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Cost development of low carbon energy technologies

Scenario-based cost trajectories to 2050, 2017 edition

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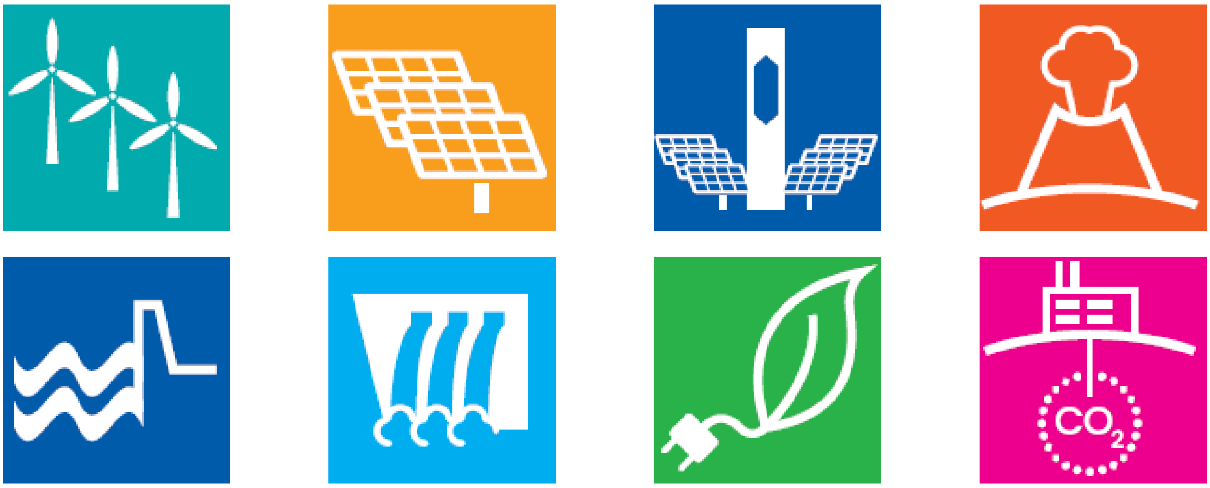

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Abstract

Future costs of low carbon energy technologies differ widely depending on assumptions and methods used. This report addresses this gap by presenting internally consistent trajectories of capital investment costs to 2050 for selected low carbon energy technologies. In order to do so, it combines global scenario projections of technology deployment with the one-factor learning rate method. Global scenarios are used to identify a range, based on potential deployment, in line with baseline assumptions and two long-term decarbonisation pathways. A sensitivity analysis is performed based on different learning rates and results are compared with literature. It is found that, depending on the technology, a 15 % to 55 % reduction in capital investment costs of offshore wind turbines, photovoltaics, solar thermal electricity and ocean energy may be achieved by 2030 compared to 2015. From then onwards, cost reduction may slow down yet remains substantial especially for photovoltaics and ocean energy. However, the assumed deployment pathway (global scenario) and learning rate influences the cost trajectories and cost reduction potential of these technologies. For onshore wind turbines, geothermal energy, biomass CHPs and CCS technologies cost reduction is less pronounced and results between scenarios do not differ significantly. The main aspects that deserve further research are firstly, the decomposition of technology cost-components and the distinction between the parts in the cost-structure that learning applies from those that need to be estimated with different methods and secondly, the influence of raw material prices in future cost trajectories of low carbon energy technologies.

1 Introduction

Investment costs of low carbon energy technologies are a crucial set of data that influences their competitiveness and as a result may affect their deployment as estimated by energy system models. The cost trajectories of Renewable Energy Supply (RES) technologies for the electricity sector (RES-E) are however largely unknown and uncertain, unlike those of more established conventional fossil fuel technologies. Publishing organisations of technology deployment scenarios scarcely report their cost assumptions and as such it is unclear how technology costs develop over time under different growth trajectories and scenarios.

A recent literature review of studies with a focus on RES-E technologies [1], summarised in the boxplot diagram of Figure 1, shows that expected investment costs of wind, photovoltaics, solar heating and cooling, ocean energy and carbon capture technologies follow a declining trend to 2050. By then, expected costs of other technologies, such as geothermal energy or biomass heat and power may increase compared to 2030. Besides these general trends, the interquartile range of investment costs of all technologies is significant. This variability could be in part attributed to different methods used to assess future cost reduction (e.g. learning curves, bottom-up engineering assessments or expert expectations), existing geographical differences, different times of reporting or different system boundaries. While these studies provide valuable insights and details with respect to the technologies in focus, they often lack a systems perspective, thereby not accounting for the competition between RES and other conventional technologies due to energy system dynamics.

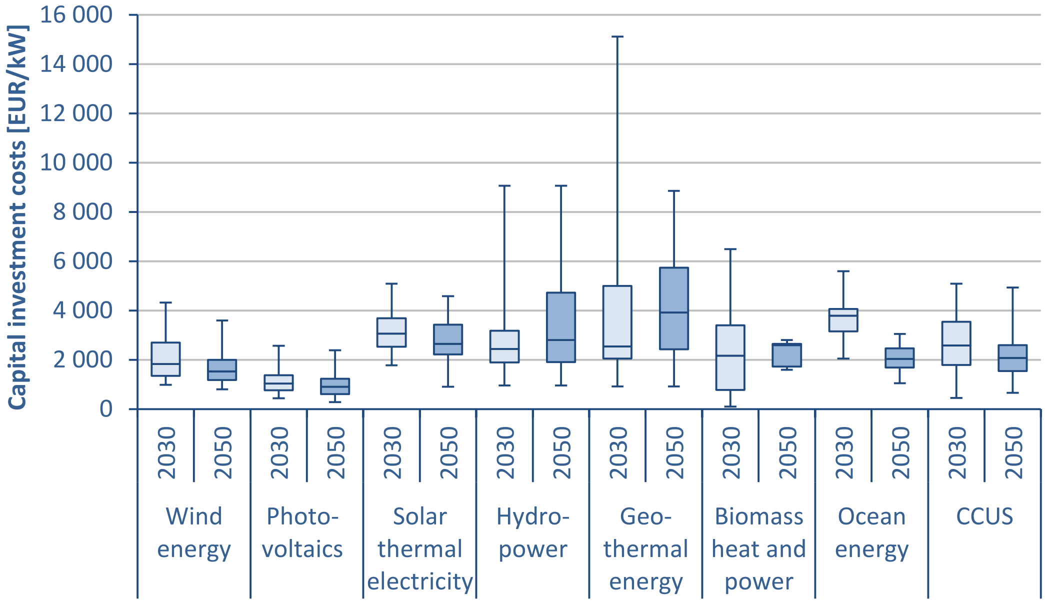

Figure 1 Investment costs of low carbon energy technologies according to literature

Technology deployment trajectories and competition in the energy system are typically discussed in scenarios that are regularly published by international organisations (e.g. International Energy Agency; IEA), consultants (e.g. Bloomberg New Energy Finance; BNEF), industry associations (e.g. Global Wind Energy Council), non-governmental organisations (e.g. Greenpeace) and academia (e.g. MIT). Scenario results describe in varying level of detail the contribution that energy technologies make to global energy supply.

