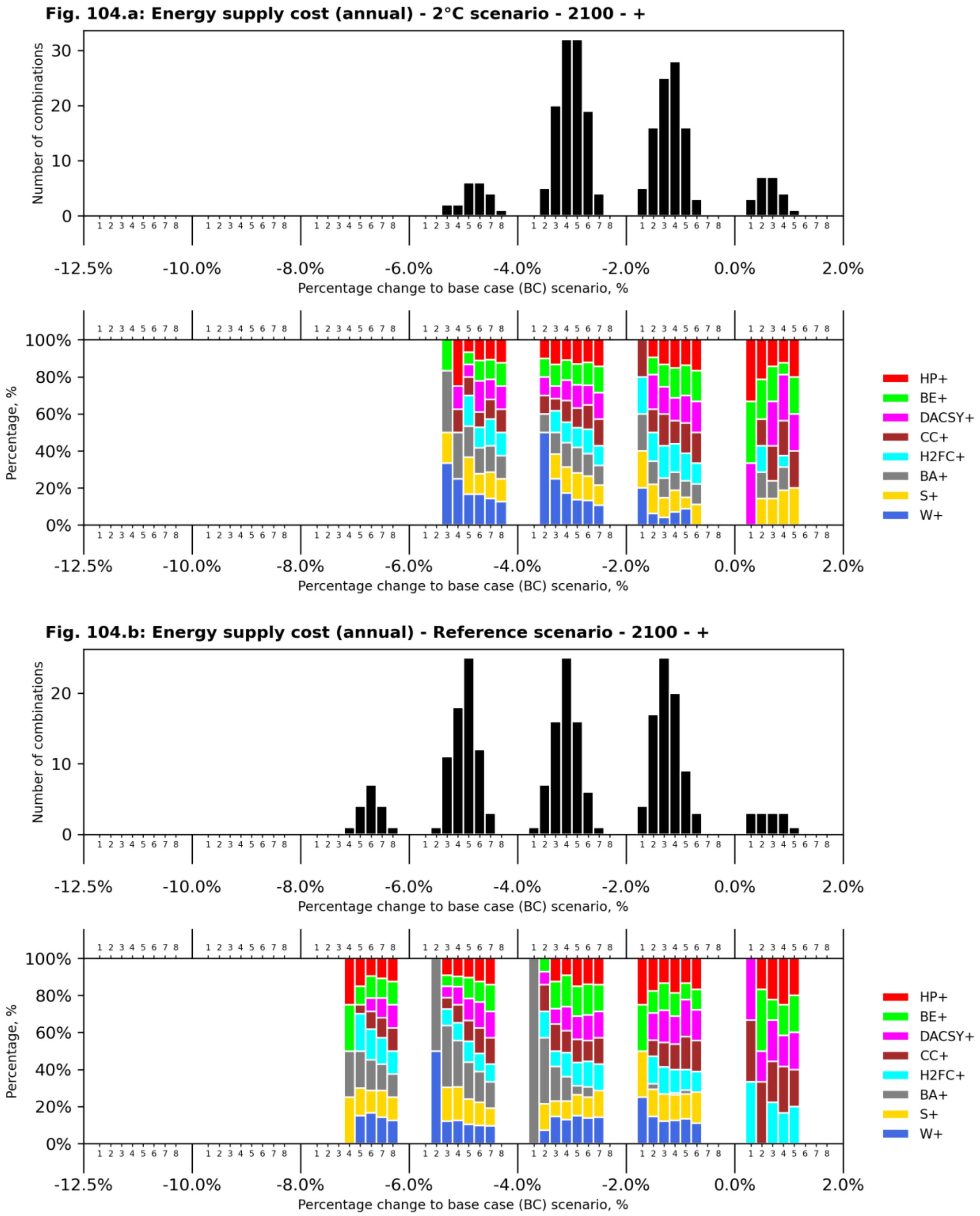
AN 4.3 Energy supply cost

Figure 103. Relative impacts on annual **energy supply costs** by **2050** of **moderately** enhanced learning (**+**) variations under the *2°C* and *Reference scenario*.



Source: POLES-JRC model

Figure 104. Relative impacts on annual **energy supply costs** by **2100** of **moderately** enhanced learning (**+**) variations under the *2°C* and *Reference scenario*.



Source: POLES-JRC model

Annex 5 Techno-economic parameters

Description

This section lists techno-economic parameters by technologies used in the POLES-JRC version of October 2024. The techno-economic parameters are listed in tables containing sections on cost parameters, learning rates and efficiencies.

The *cost section* contains

- Overnight investment costs for the technology as a whole and by component
- Floor cost refers to the minimum in investment cost, which limits the cost reduction by endogenous learning.
- Fixed and variable operation & maintenance cost (OM). The variable OM cost does not include energy cost.
- References for the cost parameters.

The shared conventional components are more expensive the CCS technologies than for the corresponding conventional technologies, as the whole CCS plant is more complex and consumes additional energy for capturing.

The *learning rate section* contains

- Default learning rate for the base case (*LR BC*);
- Acronyms for the technology groups (in **red**) of the sensitivity analysis associated with the technology or component;
- Learning rates for enhanced learning (*LR+*); and highly enhanced learning (*LR++*);
- Learning rate for efficiencies (LR_{eff});
- References for the learning rates parameters.

The *efficiency section* contains efficiencies (if applicable) for thermal power technologies, hydrogen technologies and other fuel-related technologies.

The first line of each technology (*in bold*) contains data relevant to the technology as a whole (i.e., total overnight investment cost, operation & maintenance cost) and efficiencies. The following lines (if applicable) contain data on component the level, such as overnight investment cost for the components and learning rates of the components.

All techno-economic parameters

- refer to global average figures;
- refer to the year 2022 and mark the starting point for their projected evolution in the scenarios of the POLES-JRC model (e.g., by endogenous learning)

The monetary values ($) in this section are constant US dollars of 2022.

References and data treatment

The techno-economic parameters are based on a comprehensive set of references. The main references of this comprehensive set are provided in this section.

The shown techno-economic parameters may not directly correspond to the original data in the references:

- as data in the references may vary over a broad range due to differences in perimeters and scope, regional data and currencies;
- as the shown parameters have been treated for converting currencies into USD and adapt for deflation to $2022;
- as the shown parameters may be an educated estimation based on the given references.

In the case of missing main references, the techno-economic parameters refer to an educated estimation based on secondary references.

The cost data may appear as odd numbers as a result of currency conversions and adaptation to deflation.

Floor costs
The floor cost is an estimate. In most cases, the floor cost is based on various sources [30] of long-term projections of investment cost (e.g., until 2050) to which a further cost reduction of 40% was applied.

AN 5.1 Power technologies

Table 10. Wind power technologies techno-economic parameters.

	Cost Parameters							Learning Rates						
	Overnight Investment Cost				Operational & Maintenance									
Technology Name	**Total Investment Cost in $/kW**	**Component Name**	**Component Investment Cost in $/kW**	**Floor Cost, in $/kW**	**Fixed O&M in $/kW**	**Variable O&M in $/MWh**	**References Cost**	**LR BC, %**	**Thematic group**	**LR +, %**	**LR ++, %**	**LR_{eff}, %**	**References learning**	**Efficiency, %**
Wind on-shore	**1274**				**49**	**0**	[27], [95]–[98]					**N/A**		**N/A**
		Wind turbine on-shore	1000	336			[27], [95]–[98]	14%	**W**	17.5%	21.0%		[11], [29], [67], [99], [100]	
		BOS wind on-shore	273	92			[27], [95]–[98]	14%	**W**	17.5%	21.0%		[11], [29], [67], [99], [100]	
Wind off-shore	**3461**				**128**	**0**	[27], [95]–[97], [101]					**N/A**		
		Wind turbine off-shore	1281	389			[27], [95]–[97], [101]	13%	**W**	16.3%	19.5%		[11], [29], [67], [99], [100]	

… continued from above		BOS wind off-shore	2180	662			[27], [95]–[97], [101]	13%	W	16.3%	19.5%		[11], [29], [67], [99], [100]	

Source: POLES-JRC model

Table 11. Solar power technologies techno-economic parameters.

	Cost Parameters							Learning Rates						
	Overnight Investment Cost				Operational & Maintenance									
Technology Name	**Total Investment Cost in $/kW**	**Component Name**	**Component Investment Cost in $/kW**	**Floor Cost, in $/kW**	**Fixed O&M in $/kW**	**Variable O&M in $/MWh**	**References Cost**	**LR BC, %**	**Thematic group**	**LR +, %**	**LR ++, %**	**LR_{eff}, %**	**References learning**	**Efficiency, %**
Utility PV	**875**				**17**	**0**	[27], [30]					**N/A**		**N/A**
		PV module	335	40			[27], [30]	30%	S	37.5%	45.0%		[11, p. 1], [15], [27], [29], [102]	
		BOS utility PV	540	193			[27], [30]	18%	S	22.5%	27.0%		[11, p. 1], [15], [27], [29], [102]	

Rooftop PV	**1184**				**23**	**0**	[27], [30]					**N/A**		**N/A**
		PV module	335	40			[27], [29], [30]	30%	**S**	37.5%	45.0%		[11, p. 1], [15], [27], [29], [102]	
		BOS rooftop PV	848	358			[27], [29], [30]	12%	**S**	16.3%	19.5%		[11, p. 1], [15], [27], [29], [102]	
Concentrated solar power (CSP)	**4274**			**2040**	**80**	**4.25**	[28], [30]	**17%**	**S**	**21.3%**	**25.5%**	**N/A**	[15], [29], [69], [103]	**N/A**

Source: POLES-JRC model

Table 12. Bioenergy power technologies techno-economic parameters.