Based on recently published scenarios, the growth of RES-E may differ almost by a factor 6 in 2050 (Figure 2). One reason for these diverging future views lies in scenario design. There are normative scenarios that set intermediate or long-term targets as binding conditions (e.g. RES share, emission reduction) and inductive scenarios that explore how the energy system may develop given certain drivers that follow a plausible storyline (e.g. energy security first, global cooperation). A second reason is that scenario results are based on different models and mathematical formulations intended to address specific needs. For example, the ETP-TIMES model, which is used in the IEA's Energy Technology Perspectives publications, minimises total system costs [2]. Other tools, such as IRENA's REmap, estimate the costs required to substitute conventional generation capacity by renewable technologies [3].

Scenario results are not projections of the future rather a stylised representation of possible developments based on internally consistent dynamics. As such, results are affected by uncertain parameters such as macro-economic indicators, fossil fuel or CO_2 prices, technology development and technology costs.

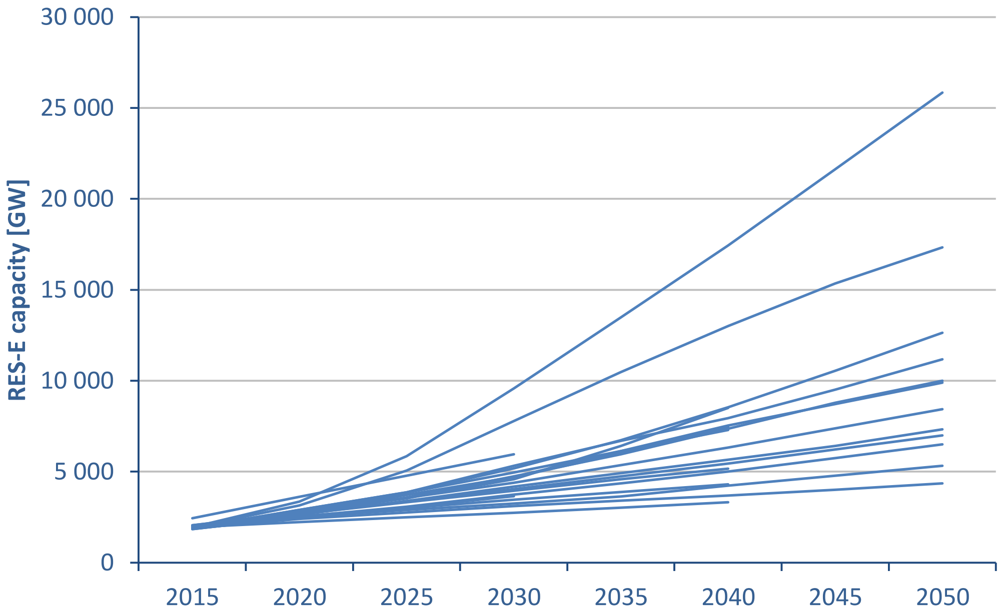

Figure 2 Possible global growth trajectories of low carbon energy technologies

Against this background, there is a need to estimate cost trajectories of low carbon energy technologies that are internally consistent in terms of scenario storyline and the resulting deployment pathways. According to the learning curve theory, explained further in the next section (section 2), historical cost reduction of technologies has been correlated with their cumulative production or installed capacity based on a learning rate. In the case of wind energy this could be the cumulative turbine installations in GW or in the case of photovoltaic (PV) the capacity of modules produced. Historically derived learning rates can then be combined with growth projections of a certain technology to derive future cost trajectories.

This report attempts to identify cost ranges of selected low carbon energy technologies of the power sector based on long-term global energy system developments using the one-factor learning rate method thus taking into account the competition between RES and conventional technologies. The costs estimated in this report are capital investment costs and Operation and Maintenance (O&M) costs.

Following this introduction, this report is structured as follows. The methodology is presented in detail in section 2. Input data relevant to the technology in focus and results on technology cost developments are presented for selected scenarios and a range of learning rates in dedicated chapters in section 3. This report concludes with the overall findings of the analysis in section 4. The Annex includes findings from the literature review on learning rates per low carbon energy technology.

2 Methodology

The learning curve method (section 2.1) is applied on representative scenarios that cover a plausible growth range (section 2.2) for selected low carbon energy technologies (section 2.3). Based on the process described in section 2.4, cost development ranges are derived.

The methodology is schematically presented in Figure 3.

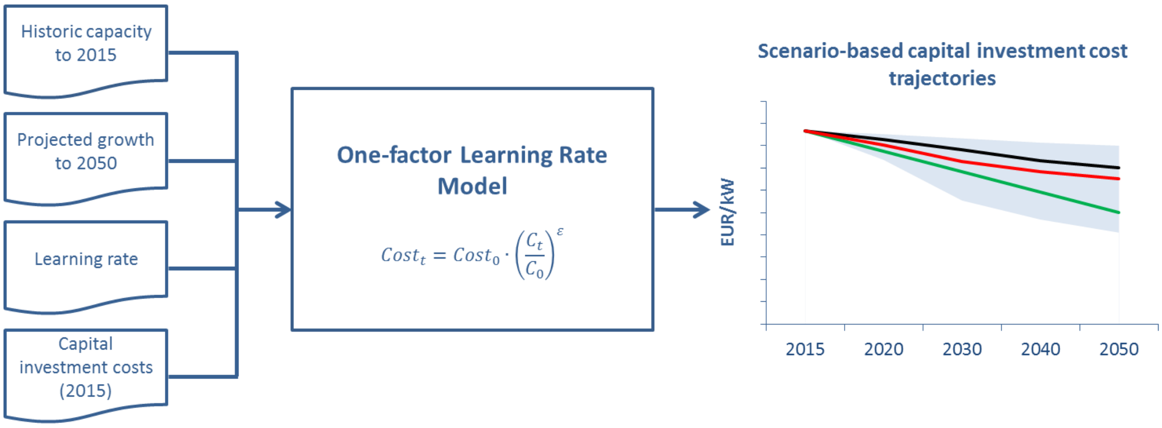

Figure 3 Schematic representation of the methodological approach

2.1 The learning curve method

Technological learning is a commonly applied theory that estimates cost developments of technologies over time. It operationalises learning curves, specific to technologies that indicate the price or cost reduction of the technology (performance indicator) by a constant factor (learning rate) with every doubling of cumulative installed capacity or cumulative output (experience indicator). The performance and experience indicator are described by the log-linear expression:

$$Cost_t = Cost_0 \cdot \left(\frac{C_t}{C_0}\right)^{\varepsilon}$$

Eq. 1 Cost reduction based on the learning rate method

, where $Cost_t$ is the unit cost of the technology in year t after the cumulative deployment of C_t units, $Cost_o$ is the cost of the unit of production at cumulative deployed capacity C_o at time $t = 0$ and ε is the experience parameter. The learning rate (LR) and the experience parameter are described by the following equation:

$$LR = 1 - 2^{\varepsilon}$$

Eq. 2 The learning rate and the experience parameter

, where the parameter 2^{ε} is also referred to as progress ratio and is the slope of the learning curve.

Using established learning rates or progress ratios, one can estimate the costs of a technology under the anticipated experience indicator. This so-called *one-factor learning curve* does not necessarily describe the underlying factors of cost reduction [4]. These may be due to changes in specific components of the production process (e.g. technical innovation, up-sizing, economies of scale and increase in labour productivity), changes of the product itself (e.g. re-design) or changes in input prices of labour or materials [4].

The *component-based learning curve* partly addresses this by expressing total technology costs as the sum of its sub-components, distinguishing those that may experience learning from those that may not. This method can be used for emerging technologies for which no direct relationship on learning can be derived from historical data or for technologies that their sub-compartments follow different learning curves. Furthermore, depending on the cost-structure of the technology, if raw material prices are the determining parameter, then ultimately the associated technology costs are also driven by market prices and not learning [4]. *Multi-factor* learning curve models associate cost reduction with other factors that drive change in production costs, such as cumulative expenditure in innovation (investments in research and development; R&D). The most prominent example is the two-factor learning curve model that distinguishes between learning factors, namely learning-by-doing from learning-by-researching [4, 5].

The analysis presented in this report uses the one-factor learning rate method as the most commonly applied approach.

2.2 Scenario selection

As seen earlier in Figure 2, total deployment of RES-E technologies varies significantly between scenarios. A review conducted by the JRC [1] shows that in few scenarios with comparable RES-E deployment levels the size of the technology portfolio varies. For example, photovoltaics grow faster in BNEF's New Energy Outlook 2016 study [6] compared to the JRC's Global Energy and Climate Outlook 2016 2^{o}C scenario [7], which shows rapid growth for wind energy. At an aggregate level, however, both studies show similar deployment of wind energy and photovoltaics (about 3,000 GW in 2030). Consequently, varying RES-E deployment in the energy system leads to different CO_2 emission levels or other cost and benefits for the society. To select scenarios that are representative of potential growth trajectories of RES-E technologies the following general criteria are applied:

- Deployment projections should differ between scenarios in order to capture effects on cost development
- Scenario storylines should have adequate differences in their technology portfolio
- Scenario results need to be comparable at least in one overarching goal

Growth scenarios are selected based on the premise that the world moves towards rapid decarbonisation by 2050, in order to embark on trajectories that realise longer-term climate goals. The most common building blocks to achieve such goals are: (a) high RES deployment, (b) energy efficiency, (c) nuclear power generation and (d) emission mitigation with Carbon Capture and Storage (CCS) [8]. Based on the general criteria and these four decarbonisation options, three representative scenarios are selected to cover the plausible range: "**Baseline**", "**Diversified**" portfolio and "**ProRES**", which are highlighted in Figure 4.

While different in RES-E deployment levels (Figure 4), the "**Diversified**" portfolio and the "**ProRES**" scenarios achieve similar emission reduction globally (about 80 % by 2050 compared to 1990), have different technology portfolio with respect to fossil fuels, nuclear energy and CCS, and are amongst those scenarios with highest reduction in primary energy demand. The scenario description is as follows:

- The "**Baseline**" scenario is used to cover the *lower end of RES-E deployment*. It is based on the "6DS" scenario of the Energy Technology Perspectives published by the International Energy Agency in 2016 [9]. It represents a "business as usual" world in which no additional efforts are taken on stabilising the atmospheric concentration of greenhouse gases. By 2050, primary energy consumption reaches about 940 EJ, renewable energy supplies about 30 % of global electricity demand and emissions climb to 55 $GtCO_2$.
- The "**Diversified**" portfolio scenario is taken from the "B2DS" scenario of the International Energy Agency's 2017 Energy Technology Perspectives [10] and is used as representative for the *mid-range deployment of RES-E* found in literature. To achieve rapid decarbonisation in line with international policy goals, all known supply, efficiency and mitigation options are available and pushed to their

practical limits. Fossil fuels and nuclear energy participate in the technology mix, and CCS is a key option to realise emission reduction goals. Primary energy consumption is comparable to 2015 levels (about 580 EJ), the share of renewable electricity in the global supply mix is 74 % while emissions decline to about 4.7 $GtCO_2$ by 2050.

- The "**ProRES**" scenario results are the *most ambitious in terms of capacity additions of RES-E technologies*. In this scenario the world moves towards decarbonisation by significantly reducing fossil fuel use, however, in parallel with rapid phase out of nuclear power. CCS does not become commercial and is not an available mitigation option. Deep emission reduction is achieved with high deployment of RES, electrification of transport and heat, and high efficiency gains. It is based on the 2015 "Energy Revolution" scenario of Greenpeace [11]. Primary energy consumption is about 430 EJ, renewables supply 93 % of electricity demand and global CO_2 emissions are about 4.5 $GtCO_2$ in 2050.

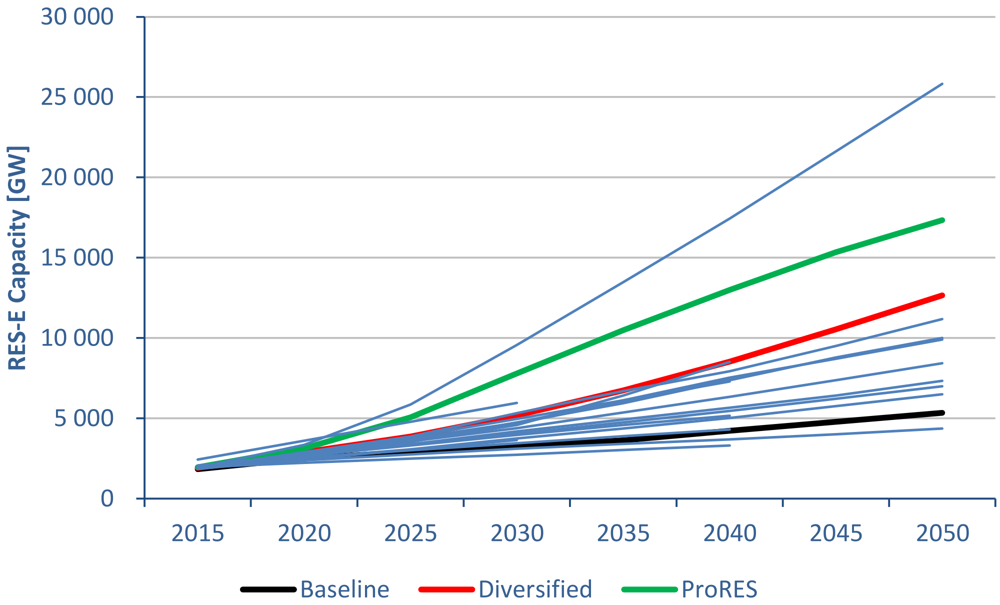

Figure 4 Growth trajectories of low carbon energy technologies based on selected scenarios

Besides the decarbonisation paradigm, other scenario selection criteria could be applied. One example could be a scenario in which only market-based incentives are assumed for RES-E technologies such as the New Energy Outlook scenario of BNEF [12]. Another example could be a scenario that prioritises energy security over other goals such as the "Hard Rock" scenario of the World Energy Council [13]. Even so, in such scenarios the RES-E deployment projections fall within the range that is covered by the decarbonisation paradigm. Another set of selection criteria could be based on growth trajectories of individual technologies as opposed to total RES-E capacity, such as pathways of wind energy or photovoltaics. The selected decarbonisation scenarios however capture the plausible range also for individual technologies. Therefore, although other scenario selection criteria could be relevant, those selected for this analysis cover a wide range which can then be used to reflect a plausible range of technology cost trajectories.

2.3 Technologies

This report covers established and emerging renewable electricity generation technologies. It also includes storage of electricity in solar thermal power plants, CCS as an option for CO_2 mitigation and heat production from biomass used in combined heat and power plants (CHP). Reference subtechnologies have been selected based on consultation with JRC experts. In the technology boundaries all cost-components are included, unless specified otherwise (e.g. equipment, construction, interconnection project development, labour, other costs). The technologies and subtechnologies that the present report covers are referred to as low carbon energy technologies and are listed in Table 1.