Technology Name	Cost Parameters: Overnight Investment Cost: Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Operational & Maintenance: Fixed O&M in $/kW	Variable O&M in $/MWh	References Cost	Learning Rates: LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	Efficiency, %
Conventional biomass power (sub-critical steam turbine)	**3168**			**669**	**206**	**8.1**						**4%**	[14]	**34%**
		BOS steam power	1158	476				11%	**BE**	13.8%	16.5%		[11], [14], [104]	
		Steam generator & turbine	1357	669				11%					[11], [14], [104]	
		Pollution control	542	268				11.5%	**BE**	14.4%	17.3%		[14], [105]	
		Cooling	110	54				11%						
Integrated biomass gasification, IBG	**4321**			**1189**	**191**	**16.5**						**5%**	[14]	**39%**
		BOS gasifier	631	327				10%	**BE**	12.5%	15.0%			
		Pollution control	299	155				11.5%	**BE**	14.4%	17.3%		[14], [105]	
		Cooling	81	42				5%						
		Gas turbine	440	228				10%					[11], [14], [105]	
		Heat recovery steam generator	572	296				10%					[11], [14], [105]	

	Cost Parameters							Learning Rates						
	Overnight Investment Cost				Operational & Maintenance									
Technology Name	**Total Investment Cost in $/kW**	**Component Name**	**Component Investment Cost in $/kW**	**Floor Cost, in $/kW**	**Fixed O&M in $/kW**	**Variable O&M in $/MWh**	**References Cost**	**LR BC, %**	**Thematic group**	**LR +, %**	**LR ++, %**	**LR_{eff}, %**	**References learning**	**Efficiency, %**
		Gasifier	2297	1189				14%	**BE**	17.5%	21.0%		[14], [106]	
Integrated biomass gasification with CO_2 capture, IBG & CC	**6593**			**174**	**333**	**12.5**						**6%**		**30%**
		BOS gasifier	719	372				10%	**BE**	12.5%	15.0%			
		Pollution control	422	218				11.5%	**BE**	14.4%	17.3%		[14], [105]	
		Cooling	102	52				5%						
		Gas turbine	504	261				10%					[11], [14], [105]	
		Heat recovery steam generator	624	323				10%					[11], [14], [105]	
		Gasifier	2613	1353				14%	**BE**	17.5%	21.0%		[14], [106]	
		Water shift	332	172				12%	**CC, BE**	15.0%	18.0%		[14]	
		BOS CCS power	849	440				11%	**CC**	13.8%	16.5%		[14], [106]	
		CO_2 compression - CCS	92	48				3%	**CC, DACSY**	3.8%	4.5%		[14], [105], [107]	
		CO_2 removal (SELEXOL) - CCS	336	174				12%	**CC**	15.0%	18.0%		[14]	

Source: POLES-JRC model

Table 13. Other renewable power technologies techno-economic parameters.

Technology Name	Cost Parameters							Learning Rates						Efficiency, %
	Overnight Investment Cost				Operational & Maintenance		References Cost							
	Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Fixed O&M in $/kW	Variable O&M in $/MWh		LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	
Hydroelectricity – lake	2245		2245	1467	44	0.8	[27]	1.4%					[11], [108]–[111]	N/A
Hydroelectricity – run-of-river	2387		2387	1432	47	0.8	[27]	1.4%					[11], [108]–[111]	N/A
Hydroelectricity – small	2849		2849	1709	77	0.2	[27]	1.4%					[11], [108]–[111]	N/A
Geothermal	3478		3478	1981	151	0	[28], [30], [112], [113]	12%					[69], [114]–[116]	N/A
Ocean (wave & tidal)	5379		5379	1229	365	0	[117]–[119]	12%					[69], [120]–[123]	N/A

Source: POLES-JRC mode

Table 14. Fuel cells (power generation) techno-economic parameters.

Technology Name	Cost Parameters: Overnight Investment Cost: Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW in $/kW	Operational & Maintenance: Fixed O&M in $/kW	Variable O&M in $/MWh	References Cost	Learning Rates: LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	Efficiency, %
Natural gas fuel cell[5] [6]	3045		3045	443	194	0.6	[36], [124]–[127]	16%	**H2FC**	20.0%	24.0%	5%	[36]–[38], [40], [68], [128], [129]	44%
Hydrogen fuel cell[5]	3045		3045	443	194	0.6	[36], [124]–[127]	16%	**H2FC**	20.0%	24.0%	5%	[36]–[38], [40], [68], [128], [129]	40%

Source: POLES-JRC model

[5] The fuel cell technologies in POLES-JRC refer to generic fuel cell technologies aiming at representing the various existing types of fuel cells for power generation. Therefore, the techno-economic parameters are assumed to be equal for both types.
[6] Fuelled with natural gas.

Table 15. Electricity Storage[7] techno-economic parameters.

Technology Name	Cost Parameters							Learning Rates						Efficiency, %
	Overnight Investment Cost				Operational & Maintenance		References Cost							
	Total Investment Cost	Component Name	Component Investment Cost	Floor Cost, in $/kW in $/kW	Fixed O&M in	Variable O&M in $/MWh		LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	
Battery – electricity storage	N/A				52 $/kW	0	[30]							90%[8]
		Battery	371 $/kWh	80 $/kWh			[30], [36], [130]	12%	BA	15.0%	18.0%		[36]	
		BOS Battery	97 $/kW	26 $/kW				12%	BA	15.0%	18.0%		[36]	
Hydroelectricity – pumped storage	3787 $/kW		3641 $/kW	2184 $/kW	22 $/kW	0.6	[30]	1%					[110], [131], [132]	75%[8]
Adiabatic compressed air energy storage	1391 $/kW			730 $/kW	28 $/kW	3.6	[132]–[134]	0%					[132]	65%[8]

Source: POLES-JRC model

[7] Additionally, POLES-JRC considers adiabatic compressed air energy storage. Moreover, vehicle-to-grid (V2G) connection is considered as storage option tapping the vast battery capacities of the electric vehicles fleet. POLES assumes that 20% of the electric cars participate in V2G.
[8] Not subject to endogenous learning. Instead the efficiency improvements follow an exogenous trajectory.

Table 16. Fossil power technologies (including CCS power technologies) techno-economic parameters.

	Cost Parameters							Learning Rates						
	Overnight Investment Cost				Operational & Maintenance									
Technology Name	Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Fixed O&M in $/kW	Variable O&M in $/MWh	References Cost	LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	Efficiency, %
Hard coal (sub-critical steam turbine)	**2503**			**600**	**108**	**9.6**	[30], [135], [136]					**4%**	[14]	**38%**
		BOS steam power	554	249			[135]	5%					[11], [14], [104]	
		Steam generator & turbine	1332	600			[135]	5%					[11], [14], [104]	
		Pollution control	509	229			[135]	11.5%					[14], [105]	
		Cooling	109	49			[135]	5%						
Lignite (sub-critical steam turbine)	**2649**			**601**	**145**	**6.9**	[135], [137], [138]					**4%**	[14]	**34%**
		BOS steam power	672	302			[135]	5%					[11], [14], [104]	
		Steam generator & turbine	1335	601			[135]	5%					[11], [14], [104]	

	Cost Parameters							Learning Rates						
	Overnight Investment Cost				Operational & Maintenance									
Technology Name	Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Fixed O&M in $/kW	Variable O&M in $/MWh	References Cost	LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	Efficiency, %
… continued from above		Pollution control	533	240			[135]	11.5%					[14], [105]	
		Cooling	109	49			[135]	5%						
Advanced pulverised coal, Adv. PC (super/ultra-critical steam turbine)	**2838**			**657**	**113**	**9.4**	[30], [135], [136]					**4%**	[14]	**41%**
		BOS steam power	642	284			[135]	5%					[11], [14], [104]	
		Steam generator & turbine	1488	657			[135]	5%					[11], [14], [104]	
		Pollution control	590	260			[135]	11.5%					[14], [105]	
		Cooling	118	52			[135]	5%						
Advanced pulverised coal with CO_2 capture, Adv. PC & CC	**6383**			**339**	**179**	**13.2**	[30], [135]–[137]					**6%**	[14]	**32%**
		BOS steam power	2226	1145			[135]	5%	**CC**	6.3%	7.5%		[11], [14], [104]	
		Steam generator & turbine	1789	920			[135]	5%					[11], [14], [104]	
		Pollution control	719	370			[135]	11.5%					[14], [105]	

Technology Name	Cost Parameters: Overnight Investment Cost: Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Operational & Maintenance: Fixed O&M in $/kW	Variable O&M in $/MWh	References Cost	Learning Rates: LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	Efficiency, %
… continued from above		Cooling	170	87			[135]	5%						
		BOS CCS power	567	294			[135]	11%	**CC**	13.8%	16.5%			
		CO_2 compression - CCS	257	133			[135]	3%	**CC, DACSY**	3.8%	4.5%		[14], [105], [107]	
		CO_2 absorption - CCS	656	339			[135]	11%	**CC**	13.8%	16.5%		[14], [105], [106]	
Integrated coal gasification, ICG	**3213**			**878**	**141**	**16.5**	[30], [135], [136]					**5%**	[14]	**41%**
		BOS gasifier	466	241			[135]	10%						
		Pollution control	221	114			[135]	11.5%					[14], [105]	
		Cooling	82	43			[135]	5%						
		Gas turbine	325	168			[135]	10%					[11], [14], [105]	
		Heat recovery steam generator	422	219			[135]	10%					[11], [14], [105]	
		Gasifier	1696	878			[135]	14%					[14], [106]	

	Cost Parameters							Learning Rates						
	Overnight Investment Cost				Operational & Maintenance									
Technology Name	**Total Investment Cost in $/kW**	**Component Name**	**Component Investment Cost in $/kW**	**Floor Cost, in $/kW**	**Fixed O&M in $/kW**	**Variable O&M in $/MWh**	**References Cost**	**LR BC, %**	**Thematic group**	**LR +, %**	**LR ++, %**	**LR_{eff}, %**	**References learning**	**Efficiency, %**
Integrated coal gasification combined cycle with CO_2 capture, ICG & CC	**4770**			**93**	**245**	**12.5**	[135], [136]					**6%**	[14]	**32%**
		BOS gasifier CCS	1127	432			[135]	10%	**CC**	12.5%	15.0%			
		Pollution control	303	116			[135]	11.5%					[14], [105]	
		Cooling	98	38			[135]	5%						
		Gas turbine	363	139			[135]	10%					[11], [14], [105]	
		Heat recovery steam generator	450	172			[135]	10%					[11], [14], [105]	
		Gasifier	1880	722			[135]	14%					[14], [106]	
		Water shift	240	92			[135]	12%	**CC, BE**	15.0%	18.0%		[14]	
		CO_2 compression - CCS	67	26			[135]	3%	**CC, DACSY**	3.8%	4.5%		[14], [105], [107]	
		CO_2 removal (SELEXOL) - CCS	242	93			[135]	12%	**CC**	15.0%	18.0%		[14]	
Oil conventional thermal (steam turbine)	**2077**			**600**	**90**	**7.9**						**4%**	[14]	**35%**
		BOS steam power	332	150				5%					[11], [14], [104]	

	Cost Parameters							Learning Rates						
	Overnight Investment Cost				Operational & Maintenance									
Technology Name	Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Fixed O&M in $/kW	Variable O&M in $/MWh	References Cost	LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	Efficiency, %
		Steam generator & turbine	1332	600				5%					[11], [14], [104]	
... continued from above		Pollution control	305	137				11.5%					[14], [105]	
		Cooling	109	49				5%						
Oil-fired gas turbine	**753**			**237**	**19**	**0.1**	[30], [135], [137], [139]–[141]					**5%**		**36%**
		BOS gas turbine	2	1				10%					[11], [14], [105]	
		Pollution control	167	79				11.5%					[14], [105]	
		Cooling	80	38				5%						
		Gas turbine	503	237			[30], [135], [137], [139]–[141]	10%					[11], [14], [105]	

Technology Name	Cost Parameters							Learning Rates						Efficiency, %
	Overnight Investment Cost				Operational & Maintenance		References Cost							
	Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Fixed O&M in $/kW	Variable O&M in $/MWh		LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	
Gas conventional thermal (steam turbine)	**1972**			**600**	**85**	**7.5**						**4%**	[14]	**36%**
		BOS steam power	277	125				5%					[11], [14], [104]	
		Steam generator & turbine	1332	600				5%					[11], [14], [104]	
		Pollution control	254	114				11.5%					[14], [105]	
		Cooling	109	49				5%						
Gas-fired gas turbine	**705**			**222**	**15**		[30], [135], [137], [139]–[141]					**5%**		**37%**
		BOS gas turbine	2	1				10%					[11], [14], [105]	
		Pollution control	157	74				11.5%					[14], [105]	
		Cooling	75	36				5%						
		Gas turbine	470	222			[30], [135], [137], [139]–[141]	10%					[11], [14], [105]	

Technology Name	Cost Parameters							Learning Rates						Efficiency, %
	Overnight Investment Cost				Operational & Maintenance									
	Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Fixed O&M in $/kW	Variable O&M in $/MWh	References Cost	LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	
Natural gas combined cycle (NGCC)	**976**			**172**	**23**	**0.2**	[30], [135], [137], [139]–[141]					**5%**	[14]	**56%**
		BOS combined cycle	2	1			[135]	10%					[11], [14], [105]	
		Pollution control	140	69			[135]	11.5%					[14], [105]	
		Cooling	68	33			[135]	5%						
		Gas turbine	419	208			[135]	10%					[11], [14], [105]	
		Heat recovery steam generator	347	172			[135]	10%					[11], [14], [105]	
Natural gas combined cycle with CO_2 capture, NGCC & CC	**1723**			**130**	**72**	**6.4**						**6%**	[14]	**44%**
		BOS combined cycle CCS	2	1			[135]	10%	**CC**	12.5%	15.0%			
		Pollution control	157	60			[135]	11.5%					[14], [105]	
		Cooling	109	41			[135]	5%						

Technology Name	Cost Parameters							Learning Rates						Efficiency, %
	Overnight Investment Cost				Operational & Maintenance		References Cost							
	Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Fixed O&M in $/kW	Variable O&M in $/MWh		LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	
… continued from above		Gas turbine	472	179			[135]	10%					[11], [14], [105]	
		Heat recovery steam generator	337	128			[135]	10%					[11], [14], [105]	
		BOS CCS power	205	78			[135]	11%	**CC**	13.8%	16.5%			
		CO_2 compression - CCS	97	37			[135]	3%	**CC, DACSY**	3.8%	4.5%		[14], [105], [107]	
		CO_2 absorption - CCS	344	130			[135]	11%	**CC**	13.8%	16.5%		[14], [105], [106]	

Source: POLES-JRC model

Table 17. Nuclear power techno-economic parameters.

Technology Name	Cost Parameters: Overnight Investment Cost: Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Operational & Maintenance: Fixed O&M in $/kW	Variable O&M in $/MWh	References Cost	Learning Rates: LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	Efficiency, %
Nuclear – Gen.III	**7987**			**4347**	**177**	**5.3**	[30], [125], [130], [142], [143]					**0%**	[144]–[146]	**34%**
Nuclear – Gen.IV[9]	**8051**			**4830**	**219**	**6.6**						**0%**		**45%**

Source: POLES-JRC model

[9] In POLES-JRC Generation IV nuclear power plants are permissible from 2060 onwards.

AN 5.2 Hydrogen production technologies

Table 18. Hydrogen production technologies techno-economic parameters.

	Cost Parameters							Learning Rates						
	Overnight Investment Cost				Operational & Maintenance									
Technology Name	**Total Investment Cost in $/kW_{H2}$**	**Component Name**	**Component Investment Cost in $/kW_{H2}$**	**Floor Cost, in $/kW_{H2}$**	**Fixed O&M in $/kW**	**Variable O&M in $/t_{H2}$**	**References Cost**	**LR BC, %**	**Thematic group**	**LR +, %**	**LR ++, %**	**LR_{eff}, %**	**References learning**	**Efficiency, %**
Steam reforming	**575**				**19**	**25**	[147]					**5%**		**76%**
		BOS hydrogen production	256	154			[147]	11%					[15], [38]	
		Cooling	22	13			[147]	5%						
		Reformer	191	114			[147]	11%					[15], [38]	
		Hydrogen production	79	47			[147]	11%	**H2FC**				[15], [38]	
		Water shift	27	16			[147]	12%	**H2FC**					
Coal gasification	**4221**				**135**	**126**						**5%**		**63%**
		BOS hydrogen production	696	418			[147]	11%						
		Pollution control	307	185			[147]	11.5%						
		Cooling	64	39			[147]	5%						
		Gasifier	2674	1604			[147]	14%					[14], [106]	
		Hydrogen production	94	56			[147]	11%	**H2FC**				[15], [38]	
		Water shift	385	231			[147]	12%	**H2FC**					

	Cost Parameters							Learning Rates						
	Overnight Investment Cost				Operational & Maintenance									
Technology Name	**Total Investment Cost in $/kW_{H2}$**	**Component Name**	**Component Investment Cost in $/kW_{H2}$**	**Floor Cost, in $/kW_{H2}$**	**Fixed O&M in $/kW**	**Variable O&M in $/t_{H2}$**	**References Cost**	**LR BC, %**	**Thematic group**	**LR +, %**	**LR ++, %**	**LR_{eff}, %**	**References learning**	**Efficiency, %**
Biomass gasification	**4549**				**168**	**104**						**5%**		**50%**
		BOS hydrogen production	1192	716				11%						
		Pollution control	75	45				11.5%	**BE**	14.4%	17.3%			
		Cooling	140	84				5%						
		Gasifier	2847	1709				14%	**BE**	17.5%	21.0%		[14], [106]	
		Hydrogen production	213	128				11%	**H2FC**				[15], [38]	
		Water shift	81	49				12%	**H2FC**					
Steam reforming with CO_2 capture	**1398**				**42**	**71**	[147]					**6%**		**69%**
		BOS hydrogen production	316	189			[147]	11%						
		Cooling	75	45			[147]	5%						
		Reformer	196	117			[147]	11%					[15], [38]	
		Hydrogen production	77	46			[147]	11%	**H2FC**				[15], [38]	
		Water shift	26	16			[147]	12%						
		CO_2 compression - CCS	158	95			[147]	3%	**CC, DACSY**	3.8%	4.5%		[14], [105], [107]	
		CO_2 absorption - CCS	551	330			[147]	11%	**CC**	13.8%	16.5%		[14], [105], [106]	

	Cost Parameters							Learning Rates						
	Overnight Investment Cost				Operational & Maintenance									
Technology Name	**Total Investment Cost in $/kW_{H2}$**	**Component Name**	**Component Investment Cost in $/kW_{H2}$**	**Floor Cost, in $/kW_{H2}$**	**Fixed O&M in $/kW**	**Variable O&M in $/t_{H2}$**	**References Cost**	**LR BC, %**	**Thematic group**	**LR +, %**	**LR ++, %**	**LR_{eff}, %**	**References learning**	**Efficiency, %**
Coal gasification with CO_2 capture	**4866**				**154**	**153**	[147]					**6%**		**63%**
		BOS hydrogen production	718	431			[147]	11%						
		Pollution control	259	155			[147]	11.5%						
		Cooling	70	42			[147]	5%						
		Gasifier	2682	1609			[147]	14%					[14], [106]	
		Hydrogen production	58	35			[147]	11%	**H2FC**				[15], [38]	
		Water shift	383	229			[147]	12%	**H2FC**					
		CO_2 compression - CCS	109	66			[147]	3%	**CC, DACSY**	3.8%	4.5%		[14], [105], [107]	
		CO_2 removal (SELEXOL) - CCS	586	351			[147]	12%	**CC**	15.0%	18.0%			
Biomass gasification with CO_2 capture	**5245**				**192**	**127**	[147]					**6%**		**50%**
		BOS hydrogen production	1749	1049			[147]	11%						
		Pollution control	63	38			[147]	11.5%	**BE**	14.4%	17.3%			
		Cooling	153	92			[147]	5%						
		Gasifier	2856	1714			[147]	14%	**BE**	17.5%	21.0%		[14], [106]	
		Hydrogen production	134	80			[147]	11%	**H2FC**				[15], [38]	
		Water shift	81	49			[147]	12%	**H2FC**					

Technology Name	Cost Parameters							Learning Rates						Efficiency, %
	Overnight Investment Cost				Operational & Maintenance		References Cost							
	Total Investment Cost in $\$/kW_{H2}$	Component Name	Component Investment Cost in $\$/kW_{H2}$	Floor Cost, in $\$/kW_{H2}$	Fixed O&M in $/kW	Variable O&M in $\$/t_{H2}$		LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	
... continued from above		CO_2 compression - CCS	80	48			[147]	3%	**CC, DACSY**	3.8%	4.5%		[14], [105], [107]	
		CO_2 removal (SELEXOL) - CCS	129	77				12%	**CC**	15.0%	18.0%			
Low-temperature electrolysis	**1197**		**1197**	**215**	**26**	**N/A**	[148], [149]	**15%**	**H2FC**	**18.8%**	**22.5%**	**5%**	[36]–[41]	**65%**
High-temperature electrolysis	**4521**		**4521**	**547**	**102**	**N/A**	[35]	**11%**	**H2FC**			**5%**		**79%**
Gas pyrolysis	**1812**		**1812**	**831**	**50**	**N/A**	[150]	**11%**	**H2FC**	**13.8%**	**16.5%**	**5%**		**40%**
Biomass pyrolysis	**1650**		**1650**	**757**	**54**	**N/A**	[150], [151]	**11%**	**H2FC**	**13.8%**	**16.5%**	**5%**		**40%**

Source: POLES-JRC model

AN 5.3 Fuels: Biofuels, biomethane and hydrogen based fuels

Table 19. Biofuels and biomethane techno-economic parameters.