Table 1 Description of low carbon energy technologies assessed in this report

Technology	Subtechnology	Section
Wind energy	Onshore, low specific capacity, high hub height	Section 3.1
	Onshore, medium specific capacity, medium hub height	
	Onshore, high specific capacity, low hub height	
	Offshore, monopole, medium distance to shore	
	Offshore, jacket, medium distance to shore	
	Offshore, floating, long distance to shore	
Photovoltaics	Utility-scale PV with one-axis tracking	Section 3.2
	Utility-scale PV without tracking	
	Commercial-scale PV, flat surface	
	Residential-scale PV, inclined	
Solar thermal electricity	Parabolic trough with storage	Section 3.3
	Solar tower with storage	
Geothermal energy	Flash geothermal	Section 3.4
	Organic Rankine Cycle (binary)	
	Enhanced Geothermal system	
Ocean energy	Tidal energy range	Section 3.5
	Tidal energy stream	
	Wave energy	
Hydropower	Large-scale hydropower and dam	Section 3.6
	Medium-scale hydropower and dam	
	Small-scale hydropower and dam	
	Run-of-river	
Heat and power from biomass	Biomass subcritical steam turbine CHP	Section 3.7
	Gasified biomass CHP	
	Biomass-fired Organic Rankine Cycle CHP	
	Anaerobic digestion CHP	
Carbon Capture and Storage	Pulverised coal supercritical, CCS post-combustion	Section 3.8
	Pulverised coal supercritical, CCS oxyfuel	
	Lignite integrated gasification combined cycle, CCS pre-combustion	
	Coal integrated gasification combined cycle, CCS pre-combustion	
	Natural gas combined cycle, CCS post-combustion	
	Biomass integrated gasification combined cycle, CCS pre-combustion	

For these technologies, investment costs are estimated using the learning curve method and are internally consistent for each of the three growth scenarios. Other low carbon energy technologies were not assessed using same method due to the limited availability of disaggregated data on global growth projections or learning rates. More specifically, for solar thermal heating and cooling, fuel cells, or storage options (e.g. batteries), different assumptions would need to be applied as the selected scenarios do not provide sufficient details. Moreover, the technology portfolio could be expanded further by assessing conversion options in other sectors (namely transport and industry). This concerns primarily advanced biomass conversion technologies and innovative industrial biotechnology options. However, for such technologies little information is available on learning and deployment at global scale. In the absence of sufficient technology disaggregation, other methods would be more suitable. Finally, established conventional fossil fuel generation (coal- and gas-based power generation) and nuclear power are not covered in this report.

2.4 Parameters and data validation process

Capital investment costs ($Cost_t$ in Eq. 1) refer to specific investment costs (i.e. €/kW), which are calculated based on the one-factor learning rate method (section 2.1) as follows:

- Historical cumulative capacity (C_o in Eq. 1) is calculated from the year 2000 until 2015 based on capacity retirement and additions in line with the technical lifetime of each technology ([1]). Global historical capacity for the period from 2000 to 2015 is based on IRENA [14].
- Cumulative capacity projections (C_t in Eq. 1), from 2015 onwards, are estimated based on net annual capacity additions required to meet the gross installed capacity trajectories in each scenario per year until 2050 at a five year time-step. Capacity retirements and additions are based on the technical lifetime of each technology.
- The capital investment costs for the year 2015 ($Cost_o$ in Eq. 1) are based on literature [1] and are typical for a reference technology ([2]).
- A *reference* learning rate (LR in Eq. 2) is selected based on data from literature (see Annex).

Literature-based capital investment costs for the year 2015 and learning rates are further refined based on consultation with JRC experts.

Based on these parameters *reference capital investment cost trajectories* are estimated for the "Baseline", "Diversified" and "ProRES" scenarios. The global deployment trajectories refer to technologies at high aggregation level with the exception of onshore and offshore wind turbines, and partly of CCS subtechnologies (coal, gas and biomass). For the remaining technologies, this analysis applies growth projections at the subtechnology level assuming that perfect spillover learning takes place.

For some technologies (e.g. offshore wind turbines), it is uncertain whether observed historical cost reduction may continue to the future. For other technologies, a component-based learning method is more appropriate (e.g. solar thermal electricity, CCS). Furthermore, for emerging technologies no timeseries on costs exist and as such historically observed learning rates are not established (e.g. ocean energy technologies). The cited cost projections of emerging technologies are primarily derived from industry targets and expectations in cost reduction. To account for the uncertainty on using one-factor learning rates, the reference estimates presented in this report are complemented by a sensitivity analysis. Next to the reference, a *high* and a *low* learning rate are assumed. This sensitivity analysis provides a lower (min) and an upper (max) bound of capital investment costs. The estimated capital investment cost trajectories are graphically compared with those reported in literature [1].

([1]) Typically, statistical information reports on the gross installed capacity of technologies. In order to estimate the historical cumulative capacity, both retirements and additions need to be accounted for. For this purpose it is assumed that a technology retires only when its technical lifetime has been reached.

([2]) Start year costs of CCS technologies are assumed for the year 2025 and are presented in Annex 8.

O&M costs are assumed as a fixed fraction of the capital investment costs (or capital expenditures; $\%_{CAPEX}$) over the entire lifetime of the technology. This fraction is based on literature and is validated through consultation with JRC experts.

All monetary units are reported in € for the year 2015. All input parameters and cost trajectories are described per technology in section 3.

3 Technology cost development

3.1 Wind energy

In order to provide a plausible future range of capital investment costs of wind turbines, these were divided into subtechnologies, which take into account the following:

- The main factors that affect capital investment costs of **onshore** wind turbines are the specific power ([3]) of the turbine and the hub height. Representative turbine types have a specific capacity of 0.2 kW/m^2, 0.3 kW/m^2 and 0.47 kW/m^2. Representative hub heights are 50 m, 100 m and 200 m. Based on these, the following onshore wind turbine subtechnologies are assessed:
    - Turbine specific capacity of 0.2 kW/m^2 (low specific capacity) and at 200 m hub height (high hub height)
    - Turbine specific capacity of 0.3 kW/m^2 (medium specific capacity), at 100 m hub height (medium hub height)
    - Turbine specific capacity of 0.47 kW/m^2 (high specific capacity), at 50 m hub height (low hub height)
- Capital investment costs of **offshore** wind turbines are primarily determined by the distance from the shore and the type of the turbine's base. In this analysis, two types of mounted bases are assessed (monopole and jacket) and one type of a floating base. As distance to shore, the following are taken into account: short (<30 km from shore), medium (30 - 60 km from shore) and long (60 km < from shore). Cost trajectories are provided for the three different base structures located at medium (monopole and jacket) and long (floating) distance from shore.

Table 2 and Table 3 provide the input assumptions that are used in the learning rate method for onshore and offshore wind turbines respectively. These are global growth projections of onshore and offshore wind energy, reference learning rates as well as the range used in the sensitivity analysis and technical lifetime. The cost trajectories of three onshore and three offshore subtechnologies are presented in the sections that follow and results are compared graphically with other literature estimates. Technology costs include turbines, hub (or base for offshore wind turbines) and other cost components (e.g. balance of system (BOS) costs, installation, indirect costs).