Technology Name	Cost Parameters							Learning Rates						Efficiency, %
	Overnight Investment Cost				Operational & Maintenance		References Cost							
	Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Fixed O&M in $/kW	Variable O&M in $/toe		LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	
1st gen. biogasoline	**539**			**253**		**2.70**	[49], [50]	**5%**	**BE**	**6.3%**	**7.5%**	**5%**	[15], [152]–[154]	**51%**
2nd gen. biogasoline	**2980**			**1074**		**16.61**	[52], [155]	**5%**	**BE**	**6.3%**	**7.5%**	**5%**	[15], [152], [153], [155]	**42%**
1st gen. biodiesel	**483**			**223**		**3.29**	[50], [156], [157]	**5%**	**BE**	**6.3%**	**7.5%**	**5%**	[15], [152]	**52%**
2nd gen. biodiesel	**4961**			**1594**		**10.79**	[158]	**8%**	**BE**	**10.0%**	**12.0%**	**5%**	[15], [152], [153], [155]	**44%**
Biomethane	**1251**			**649**	**39**			**5%**	**BE**	**6.3%**	**7.5%**	**5%**	[11], [15], [159]	**65%**

Source: POLES-JRC model

Table 20. Hydrogen based fuels (trade and production) techno-economic parameters.

	Cost Parameters				Learning					Process Parameters			
Technology Name	**Overnight Investment Cost (2022)**	**Floor Cost**	**Fixed O&M (2022)**	**References Cost**	**LR BC**	**Thematic group**	**LR +**	**LR ++**	**References learning**	**Conversion efficiency (2022)**	**Electricity (2022)**	**LR_{eff}, %**	**References Process Param.**
Ammonia	*$\$/kW_{NH3}$*	*$\$/kW_{NH3}$*	*% of OIC[10]*							*% of H2 converted*	*kWh/kg_{H2}*		
NH_3 - conversion	510	229	2%	[160]	8%	**H2FC**	10%	12%		88%	4.3	5%	[160]
NH_3 - reconversion	1154	153	3.5%	[160]	8%	**H2FC**	10%	12%		70%	2.0	10%[11], 5%[12]	[160]
Liquid Hydrogen	*$\$/kW_{H2}$*		*% of OIC[10]*										
Liquid H2 - liquefaction	2772[13]	N/A	3.5%	[160]	N/A	N/A	N/A	N/A		95%	8.5	5%	[160]
Liquid H2 - reconversion	649[13]	N/A	3.5%	[160]	N/A	N/A	N/A	N/A		98%	0.8	5%	[160]
Synfuels	*$\$/kW_{Product}$*	*$\$/kW_{Product}$*	*$\$/kW_{Product}$*							*H2 energy input per unit of energy product*	*Electricity input per unit of energy product*		
Synfuel, gaseous	2035	562	168	[44], [45]	11%	**DACSY**	14%	17%	[161]	1.26	0.10	5%	[44]
Synfuel, liquid	1510	321	48	[43]	11%	**DACSY**	14%	17%		1.62	0.08	5%	[162]

[10] OIC: Overnight investment cost
[11] Learning rate (LR) for hydrogen conversion.
[12] Learning rate (LR) for electricity consumption.
[13] Exogenous cost evolution assumed until 2050.

AN 5.4 Energy demand

AN 5.4.1 Transport – Battery vehicles and fuel cells vehicles

Table 21. Battery vehicles techno-economic parameters.

Technology Name	Cost Parameters							Learning Rates						Efficiency, %
	Overnight Investment Cost				Operational & Maintenance									
	Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Fixed O&M in $/kW	Variable O&M in $/MWh	References Cost	LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	
Battery - electric cars	140	Battery component	140	42	N/A	N/A	[163]	13%	**BA**	16.3%	19.5%	N/A	[36], [164]	N/A
Battery - electric trucks	319	Battery component	319	64	N/A	N/A	[148]	13%	**BA**	16.3%	19.5%	N/A	[36], [164]	N/A
Battery - electric aircrafts	420	Battery component	420	99	N/A	N/A		13%	**BA**	16.3%	19.5%	N/A	[36], [164]	N/A

Source: POLES-JRC model

Table 22. Fuel cell vehicles techno-economic parameters.

Technology Name	Cost Parameters							Learning Rates						Efficiency, %
	Overnight Investment Cost				Operational & Maintenance		References Cost							
	Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Fixed O&M in $/kW	Variable O&M in $/MWh		LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	
Fuel cells - cars	106	Fuel cell component	106	27	N/A	N/A	[130], [165]	15%	**H2FC**	18.8%	22.5%	N/A	[39], [36], [68], [37], [128], [40], [38], [129]	N/A
Fuel cells - trucks	400	Fuel cell component	400	74	N/A	N/A	[148]	11%	**H2FC**	13.8%	16.5%	N/A	[39], [36], [68], [37], [128], [40], [38], [129]	N/A
Fuel cells - ships	2124	Fuel cell component	2124	122	N/A	N/A	[166]	11%	**H2FC**	13.8%	16.5%	N/A	[39], [36], [68], [37], [128], [40],	N/A

Technology Name	Cost Parameters							Learning Rates						Efficiency, %
	Overnight Investment Cost				Operational & Maintenance									
	Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Fixed O&M in $/kW	Variable O&M in $/MWh	References Cost	LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning	
													[38], [129]	
Fuel cells - electric aircrafts	3186	Fuel cell component	3186	704	N/A	N/A		11%	**H2FC**	13.8%	16.5%	N/A	[39], [36], [68], [37], [128], [40], [38], [129]	N/A

Source: POLES-JRC model

AN 5.4.2 Heat pump technologies

Table 23. Heat pump technologies techno-economic parameters.

	Cost Parameters							Learning Rates						
	Overnight Investment Cost				Operational & Maintenance									
Technology Name	**Total Investment Cost in $/kW_{th}$**	**Component Name**	**Component Investment Cost in $/kW_{th}$**	**Floor Cost, in $/kW**	**Fixed O&M**	**Variable O&M**	**References Cost**	**LR BC, %**	**Thematic group**	**LR +, %**	**LR ++, %**	**LR_{eff}, %**	**References learning**	**SCOP**
Heat pumps for heating - Residential	1152	Heat pump for heating component	1152	288	N/A	N/A	[167]–[169]	9%	**HP**	11.3%	13.5%	10%	[168], [170]–[172]	**Benchmark:** SCOP 3.3 (2570 HDD)
Heat pumps for heating - Services	641	Heat pump for heating component	641	160	N/A	N/A	[167]–[169]	9%	**HP**	11.3%	13.5%	10%	[168], [170]–[172]	**SCOP range:** 4.0 (800 HDD) to 2.3 (6500 HDD)
Cooling appliance - Residential	376	Heat pump for cooling component	376	206	N/A	N/A	[167]–[169]	9%	**HP**	11.3%	13.5%	10%	[168], [170]–[172]	**Benchmark:** SCOP 3.7 (1150 CDD)
Cooling appliance - Services	209	Heat pump for cooling component	209	114	N/A	N/A	[167]–[169]	9%	**HP**	11.3%	13.5%	10%	[168], [170]–[172]	**SCOP range:** 3.9 (200 CDD) to 3.0 (4000 CDD)

Source: POLES-JRC model

AN 5.5 Direct air capture (DAC)

Table 24. Direct air capture (DAC) techno-economic parameters.

Technology Name	Cost Parameters							Learning Rates						Thermal energy consumption, GJ/t_{CO2}	Electricity energy consumption, GJ/t_{CO2}
	Overnight Investment Cost				Operational & Maintenance		References Cost								
	Total Investment Cost in $/kW	Component Name	Component Investment Cost in $/kW	Floor Cost, in $/kW	Fixed O&M in $/kW	Variable O&M in $/MWh		LR BC, %	Thematic group	LR +, %	LR ++, %	LR_{eff}, %	References learning		
Direct air capture (DAC)	**961**				**31**	**5**	[43], [173], [174]		**DACSY**			**5%**		**6**	**1.8**
		Direct air capture process	885	158			[14], [106], [107]	14%	**DACSY**	17.5%	21.0%		[43], [175], [176]		
		CO_2 compression - CCS	77	27			[176]	3%	**DACSY, CC**	3.8%	4.5%		[14], [106], [107]		

Source: POLES-JRC model

Annex 6 Energy balances

AN 6.1 Reference scenario – Energy balance

Table 25. Energy balance of the Reference scenario.

Reference scenario

World	1990	2000	2005	2010	2015	2020	2030	2040	2050	2060	2070	2080	2090	2100
Main Economic Indicators														
Population (Million)	5 333	6 147	6 544	6 960	7 384	7 786	8 484	9 037	9 448	9 693	9 797	9 785	9 675	9 482
GDP per capita (ppp, k$'15)	9	11	12	13	15	16	20	24	28	33	40	48	58	69
Value added - Industry (ppa, M$'15)	14855266	19910014	24279880	28565604	34104164	38104264	51415372	64247468	76882352	90918168	106189168	122055688	138061744	153438 704
Value added - Services (ppa, M$'15)	31147438	41402312	49290924	58320312	68732312	75595872	106597816	138718528	174222368	217228656	269612192	330607680	401308128	481717 376
Value added - Agriculture and Forestry (ppa, M$'15)	2743760	3873766	4441042	5407741	6335994	7014349	9049262	11008285	12917163	14900534	16927410	18913540	20804456	22529864
Prices														
International ($'15/boe)														
Coal	19	11	15	23	20	17	29	26	26	28	28	29	31	32
Oil	39	38	65	87	52	38	92	101	106	118	126	126	126	126
Gas	20	26	40	35	37	21	53	47	57	56	79	64	81	75
GHG emissions ($MtCO_2$ eq.)														
Total GHG (all, including LULUCF)	**39 761**	**41 177**	**45 247**	**49 793**	**52 842**	**52 091**	**52 338**	**50 442**	**47 802**	**45 952**	**45 113**	**45 586**	**45 477**	**44 813**
Total GHG (all, excluding LULUCF)	**34 470**	**36 775**	**41 489**	**46 550**	**49 325**	**49 218**	**50 839**	**49 161**	**46 951**	**45 487**	**45 205**	**46 212**	**46 474**	**46 031**
CO_2	22 960	25 280	28 954	33 232	35 288	34 593	36 052	34 661	33 118	31 652	31 318	32 284	32 641	32 503
CH_4	9 053	8 783	9 433	9 988	10 355	10 634	10 483	10 472	10 531	10 686	10 711	10 745	10 669	10 402
N_2O	2 127	2 237	2 401	2 465	2 623	2 647	2 707	2 680	2 684	2 679	2 698	2 709	2 703	2 685
F gases	330	475	700	865	1 059	1 344	1 598	1 348	618	469	478	474	461	441
Total GHG from Energy and Industry	**28 633**	**30 938**	**35 303**	**40 070**	**42 566**	**42 258**	**43 791**	**42 169**	**39 963**	**38 520**	**38 312**	**39 409**	**39 810**	**39 509**
CO_2 Emissions from Fuel Comb.	**21 051**	**23 106**	**26 183**	**29 651**	**31 321**	**30 249**	**31 212**	**29 935**	**28 387**	**26 550**	**25 780**	**26 685**	**27 163**	**27 141**

Power generation/District heating	6 865	7 919	9 151	10 418	11 176	11 178	14 424	15 555	15 616	14 420	13 374	13 790	14 148	13 975
Industry	4 170	4 189	5 270	6 187	6 321	6 129	5 802	5 348	4 998	4 936	4 982	4 782	4 497	4 261
Buildings	2 955	2 750	2 912	2 970	2 949	2 922	2 123	1 473	1 248	1 099	986	889	802	753
Agriculture	425	365	430	428	442	423	457	464	470	478	486	494	502	511
Transport	4 676	5 678	6 341	7 021	8 024	7 222	6 658	5 119	3 485	2 499	2 531	2 952	3 233	3 544
Other	1 960	2 205	2 079	2 628	2 409	2 373	1 748	1 977	2 570	3 118	3 421	3 777	3 981	4 097
CO_2 captured	**0**	**0**	**0**	**0**	**0**	**1**	**13**	**190**	**563**	**1 103**	**1 582**	**2 070**	**2 732**	**2 910**
Fossil fuels	0	0	0	0	0	1	8	141	395	722	966	1 145	1 301	1 359
Biomass	0	0	0	0	0	0	1	14	109	227	338	421	630	592
Industrial processes	0	0	0	0	0	0	0	7	25	44	71	136	179	172
Direct Air Capture	0	0	0	0	0	0	4	29	35	110	207	369	622	787
Air pollutants (Mt)														
SO_2	92	93	97	84	75	60	61	45	30	31	30	29	27	24
NO_x	90	104	109	110	106	91	77	63	47	43	42	41	41	38
$PM_{2.5}$	38	38	39	39	38	37	59	57	57	60	72	72	77	81
NH_3	41	46	51	54	56	56	59	55	50	52	54	57	58	59
Energy Balance, by fuel (Mtoe)														
Primary Production	**8 549**	**9 941**	**11 389**	**12 728**	**13 890**	**13 986**	**15 146**	**16 262**	**17 459**	**18 666**	**19 974**	**21 284**	**22 324**	**22 884**
Coal	2 115	2 314	2 926	3 560	3 833	3 720	4 120	4 030	3 663	3 499	2 942	2 872	2 916	2 603
Oil	3 398	3 986	4 366	4 505	4 889	4 418	3 756	2 991	2 309	1 978	1 926	2 012	2 147	2 232
Natural gas	1 770	2 149	2 467	2 815	3 113	3 492	3 599	4 101	4 888	5 041	5 919	6 488	6 401	6 818
Biomass	871	984	1 065	1 200	1 295	1 417	1 827	2 008	1 885	1 987	2 039	2 109	2 446	2 342
Nuclear[1]	173	223	238	237	221	230	219	152	142	142	118	88	84	82
Non-biomass renewables	223	284	326	411	540	709	1 624	2 979	4 572	6 019	7 030	7 715	8 331	8 806
International Bunkers[14]	**219**	**297**	**331**	**373**	**412**	**342**	**487**	**584**	**659**	**718**	**861**	**1 042**	**1 255**	**1 487**
Maritime Bunkers	122	162	187	217	217	253	235	282	326	366	413	460	516	571
Oil	122	162	187	217	208	237	127	96	77	77	72	70	75	78
Gas	0	0	0	0	9	13	42	86	98	100	111	127	130	139
Biofuels	0	0	0	0	0	3	45	27	19	19	18	17	18	18

[14] Refers to international transport.

Hydrogen	0	0	0	0	0	0	2	13	28	36	45	54	63	71
E-fuels	0	0	0	0	0	0	0	2	2	7	12	15	21	23
Ammonia	0	0	0	0	0	0	19	57	100	126	155	178	209	242
Aviation Bunkers	98	135	144	156	195	90	252	302	334	352	449	582	739	916
Oil	98	135	144	156	195	89	222	246	241	146	144	168	210	267
Hydrogen	0	0	0	0	0	0	0	3	23	97	158	224	284	339
Power	0	0	0	0	0	0	0	12	24	55	78	102	124	143
Biofuels	0	0	0	0	0	1	30	42	46	52	62	76	99	133
E-fuels	0	0	0	0	0	0	0	0	0	2	6	13	22	33
Statistical differences (Mtoe)	**0**	**133**	**304**	**438**	**439**	**650**	**650**	**650**	**650**	**650**	**650**	**650**	**650**	**650**
Coal	0	47	159	232	233	330	333	333	333	333	333	333	333	333
Oil	0	- 27	11	36	37	64	40	40	40	40	40	40	40	40
Natural gas	0	113	134	170	169	256	277	277	277	277	277	277	277	277
Primary Energy Demand, by sector (Mtoe)														
Total Primary Energy Demand[15]	**8 514**	**9 516**	**10 762**	**12 053**	**12 925**	**13 051**	**14 689**	**15 885**	**17 193**	**18 566**	**20 026**	**21 510**	**22 947**	**23 689**
Primary Energy Demand[16]	**8 294**	**9 219**	**10 431**	**11 680**	**12 513**	**12 709**	**14 202**	**15 300**	**16 534**	**17 848**	**19 164**	**20 467**	**21 692**	**22 202**
Coal	2 193	2 264	2 793	3 358	3 530	3 326	3 787	3 698	3 330	3 166	2 609	2 539	2 584	2 271
Oil	3 087	3 410	3 672	3 772	4 004	3 763	3 367	2 608	1 951	1 714	1 670	1 734	1 821	1 847
Natural gas	1 739	2 034	2 312	2 666	2 877	3 204	3 330	3 803	4 601	4 759	5 639	6 217	6 357	6 791
Biomass	879	1 004	1 090	1 237	1 342	1 477	1 874	2 059	1 938	2 048	2 099	2 174	2 515	2 405
Nuclear[17]	173	223	238	237	221	230	219	152	142	142	118	88	84	82
Hydro	188	232	259	304	342	384	495	546	600	625	633	653	677	685
Wind	0	3	9	29	72	138	472	1 017	1 750	2 442	3 070	3 573	4 102	4 640
Solar	3	5	8	19	56	106	525	1 063	1 690	2 348	2 657	2 853	2 893	2 852
Geothermal	31	45	50	59	70	82	132	348	523	594	660	627	646	615
Ocean	0	0	0	0	0	0	2	5	9	10	10	10	13	14
Energy for Power Generation	**2 424**	**2 806**	**3 243**	**3 733**	**4 105**	**4 376**	**6 146**	**7 980**	**9 787**	**10 934**	**11 782**	**12 641**	**13 510**	**13 740**
Other Energy Transformation & Losses	**588**	**558**	**604**	**736**	**780**	**872**	**964**	**1 114**	**1 275**	**1 727**	**2 062**	**2 334**	**2 539**	**2 640**
Final consumption (incl. bunkers)	**6 461**	**7 214**	**8 173**	**9 100**	**9 760**	**9 880**	**10 591**	**11 032**	**11 859**	**12 702**	**13 818**	**14 838**	**15 668**	**16 278**

[15] Calculated as primary energy demand including oil and gas bunkers.
[16] Balances exclude bunkers for primary fuels (oil and gas); include energy inputs into the production of secondary fuels for bunkers (hydrogen and e-fuels); include net imports of liquid biofuels and electricity.
[17] Nuclear energy is accounted as primary electricity.

Steel, Non-Met. Minerals and Chem.	1 019	1 138	1 390	1 655	1 831	1 886	1 855	1 736	1 734	1 897	2 041	2 078	2 076	2 076
Other Industry	1 078	1 072	1 242	1 425	1 445	1 503	1 805	2 113	2 315	2 460	2 647	2 845	3 040	3 223
Non-Energy Use	425	534	612	664	704	787	788	813	845	868	883	889	885	881
Residential	1 605	1 772	1 858	1 940	1 962	2 092	2 313	2 367	2 411	2 461	2 535	2 593	2 593	2 591
Services	584	624	731	816	879	912	1 047	1 172	1 315	1 456	1 629	1 821	1 955	1 944
Agriculture	167	148	174	181	195	202	228	243	256	269	282	294	307	321
Road	1 133	1 439	1 636	1 815	2 024	1 934	1 747	1 651	1 968	2 234	2 570	2 859	3 082	3 210
Rail	56	43	51	48	52	52	60	65	68	71	75	78	81	84
Aviation	233	239	245	293	391	202	444	514	539	535	655	827	1 038	1 281
Other Transport	161	204	233	264	277	309	303	358	406	450	502	552	611	668