Table 2 Learning rate method input assumptions for onshore wind energy

		Unit	2015	2020	2025	2030	2035	2040	2045	2050
Global installed capacity	Baseline	GW	404	606	766	927	1074	1221	1371	1521
	Diversified	GW	404	785	1223	1660	2043	2426	2732	3037
	ProRES	GW	404	784	1484	2184	2843	3502	3973	4444
Global capacity additions	Baseline	GW/yr	45	40	38	37	57	71	65	74
	Diversified	GW/yr	45	76	77	109	107	115	129	147
	ProRES	GW/yr	45	76	133	159	165	167	185	212
Learning rate	Reference	%	5%	5%	5%	5%	5%	5%	5%	5%
	High	%	10%	10%	10%	10%	10%	10%	10%	10%
	Low	%	2%	2%	2%	2%	2%	2%	2%	2%
Lifetime	-	Years	25	25	25	25	25	25	25	25

([3]) Specific capacity (or power) is the ratio of a turbine's nameplate capacity to its rotor-swept area. Ceteris paribus, decline in specific power should lead to increase in capacity factor [52].

Table 3 Learning rate method input assumptions for offshore wind energy

		Unit	2015	2020	2025	2030	2035	2040	2045	2050
Global installed capacity	Baseline	GW	12	30	38	47	60	73	91	108
	Diversified	GW	12	38	80	122	195	267	352	437
	ProRES	GW	12	37	182	326	570	814	973	1131
Global capacity additions	Baseline	GW/yr	2	4	2	2	3	3	5	7
	Diversified	GW/yr	2	5	5	12	14	15	17	24
	ProRES	GW/yr	2	5	21	37	49	49	44	26
Learning rate	Reference	%	11%	11%	8%	5%	5%	5%	5%	5%
	High	%	20%	20%	15%	10%	10%	10%	10%	10%
	Low	%	5%	5%	5%	2%	2%	2%	2%	2%
Lifetime	-	Years	30	30	30	30	30	30	30	30

Capital investment cost trajectories and O&M shares for the selected wind subtechnologies are presented in Table 4 - Table 6 for onshore wind and Table 7 - Table 9 for offshore wind. Cost trajectories are presented in Figure 5 - Figure 7 and Figure 8 - Figure 10 for onshore and offshore wind turbines, respectively and are compared with literature estimates. The literature estimates are not differentiated by the hub height, specific capacity or distance to shore as these were not reported; they represent available data on onshore wind (Figure 5 - Figure 7) and offshore wind power plants (Figure 8 - Figure 10). The figures show the cost projections for a reference learning rate with continuous lines and indicate a range by a shaded area that is an outcome of deployment scenario and the range of learning rates. Annex 1 describes the findings on learning rates of onshore and offshore wind power plants that stem from literature review.

3.1.1 Onshore, low specific capacity, high hub height

Table 4 Capital investment cost trajectories of onshore wind turbines (low specific capacity, high hub height)

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	1850	1800	1730	1670	1630
	Diversified	EUR/kW		1760	1660	1600	1560
	ProRES	EUR/kW		1760	1630	1560	1520
	Min	EUR/kW		1670	1430	1310	1230
	Max	EUR/kW		1830	1800	1780	1760
O&M costs	-	$\%_{CAPEX}$	3%	3%	3%	3%	3%

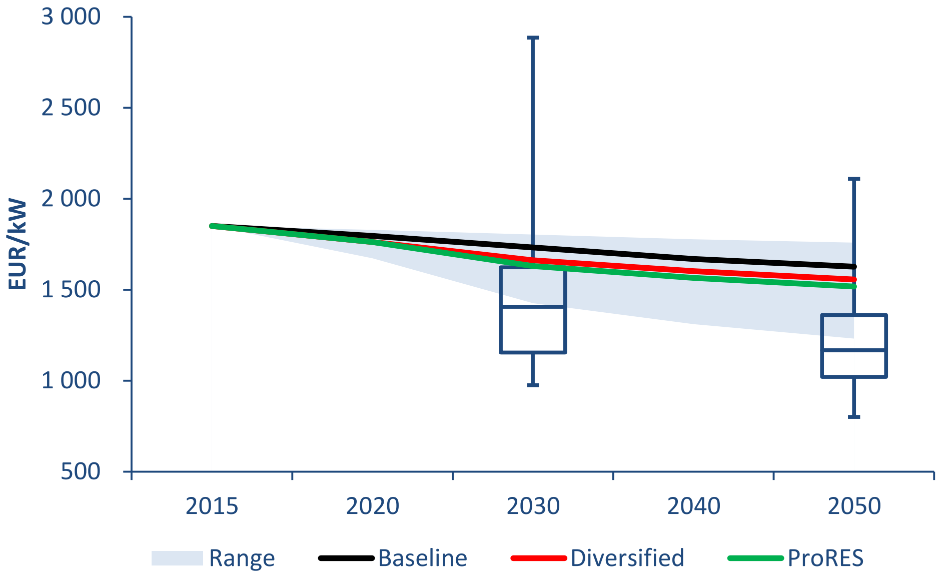

Figure 5 Capital investment cost trajectories onshore, low specific capacity, high hub height under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include all onshore wind turbine types)

3.1.2 Onshore, medium specific capacity, medium hub height

Table 5 Capital investment cost trajectories of onshore wind turbines (medium specific capacity, medium hub height)

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	1350	1310	1260	1220	1190
	Diversified	EUR/kW		1290	1210	1170	1130
	ProRES	EUR/kW		1290	1190	1140	1110
	Min	EUR/kW		1220	1040	960	900
	Max	EUR/kW		1330	1320	1300	1280
O&M costs	-	$\%_{CAPEX}$	3%	3%	3%	3%	3%

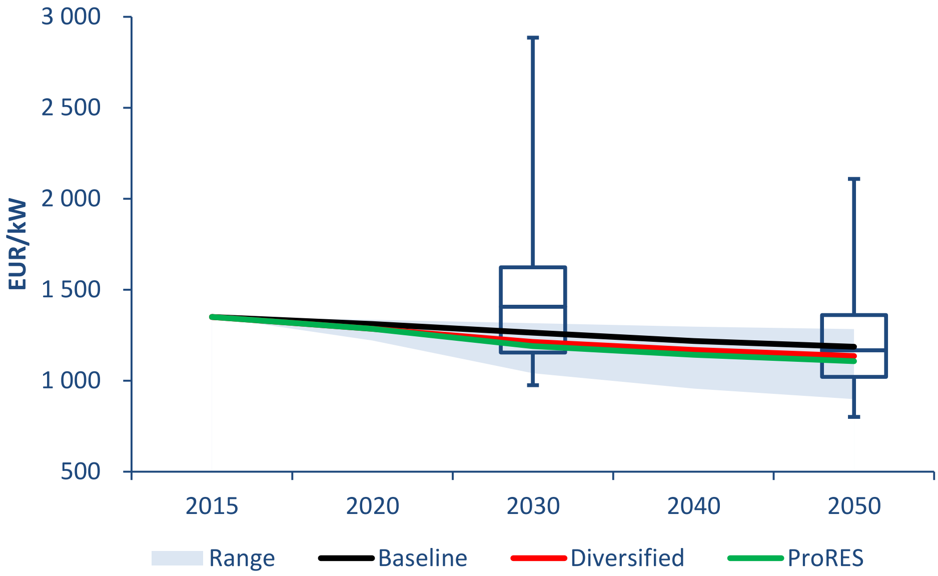

Figure 6 Capital investment cost trajectories onshore, medium specific capacity, medium hub height under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include all onshore wind turbine types)

3.1.3 Onshore, high specific capacity, low hub height

Table 6 Capital investment cost trajectories of onshore wind turbines (high specific capacity, low hub height)