Power Generation														
Fuel Inputs Therm. Power (Mtoe)	**2 062**	**2 349**	**2 736**	**3 159**	**3 444**	**3 552**	**4 502**	**5 310**	**5 868**	**5 809**	**5 903**	**6 175**	**6 654**	**6 566**
Coal	1 165	1 442	1 694	1 941	2 072	2 053	2 620	2 730	2 492	2 266	1 699	1 676	1 747	1 475
Oil	337	270	227	185	185	127	177	134	97	58	26	16	38	14
Gas	476	541	691	864	962	1 073	1 412	1 784	2 286	2 243	2 841	3 109	3 184	3 576
Biomass & Waste	53	51	74	110	155	217	161	315	471	647	677	747	1 039	886
Geothermal	31	45	50	59	70	82	132	348	523	594	660	627	646	615
Gross Elec. Generation (TWh_e)	**11 896**	**15 601**	**18 455**	**21 733**	**24 557**	**27 111**	**40 139**	**56 525**	**75 321**	**91 616**	**102 714**	**112 657**	**120 449**	**124 838**
Coal	4 430	5 993	7 317	8 654	9 524	9 453	11 232	12 116	11 697	11 304	8 981	8 999	9 574	8 242
of which CCS	0	0	0	0	0	0	3	38	31	21	30	44	42	44
Oil	1 276	1 162	1 102	942	1 004	658	728	557	411	245	110	68	179	65
Gas	1 748	2 770	3 698	4 855	5 541	6 352	7 635	9 584	12 603	12 778	16 511	18 774	20 024	23 003
of which CCS	0	0	0	0	0	0	0	73	176	223	263	370	404	372
Biomass & Waste	97	162	228	362	510	685	575	1 214	1 936	2 933	3 066	3 370	4 778	4 039
of which CCS	0	0	0	0	0	0	0	5	50	121	195	292	495	447
Nuclear	2 013	2 591	2 768	2 756	2 570	2 676	2 525	1 731	1 561	1 520	1 204	814	740	709
Hydro	2 190	2 694	3 017	3 535	3 981	4 462	5 751	6 352	6 977	7 266	7 361	7 589	7 871	7 969
Wind	4	31	104	342	834	1 599	5 281	11 314	18 855	25 952	32 238	37 427	42 048	46 868

Solar	1	2	5	40	300	844	5 513	11 517	17 969	24 620	27 335	29 123	28 759	27 553
Other	137	196	216	248	294	381	898	2 140	3 312	4 997	5 908	6 495	6 476	6 391
Share of Renewables (%)	*20%*	*19%*	*18%*	*20%*	*23%*	*28%*	*44%*	*55%*	*62%*	*68%*	*69%*	*70%*	*70%*	*70%*
Generation Capacity (GW_e)	**2 749**	**3 541**	**4 184**	**5 182**	**6 374**	**7 890**	**13 318**	**21 025**	**29 040**	**38 566**	**43 859**	**46 792**	**47 961**	**51 218**
Coal	897	1 132	1 298	1 655	1 985	2 180	2 052	2 109	1 895	1 852	1 551	1 569	1 643	1 571
of which CCS	0	0	0	0	0	0	1	9	12	9	11	13	13	12
Oil	420	426	400	419	413	363	293	296	265	267	228	241	306	391
Gas	454	734	1 066	1 324	1 569	1 799	2 174	3 019	4 058	5 011	6 082	6 685	7 332	9 828
of which CCS	0	0	0	0	0	0	0	16	49	92	117	144	120	102
Biomass & Waste	20	34	48	78	108	146	251	491	685	1 031	1 221	1 406	1 571	1 575
of which CCS	0	0	0	0	0	0	0	2	22	63	99	142	164	158
Nuclear	327	364	381	383	350	388	372	253	221	212	165	110	100	95
Hydro	617	816	911	1 081	1 291	1 518	1 790	1 969	2 149	2 204	2 198	2 212	2 261	2 286
Wind	2	17	59	183	417	735	2 266	4 529	7 204	9 608	11 464	12 796	14 118	15 561
Solar	0	1	4	38	213	737	4 075	8 233	12 353	18 104	20 642	21 437	20 229	19 445
Other	13	15	17	21	27	25	45	127	211	277	308	336	401	466
Other Renewable Capacity (GW_e)	**0**	**0**	**0**	**0**	**1**	**1**	**169 918**	**440 568**	**1532 408**	**2944 208**	**3634 636**	**4429 768**	**5383 476**	**6303 560**
Hydrogen	0	0	0	0	0	0	168	425	1 514	2 892	3 548	4 278	5 138	6 024
DAC	0	0	0	0	0	0	169 750	440 143	1530 894	2941 316	3631 088	4425 490	5378 338	6297 536
Total Final Consumption[18] (Mtoe)	**5816.2 91158**	**6382.9 4342**	**7229.4 62608**	**8063.8 60261**	**8644.0 09886**	**8750.0 18876**	**9315.8 04851**	**9634.7 11393**	**10354. 37276**	**11115. 99766**	**12073. 91616**	**12906. 66481**	**13527. 54354**	**13910. 2968**
Coal	872	687	1 004	1 279	1 321	1 160	1 102	890	695	700	688	654	609	564
Oil	2 086	2 367	2 572	2 672	2 890	2 679	2 331	1 690	1 101	917	918	993	1 046	1 086
Gas	933	1 110	1 176	1 316	1 390	1 547	1 251	1 167	1 218	1 058	1 075	1 046	959	921
Electricity	832	1 091	1 298	1 537	1 741	1 960	2 867	4 060	5 526	6 506	7 367	8 154	8 761	9 107
Heat	340	257	271	295	311	365	422	448	449	442	433	423	404	385
Biomass	754	870	909	966	991	1 038	1 293	1 297	1 088	1 019	991	965	944	920
Hydrogen	0	0	0	0	0	0	50	79	276	456	565	611	681	765
E-fuels	0	0	0	0	0	0	1	3	1	18	37	59	124	162
Share of Renewables[19] (%)	*16%*	*17%*	*16%*	*16%*	*17%*	*20%*	*31%*	*41%*	*49%*	*56%*	*57%*	*58%*	*59%*	*59%*

[18] Does not include international aviation and maritime bunkers; does not include non-energy uses.
[19] Ratio of renewable energy over final energy demand increased by distribution losses and self consumption of electricity and steam plants.

Industry (excl. non-energy use)	**2 096**	**2 210**	**2 632**	**3 080**	**3 277**	**3 390**	**3 660**	**3 849**	**4 050**	**4 357**	**4 688**	**4 923**	**5 117**	**5 298**
Coal	610	570	864	1 126	1 167	1 047	999	800	617	635	634	610	571	532
Oil	337	328	331	311	288	290	259	252	238	243	238	233	232	233
Gas	491	574	595	670	732	820	716	737	780	717	753	712	659	629
Electricity	391	468	544	648	743	829	1 139	1 479	1 846	2 181	2 495	2 808	3 105	3 385
Heat	164	107	118	129	127	155	167	178	179	175	171	167	163	160
Biomass	103	163	179	198	220	248	356	376	346	342	333	322	308	285
Hydrogen	0	0	0	0	0	0	22	28	44	61	59	62	64	62
E-fuels	0	0	0	0	0	0	0	1	0	4	5	8	13	13
Buildings	**2 190**	**2 396**	**2 589**	**2 756**	**2 841**	**3 004**	**3 360**	**3 539**	**3 725**	**3 917**	**4 164**	**4 415**	**4 548**	**4 535**
Coal	238	109	128	140	139	100	90	79	67	55	44	36	30	26
Oil	312	340	342	309	305	302	213	168	158	162	156	154	154	154
Gas	433	528	562	608	604	663	450	261	200	151	131	107	79	66
Electricity	394	578	702	830	928	1 044	1 568	2 077	2 426	2 719	3 051	3 383	3 600	3 643
Heat	176	150	153	167	183	210	254	270	270	267	262	256	241	226
Biomass	638	691	703	702	682	685	763	665	586	546	503	464	433	412
Hydrogen	0	0	0	0	0	0	21	19	18	16	16	14	10	9
Agriculture	**800**	**835**	**871**	**874**	**867**	**875**	**977**	**891**	**823**	**794**	**764**	**736**	**717**	**709**
Coal	14	8	12	13	15	13	13	12	11	10	9	8	7	7
Oil	110	101	114	112	113	109	120	124	127	130	134	137	140	144
Gas	8	6	8	8	9	11	10	10	10	10	10	9	9	9
Electricity	30	29	33	39	47	58	71	81	90	99	108	117	127	137
Heat	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass	638	691	703	702	682	685	763	665	586	546	503	464	433	412
Hydrogen	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Domestic transport[20]	**1 363**	**1 629**	**1 834**	**2 047**	**2 332**	**2 155**	**2 067**	**2 003**	**2 323**	**2 573**	**2 940**	**3 274**	**3 556**	**3 756**
Coal	9	1	0	0	0	0	0	0	0	0	0	0	0	0
Oil	1 327	1 598	1 785	1 940	2 184	1 978	1 738	1 147	578	381	390	469	520	555
Gas	2	3	11	30	45	54	74	159	228	180	182	217	211	217
Electricity	17	16	18	20	23	29	89	423	1 164	1 508	1 713	1 845	1 930	1 942
Heat	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass	8	11	20	57	80	94	160	240	137	111	133	157	180	200

[20] Does not include international aviation and maritime bunkers.

Hydrogen	0	0	0	0	0	0	6	33	215	380	490	535	606	694
E-fuels	0	0	0	0	0	0	0	2	1	14	32	51	110	148
Non-Energy Uses	**535**	**667**	**765**	**828**	**897**	**986**	**983**	**1 004**	**1 030**	**1 058**	**1 080**	**1 092**	**1 092**	**1 091**
International transport[21]	**219**	**297**	**331**	**373**	**412**	**342**	**487**	**584**	**659**	**718**	**861**	**1 042**	**1 255**	**1 487**
Aviation	98	135	144	156	195	90	252	302	334	352	449	582	739	916
Maritime	122	162	187	217	217	253	235	282	326	366	413	460	516	571
Other Energy Transformation. & Losses	**588**	**558**	**604**	**736**	**780**	**872**	**964**	**1 114**	**1 275**	**1 727**	**2 062**	**2 334**	**2 539**	**2 640**

Source: POLES-JRC model

[21] Refers to aviation and maritime bunkers.

AN 6.2 2°C Scenario – Energy balance

Table 26. Energy balance of the 2°C Scenario.