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	1090	1060	1020	980	960
	Diversified	EUR/kW		1040	980	940	920
	ProRES	EUR/kW		1040	960	920	890
	Min	EUR/kW		990	840	770	730
	Max	EUR/kW		1080	1060	1050	1040
O&M costs	-	$\%_{CAPEX}$	3%	3%	3%	3%	3%

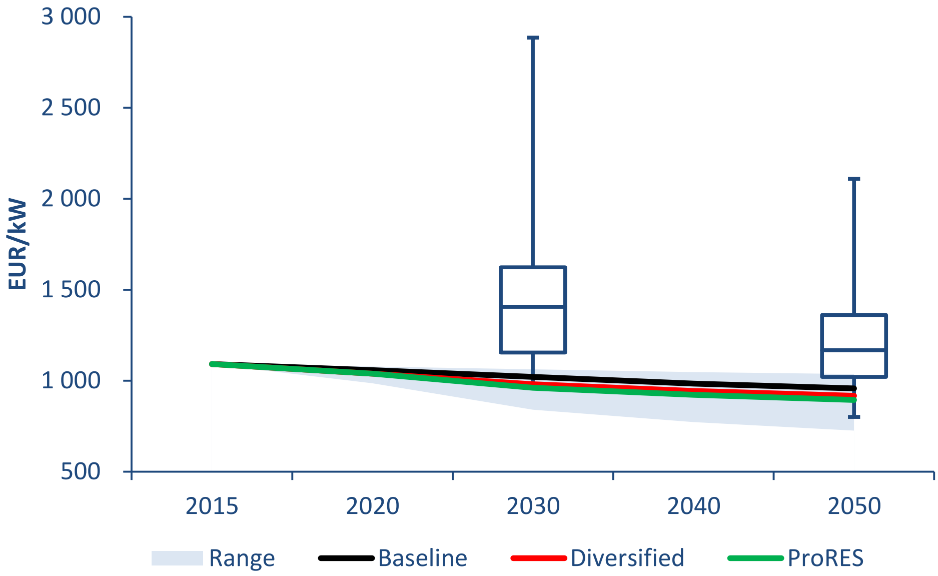

Figure 7 Capital investment cost trajectories onshore, high specific capacity, low hub height under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include all onshore wind turbine types)

3.1.4 Offshore, monopole, medium distance to shore

Table 7 Capital investment cost trajectories of offshore wind turbines (monopole, medium distance to shore)

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	3500	2990	2850	2750	2640
	Diversified	EUR/kW		2870	2570	2430	2330
	ProRES	EUR/kW		2890	2310	2150	2100
	Min	EUR/kW		2390	1550	1350	1280
	Max	EUR/kW		3260	3180	3140	3090
O&M costs	-	$\%_{CAPEX}$	2%	2%	2%	2%	2%

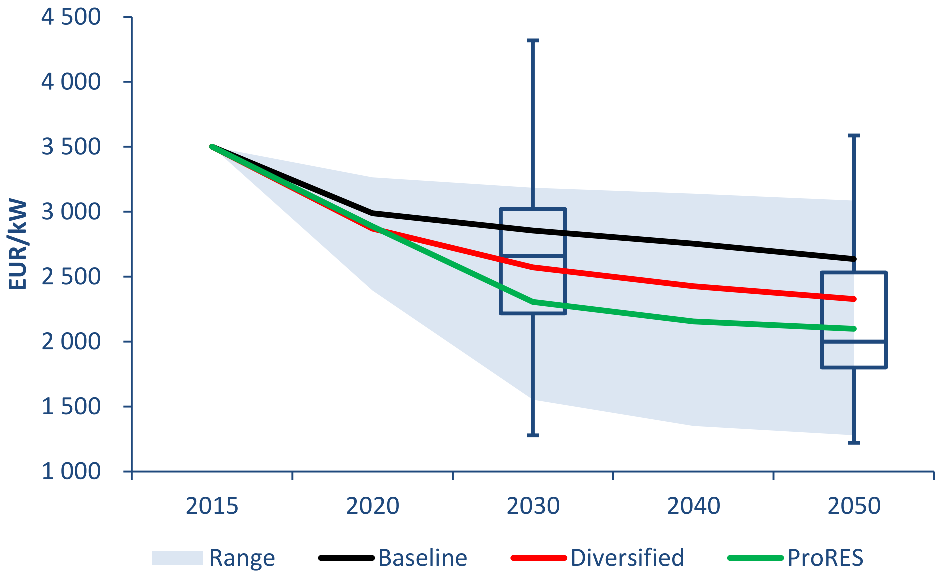

Figure 8 Capital investment cost trajectories offshore, monopole, medium distance to shore under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include all offshore wind turbine types)

3.1.5 Offshore, jacket, medium distance to shore

Table 8 Capital investment cost trajectories of offshore wind turbines (jacket, medium distance to shore)

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	3600	3070	2940	2830	2710
	Diversified	EUR/kW		2950	2650	2490	2390
	ProRES	EUR/kW		2970	2370	2220	2160
	Min	EUR/kW		2460	1600	1390	1320
	Max	EUR/kW		3360	3280	3230	3170
O&M costs	-	$\%_{CAPEX}$	2%	2%	2%	2%	2%

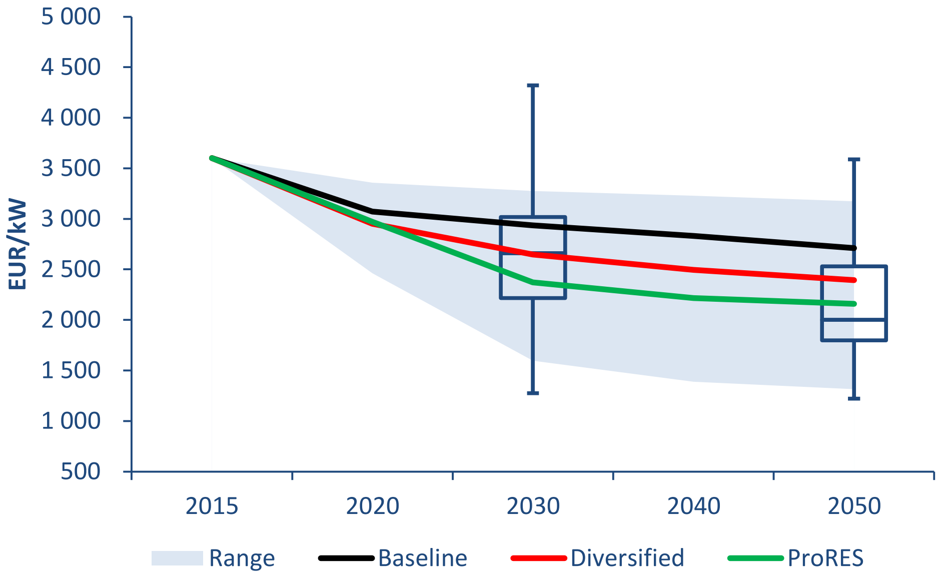

Figure 9 Capital investment cost trajectories offshore, jacket, medium distance to shore under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include all offshore wind turbine types)

3.1.6 Offshore, floating, long distance to shore

Table 9 Capital investment cost trajectories of offshore wind turbines (floating, long distance to shore)