2°C scenario

World	1990	2000	2005	2010	2015	2020	2030	2040	2050	2060	2070	2080	2090	2100
Main Economic Indicators														
Population (Million)	5 333	6 147	6 544	6 960	7 384	7 786	8 484	9 037	9 448	9 693	9 797	9 785	9 675	9 482
GDP per capita (ppp, k$'15)	9	11	12	13	15	16	20	24	28	33	40	48	58	69
Value added - Industry (ppa, M$'15)	14855 266	19910 014	24279 880	28565 604	34104 164	38104 264	51415 372	64247 468	76882 352	90918 168	10618 9 168	12205 5 688	13806 1 744	153438 704
Value added - Services (ppa, M$'15)	31147 438	41402 312	49290 924	58320 312	68732 312	75595 872	10659 7 816	13871 8 528	17422 2 368	21722 8 656	26961 2 192	33060 7 680	40130 8 128	481717 376
Value added - Agriculture and Forestry (ppa, M$'15)	2743 760	3873 766	4441 042	5407 741	6335 994	7014 349	9049 262	11008 285	12917 163	14900 534	16927 410	18913 540	20804 456	22529 864
Prices														
International ($'15/boe)														
Coal	19	11	15	23	20	17	28	21	20	20	22	24	25	26
Oil	39	38	65	87	52	38	88	98	107	114	128	135	130	125
Gas	20	26	40	35	37	21	59	53	70	63	68	81	66	71
GHG emissions ($MtCO_2$ eq.)														
Total GHG (all, including LULUCF)	**39 761**	**41 177**	**45 247**	**49 793**	**52 842**	**52 091**	**41 816**	**29 521**	**21 544**	**18 465**	**16 233**	**15 741**	**15 023**	**14 173**
Total GHG (all, excluding LULUCF)	**34 470**	**36 775**	**41 489**	**46 550**	**49 325**	**49 218**	**42 084**	**31 187**	**23 845**	**21 186**	**19 328**	**19 315**	**18 701**	**17 817**
CO_2	22 960	25 280	28 954	33 232	35 288	34 593	30 243	21 242	14 989	12 461	10 815	11 090	10 886	10 391
CH_4	9 053	8 783	9 433	9 988	10 355	10 634	8 096	6 827	6 335	6 339	6 148	5 877	5 508	5 175
N_2O	2 127	2 237	2 401	2 465	2 623	2 647	2 497	2 261	2 193	2 192	2 167	2 152	2 119	2 072
F gases	330	475	700	865	1 059	1 344	1 248	858	328	194	198	196	188	179
Total GHG from Energy and Industry	**28 633**	**30 938**	**35 303**	**40 070**	**42 566**	**42 258**	**35 518**	**25 475**	**18 368**	**15 844**	**14 197**	**14 397**	**14 013**	**13 341**
CO_2 Emissions from Fuel Comb.	**21 051**	**23 106**	**26 183**	**29 651**	**31 321**	**30 249**	**25 538**	**17 272**	**12 013**	**10 079**	**8 733**	**9 063**	**8 884**	**8 168**
Power generation/District heating	6 865	7 919	9 151	10 418	11 176	11 178	10 251	7 169	5 251	4 670	3 955	4 579	4 768	4 438
Industry	4 170	4 189	5 270	6 187	6 321	6 129	5 178	3 586	2 604	2 255	1 879	1 634	1 442	1 312
Buildings	2 955	2 750	2 912	2 970	2 949	2 922	1 795	891	611	543	486	454	437	406

Agriculture	425	365	430	428	442	423	356	221	137	85	53	33	21	13
Transport	4 676	5 678	6 341	7 021	8 024	7 222	6 460	4 192	2 428	1 721	1 717	1 853	2 025	2 164
Other	1 960	2 205	2 079	2 628	2 409	2 373	1 497	1 214	983	805	644	510	192	- 165
CO_2 captured	**0**	**0**	**0**	**0**	**0**	**1**	**118**	**1 779**	**4 832**	**8 100**	**10 481**	**12 013**	**12 781**	**13 430**
Fossil fuels	0	0	0	0	0	1	76	1 021	2 367	3 993	5 146	5 844	6 172	6 486
Biomass	0	0	0	0	0	0	4	110	457	825	1 303	1 625	1 797	2 035
Industrial processes	0	0	0	0	0	0	7	452	1 477	2 591	3 199	3 385	3 322	2 978
Direct Air Capture	0	0	0	0	0	0	31	195	531	691	833	1 158	1 489	1 931
Air pollutants (Mt)														
SO_2	92	93	97	84	75	60	49	30	22	22	24	23	22	20
NO_x	90	104	109	110	106	91	72	52	37	32	33	33	32	30
$PM_{2.5}$	38	38	39	39	38	37	50	46	44	55	48	48	50	46
NH_3	41	46	51	54	56	56	57	50	46	49	49	51	51	52
Energy Balance, by fuel (Mtoe)														
Primary Production	**8 549**	**9 941**	**11 389**	**12 728**	**13 890**	**13 986**	**13 830**	**13 931**	**15 050**	**16 604**	**17 959**	**19 384**	**20 417**	**21 284**
Coal	2 115	2 314	2 926	3 560	3 833	3 720	2 975	1 714	1 482	1 477	1 603	1 613	1 653	1 616
Oil	3 398	3 986	4 366	4 505	4 889	4 418	3 501	2 444	1 748	1 392	1 340	1 275	1 278	1 294
Natural gas	1 770	2 149	2 467	2 815	3 113	3 492	3 341	3 558	3 292	3 901	3 864	4 576	4 679	4 758
Biomass	871	984	1 065	1 200	1 295	1 417	1 962	2 325	2 464	2 202	2 539	2 702	2 774	2 929
Nuclear[1]	173	223	238	237	221	230	221	193	217	231	187	179	202	188
Non-biomass renewables	223	284	326	411	540	709	1 831	3 696	5 847	7 401	8 427	9 040	9 832	10 500
International Bunkers[22]	**219**	**297**	**331**	**373**	**412**	**342**	**484**	**561**	**612**	**678**	**822**	**1 009**	**1 209**	**1 413**
Maritime Bunkers	122	162	187	217	217	253	238	269	291	336	383	438	481	520
Oil	122	162	187	217	208	237	164	122	95	79	79	73	71	73
Gas	0	0	0	0	9	13	42	89	97	122	126	141	153	153
Biofuels	0	0	0	0	0	3	25	19	14	13	14	15	15	15
Hydrogen	0	0	0	0	0	0	1	10	22	31	40	50	58	66
E-fuels	0	0	0	0	0	0	0	2	5	8	11	12	14	16
Ammonia	0	0	0	0	0	0	6	28	58	84	114	146	172	198

[22] Refers to international transport.

Aviation Bunkers	98	135	144	156	195	90	246	292	321	342	438	571	728	893
Oil	98	135	144	156	195	89	213	228	202	104	102	110	136	174
Hydrogen	0	0	0	0	0	0	0	3	23	99	158	224	282	333
Power	0	0	0	0	0	0	0	11	22	54	78	103	127	145
Biofuels	0	0	0	0	0	1	32	47	55	60	72	95	127	171
E-fuels	0	0	0	0	0	0	0	3	19	25	28	38	57	69
Statistical differences (Mtoe)	**0**	**133**	**304**	**438**	**439**	**650**	**650**	**650**	**650**	**650**	**650**	**650**	**650**	**650**
Coal	0	47	159	232	233	330	333	333	333	333	333	333	333	333
Oil	0	- 27	11	36	37	64	40	40	40	40	40	40	40	40
Natural gas	0	113	134	170	169	256	277	277	277	277	277	277	277	277
Primary Energy Demand, by sector (Mtoe)														
Total Primary Energy Demand[23]	**8 514**	**9 516**	**10 762**	**12 053**	**12 925**	**13 051**	**13 386**	**13 577**	**14 838**	**16 575**	**18 107**	**19 723**	**20 941**	**21 996**
Primary Energy Demand[24]	**8 294**	**9 219**	**10 431**	**11 680**	**12 513**	**12 709**	**12 902**	**13 017**	**14 226**	**15 897**	**17 285**	**18 714**	**19 732**	**20 582**
Coal	2 193	2 264	2 793	3 358	3 530	3 326	2 642	1 382	1 149	1 145	1 270	1 280	1 320	1 283
Oil	3 087	3 410	3 672	3 772	4 004	3 763	3 084	2 054	1 411	1 169	1 118	1 052	1 031	1 007
Natural gas	1 739	2 034	2 312	2 666	2 877	3 204	3 112	3 306	3 076	3 687	3 677	4 389	4 499	4 597
Biomass	879	1 004	1 090	1 237	1 342	1 477	2 012	2 386	2 526	2 264	2 606	2 775	2 848	3 008
Nuclear[25]	173	223	238	237	221	230	221	193	217	231	187	179	202	188
Hydro	188	232	259	304	342	384	511	564	614	622	631	643	667	677
Wind	0	3	9	29	72	138	621	1 456	2 656	3 566	4 280	4 779	5 444	5 972
Solar	3	5	8	19	56	106	558	1 153	1 889	2 457	2 762	2 906	3 039	3 147
Geothermal	31	45	50	59	70	82	140	517	674	735	729	683	643	658
Ocean	0	0	0	0	0	0	1	6	14	21	25	28	39	45
Energy for Power Generation	**2 424**	**2 806**	**3 243**	**3 733**	**4 105**	**4 376**	**5 373**	**6 965**	**8 883**	**10 286**	**11 377**	**12 456**	**13 194**	**13 655**
Other Energy Transformation & Losses	**588**	**558**	**604**	**736**	**780**	**872**	**875**	**1 036**	**1 246**	**1 649**	**1 894**	**2 122**	**2 296**	**2 552**
Final consumption (incl. bunkers)	**6 461**	**7 214**	**8 173**	**9 100**	**9 760**	**9 880**	**10 018**	**9 787**	**10 370**	**11 573**	**12 613**	**13 568**	**14 396**	**15 095**
Steel, Non-Met. Minerals and Chem.	1 019	1 138	1 390	1 655	1 831	1 886	1 757	1 548	1 639	1 869	2 012	2 053	2 067	2 104
Other Industry	1 078	1 072	1 242	1 425	1 445	1 503	1 695	1 800	1 945	2 146	2 341	2 501	2 671	2 860
Non-Energy Use	425	534	612	664	704	787	701	673	671	680	671	644	614	582

[23] Calculated as primary energy demand including oil and gas bunkers.
[24] Balances exclude bunkers for primary fuels (oil and gas); include energy inputs into the production of secondary fuels for bunkers (hydrogen and e-fuels); include net imports of liquid biofuels and electricity.
[25] Nuclear energy is accounted as primary electricity.