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	5500	4690	4490	4330	4140
	Diversified	EUR/kW		4510	4040	3810	3660
	ProRES	EUR/kW		4540	3620	3390	3300
	Min	EUR/kW		3760	2440	2120	2010
	Max	EUR/kW		5130	5000	4930	4850
O&M costs	-	$\%_{CAPEX}$	2%	2%	2%	2%	2%

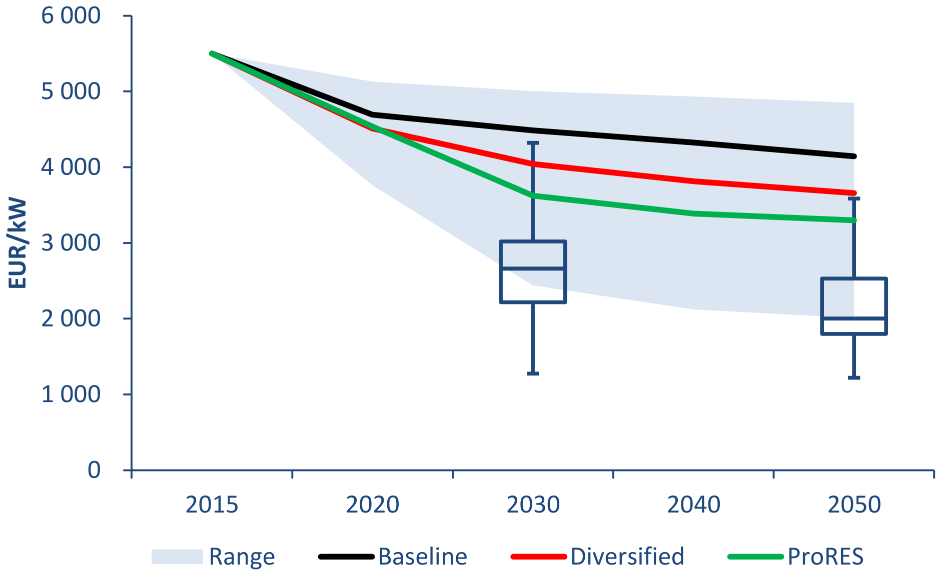

Figure 10 Capital investment cost trajectories offshore, floating, long distance to shore under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include all offshore wind turbine types)

3.2 Photovoltaics

Global growth projections of photovoltaics are presented in Table 10 for the three selected scenarios. The table also shows the estimated annual capacity additions that are required globally in order to meet these deployment levels based on an assumed technical lifetime. The range of learning rates that is used in this analysis is also presented in Table 10. These parameters are used to estimate capital investment cost trajectories based on the learning curve method.

The capital investment costs are differentiated based on four subtechnologies based on size. The parameters described in Table 10 are assumed to be the same for the following four photovoltaic subtechnologies:

- Utility-scale with one-axis tracking, >10 MW
- Utility-scale without tracking, >10 MW
- Commercial-scale on flat surface, 20 kW - 2 MW
- Residential-scale on inclined surface, <20 kW

Technology costs include module costs, inverter costs and other costs (e.g. balance of system, installation, and other indirect costs).

Table 10 Learning rate method input assumptions for photovoltaics

		Unit	2015	2020	2025	2030	2035	2040	2045	2050
Global installed capacity	Baseline	GW	220	424	534	643	834	1025	1244	1464
	Diversified	GW	220	492	827	1162	1851	2540	3482	4424
	ProRES	GW	220	732	1785	2839	3913	4988	5866	6745
Global capacity additions	Baseline	GW/yr	36	41	23	21	26	94	92	61
	Diversified	GW/yr	36	54	52	83	129	190	243	241
	ProRES	GW/yr	36	102	174	248	233	240	283	345
Learning rate	Reference	%	20%	20%	20%	20%	20%	20%	20%	20%
	High	%	23%	23%	23%	23%	23%	23%	23%	23%
	Low	%	10%	10%	10%	10%	10%	10%	10%	10%
Lifetime	-	Years	25	25	25	25	25	25	25	25

Capital investment cost trajectories and O&M shares of the selected photovoltaic subtechnologies are presented in Table 11 - Table 14 and graphically in Figure 11 - Figure 14. The figures show the cost projections for a reference learning rate with continuous lines and indicate a range by a shaded area that is an outcome of deployment scenario and learning rate combinations (sensitivity analysis). The results are graphically compared with literature estimates. These literature estimates are representative for a wider range of subtechnologies as the source does not always specify, for example, whether tracking is included or the inclination of the panel. Annex 2 describes the findings on learning rates of photovoltaics based on the literature review.

3.2.1 Utility-scale PV with one-axis tracking

Table 11 Capital investment cost trajectories of utility-scale photovoltaics with one-axis tracking

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	1120	910	790	640	550
	Diversified	EUR/kW		860	650	500	410
	ProRES	EUR/kW		760	490	400	350
	Min	EUR/kW		710	430	340	280
	Max	EUR/kW		1010	950	860	800
O&M costs	-	$\%_{CAPEX}$	2.3%	2.3%	2.3%	2.3%	2.3%

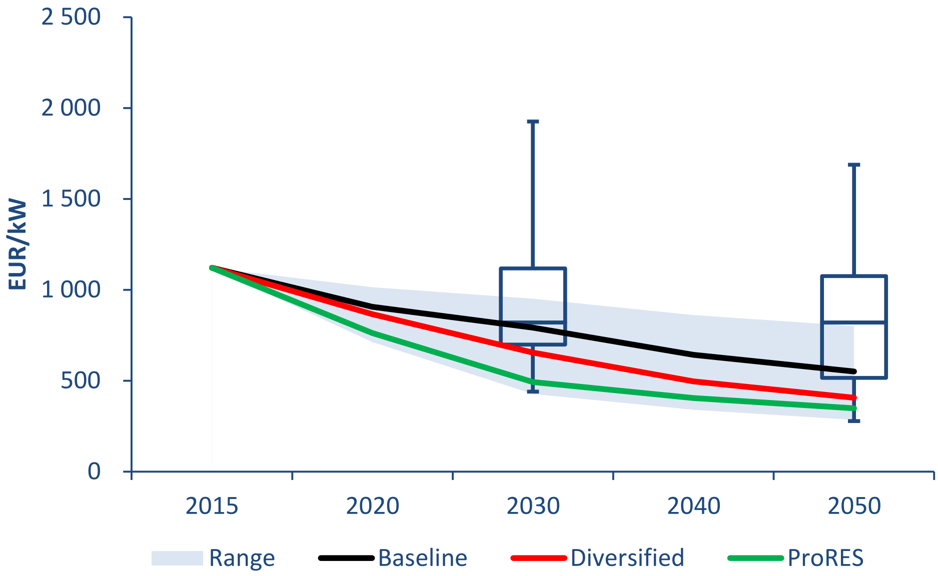

Figure 11 Capital investment cost trajectories of utility-scale photovoltaics with tracking under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include systems with and without tracking)

3.2.2 Utility-scale PV without tracking

Table 12 Capital investment cost trajectories of utility-scale photovoltaics without tracking

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	1020	830	720	580	500
	Diversified	EUR/kW		790	600	450	370
	ProRES	EUR/kW		690	450	370	320
	Min	EUR/kW		650	390	310	260
	Max	EUR/kW		920	870	780	730
O&M costs	-	$\%_{CAPEX}$	1.7%	1.7%	1.7%	1.7%	1.7%