Residential	1 605	1 772	1 858	1 940	1 962	2 092	2 204	2 144	2 142	2 197	2 255	2 330	2 340	2 351
Services	584	624	731	816	879	912	965	1 040	1 178	1 361	1 509	1 708	1 864	1 875
Agriculture	167	148	174	181	195	202	228	242	254	267	280	293	307	323
Road	1 133	1 439	1 636	1 815	2 024	1 934	1 675	1 453	1 615	2 082	2 408	2 678	2 919	3 120
Rail	56	43	51	48	52	52	60	63	67	68	71	73	76	78
Aviation	233	239	245	293	391	202	433	495	516	517	640	813	1 025	1 255
Other Transport	161	204	233	264	277	309	300	328	344	385	426	475	513	547

Power Generation														
Fuel Inputs Therm. Power (Mtoe)	**2 062**	**2 349**	**2 736**	**3 159**	**3 444**	**3 552**	**3 541**	**3 778**	**3 946**	**4 075**	**4 337**	**4 934**	**5 091**	**5 145**
Coal	1 165	1 442	1 694	1 941	2 072	2 053	1 669	798	642	583	720	752	804	791
Oil	337	270	227	185	185	127	124	110	81	28	11	2	1	2
Gas	476	541	691	864	962	1 073	1 351	1 794	1 612	1 962	1 854	2 361	2 492	2 473
Biomass & Waste	53	51	74	110	155	217	257	558	937	767	1 024	1 136	1 151	1 222
Geothermal	31	45	50	59	70	82	140	517	674	735	729	683	643	658
Gross Elec. Generation (TWh_e)	**11 896**	**15 601**	**18 455**	**21 733**	**24 557**	**27 111**	**38 063**	**55 158**	**77 046**	**94 255**	**106 400**	**115 905**	**124 240**	**130 514**
Coal	4 430	5 993	7 317	8 654	9 524	9 453	7 146	3 590	3 053	2 794	3 473	3 694	4 041	4 014
of which CCS	0	0	0	0	0	0	21	378	927	1 426	2 106	2 341	2 545	2 664
Oil	1 276	1 162	1 102	942	1 004	658	506	460	349	123	47	6	6	8
Gas	1 748	2 770	3 698	4 855	5 541	6 352	7 286	9 515	8 790	11 046	10 802	13 906	14 987	15 537
of which CCS	0	0	0	0	0	0	37	610	1 166	2 211	2 582	3 322	3 645	3 752
Biomass & Waste	97	162	228	362	510	685	963	2 253	4 028	3 251	4 486	5 070	5 185	5 453
of which CCS	0	0	0	0	0	0	1	21	145	319	629	843	937	1 134
Nuclear	2 013	2 591	2 768	2 756	2 570	2 676	2 536	2 178	2 385	2 504	1 939	1 804	2 039	1 863
Hydro	2 190	2 694	3 017	3 535	3 981	4 462	5 947	6 561	7 134	7 234	7 332	7 483	7 759	7 875
Wind	4	31	104	342	834	1 599	6 945	16 006	28 311	37 489	44 689	49 279	54 841	58 991
Solar	1	2	5	40	300	844	5 836	12 160	19 249	24 492	27 347	28 251	28 681	29 155
Other	137	196	216	248	294	381	898	2 436	3 747	5 322	6 284	6 412	6 700	7 619
Share of Renewables (%)	*20%*	*19%*	*18%*	*20%*	*23%*	*28%*	*53%*	*69%*	*78%*	*78%*	*80%*	*79%*	*79%*	*79%*

Generation Capacity (GW_e)	**2 749**	**3 541**	**4 184**	**5 182**	**6 374**	**7 890**	**13 972**	**22 459**	**33 511**	**42 492**	**49 535**	**52 226**	**57 414**	**63 135**
Coal	897	1 132	1 298	1 655	1 985	2 180	1 751	799	603	601	794	802	850	887
of which CCS	0	0	0	0	0	0	9	84	206	338	533	563	593	637
Oil	420	426	400	419	413	363	261	250	245	229	212	241	284	360
Gas	454	734	1 066	1 324	1 569	1 799	2 044	2 710	3 728	5 292	7 510	8 459	10 779	13 907
of which CCS	0	0	0	0	0	0	11	134	347	724	1 076	1 215	1 311	1 442
Biomass & Waste	20	34	48	78	108	146	256	641	1 073	1 375	1 830	1 943	2 177	2 299
of which CCS	0	0	0	0	0	0	0	11	65	196	345	416	483	555
Nuclear	327	364	381	383	350	388	374	318	340	355	272	250	279	255
Hydro	617	816	911	1 081	1 291	1 518	1 840	2 023	2 186	2 187	2 184	2 175	2 224	2 249
Wind	2	17	59	183	417	735	3 032	6 681	11 520	14 661	16 794	17 726	19 534	21 021
Solar	0	1	4	38	213	737	4 371	8 860	13 515	17 398	19 489	20 134	20 659	21 386
Other	13	15	17	21	27	25	43	176	300	395	449	495	628	770
Other Renewable Capacity (GW_e)	**0**	**0**	**0**	**0**	**1**	**1**	**238442**	**886774**	**2785262**	**4390136**	**5197064**	**6354656**	**7913260**	**9450564**
Hydrogen	0	0	0	0	0	0	222	789	2 513	4 046	4 740	5 754	7 159	8 478
DAC	0	0	0	0	0	0	238220	885985	2782749	4386090	5192324	6348902	7906101	9442086
Total Final Consumption[26] (Mtoe)	**5816.29116**	**6382.9434**	**7229.46261**	**8063.86026**	**8644.00989**	**8750.01888**	**8832.63426**	**8553.08244**	**9087.4821**	**10214.436**	**11120.2877**	**11916.0999**	**12572.9828**	**13099.2686**
Coal	872	687	1 004	1 279	1 321	1 160	928	545	425	440	411	385	369	336
Oil	2 086	2 367	2 572	2 672	2 890	2 679	2 176	1 265	680	511	490	479	490	492
Gas	933	1 110	1 176	1 316	1 390	1 547	1 175	871	668	646	591	585	550	535
Electricity	832	1 091	1 298	1 537	1 741	1 960	2 723	3 955	5 439	6 672	7 591	8 364	8 984	9 430
Heat	340	257	271	295	311	365	422	444	424	402	375	350	325	308
Biomass	754	870	909	966	991	1 038	1 351	1 331	1 134	1 051	1 068	1 062	1 041	1 018
Hydrogen	0	0	0	0	0	0	55	109	249	417	494	553	650	761
E-fuels	0	0	0	0	0	0	4	32	68	75	100	138	164	219
Share of Renewables[27] (%)	*16%*	*17%*	*16%*	*16%*	*17%*	*20%*	*36%*	*53%*	*66%*	*69%*	*72%*	*71%*	*71%*	*72%*
Industry (excl. non-energy use)	**2 096**	**2 210**	**2 632**	**3 080**	**3 277**	**3 390**	**3 452**	**3 348**	**3 584**	**4 015**	**4 353**	**4 554**	**4 739**	**4 964**
Coal	610	570	864	1 126	1 167	1 047	878	535	422	440	411	385	369	336
Oil	337	328	331	311	288	290	238	200	178	175	163	147	141	134

[26] Does not include international aviation and maritime bunkers; does not include non-energy uses.
[27] Ratio of renewable energy over final energy demand increased by distribution losses and self consumption of electricity and steam plants.

Gas	491	574	595	670	732	820	678	570	461	453	428	408	373	374
Electricity	391	468	544	648	743	829	1 084	1 418	1 884	2 310	2 682	2 955	3 216	3 503
Heat	164	107	118	129	127	155	167	178	179	175	171	167	163	160
Biomass	103	163	179	198	220	248	378	389	383	379	416	412	398	376
Hydrogen	0	0	0	0	0	0	28	56	66	69	68	64	61	61
E-fuels	0	0	0	0	0	0	0	2	10	14	15	17	18	21
Buildings	**2 190**	**2 396**	**2 589**	**2 756**	**2 841**	**3 004**	**3 169**	**3 184**	**3 319**	**3 558**	**3 764**	**4 039**	**4 204**	**4 226**
Coal	238	109	128	140	139	100	41	7	1	0	0	0	0	0
Oil	312	340	342	309	305	302	194	131	121	110	103	94	89	86
Gas	433	528	562	608	604	663	421	187	93	79	65	64	63	54
Electricity	394	578	702	830	928	1 044	1 468	1 966	2 345	2 677	2 975	3 315	3 546	3 623
Heat	176	150	153	167	183	210	254	266	246	227	204	183	162	148
Biomass	638	691	703	702	682	685	770	608	501	453	407	373	335	307
Hydrogen	0	0	0	0	0	0	21	19	13	11	9	9	9	8
Agriculture	**800**	**835**	**871**	**874**	**867**	**875**	**960**	**780**	**666**	**619**	**580**	**555**	**529**	**515**
Coal	14	8	12	13	15	13	9	4	2	1	0	0	0	0
Oil	110	101	114	112	113	109	95	60	38	23	15	9	6	3
Gas	8	6	8	8	9	11	9	6	4	3	2	1	1	1
Electricity	30	29	33	39	47	58	78	101	122	139	156	171	187	204
Heat	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass	638	691	703	702	682	685	770	608	501	453	407	373	335	307
Hydrogen	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Domestic transport[28]	**1 363**	**1 629**	**1 834**	**2 047**	**2 332**	**2 155**	**1 984**	**1 779**	**1 930**	**2 374**	**2 723**	**3 030**	**3 323**	**3 586**
Coal	9	1	0	0	0	0	0	0	0	0	0	0	0	0
Oil	1 327	1 598	1 785	1 940	2 184	1 978	1 649	874	343	202	209	229	254	268
Gas	2	3	11	30	45	54	68	109	109	110	95	112	113	107
Electricity	17	16	18	20	23	29	93	469	1 088	1 546	1 778	1 922	2 035	2 100
Heat	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass	8	11	20	57	80	94	165	263	161	119	138	166	195	220
Hydrogen	0	0	0	0	0	0	5	33	171	336	417	480	580	692
E-fuels	0	0	0	0	0	0	4	30	58	61	85	121	146	199

[28] Does not include international aviation and maritime bunkers.

Non-Energy Uses	**535**	**667**	**765**	**828**	**897**	**986**	**879**	**832**	**820**	**833**	**829**	**803**	**772**	**740**
International transport[29]	**219**	**297**	**331**	**373**	**412**	**342**	**484**	**561**	**612**	**678**	**822**	**1 009**	**1 209**	**1 413**
Aviation	98	135	144	156	195	90	246	292	321	342	438	571	728	893
Maritime	122	162	187	217	217	253	238	269	291	336	383	438	481	520
Other Energy Transformation. & Losses	**588**	**558**	**604**	**736**	**780**	**872**	**875**	**1 036**	**1 246**	**1 649**	**1 894**	**2 122**	**2 296**	**2 552**

Source: POLES-JRC model

[29] Refers to aviation and maritime bunkers.

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