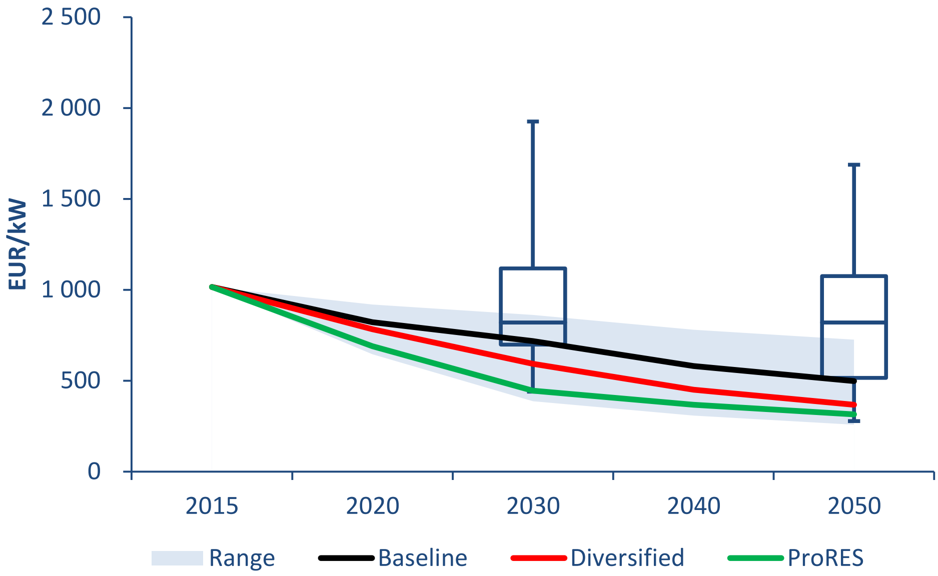

Figure 12 Capital investment cost trajectories of utility-scale photovoltaics without tracking under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include systems with and without tracking)

3.2.3 Commercial-scale PV flat surface

Table 13 Capital investment cost trajectories of commercial-scale PV, flat surface

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	1140	920	810	650	560
	Diversified	EUR/kW		880	670	510	410
	ProRES	EUR/kW		770	500	410	350
	Min	EUR/kW		720	430	350	290
	Max	EUR/kW		1030	970	880	810
O&M costs	-	$\%_{CAPEX}$	2.5%	2.5%	2.5%	2.5%	2.5%

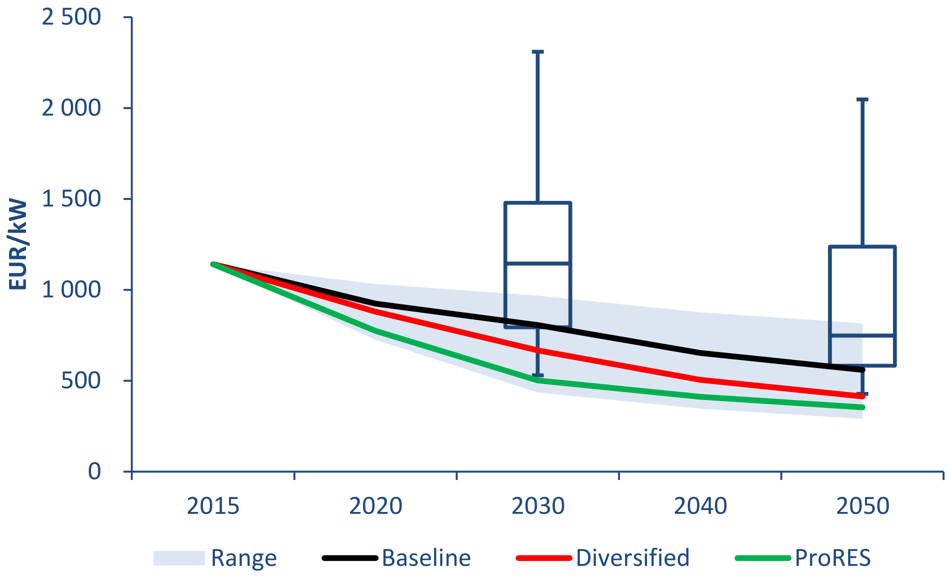

Figure 13 Capital investment cost trajectories of commercial-scale PV, flat surface under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include both flat and inclined commercial-scale PV systems)

3.2.4 Residential-scale PV inclined surface

Table 14 Capital investment cost trajectories of residential-scale PV, inclined surface

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	1360	1100	960	780	670
	Diversified	EUR/kW		1050	800	600	490
	ProRES	EUR/kW		920	600	490	420
	Min	EUR/kW		860	520	410	350
	Max	EUR/kW		1230	1150	1050	970
O&M costs	-	$\%_{CAPEX}$	2%	2%	2%	2%	2%

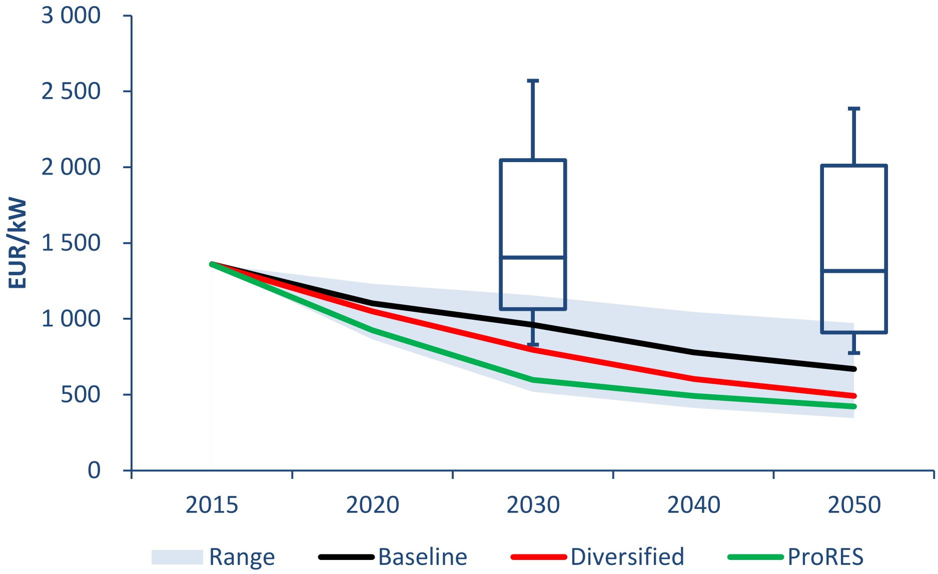

Figure 14 Capital investment cost trajectories of residential-scale PV, inclined surface under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart)

3.3 Solar thermal electricity

The cost trajectories of solar thermal electricity power plants are presented for parabolic trough and solar tower technologies with 6 to 8 hours storage. While capital investment costs of systems without storage are lower than systems with storage, the latter may introduce higher flexibility and increase the penetration of solar thermal electricity in the power system. Table 15 presents growth projections and capacity additions of solar thermal electricity plants next to the assumed range of learning rates and technical lifetime. Global scenario studies do not specify whether the solar thermal electricity plants include storage. In this analysis it is assumed that all deployed capacity includes storage.

Table 15 Learning rate method input assumptions for solar thermal electricity

		Unit	2015	2020	2025	2030	2035	2040	2045	2050
Global installed capacity	Baseline	GW	5	8	15	22	44	67	100	134
	Diversified	GW	5	56	129	203	384	565	752	939
	ProRES	GW	5	31	218	405	694	984	1229	1473
Global capacity additions	Baseline	GW/yr	1	1	1	2	3	6	6	9
	Diversified	GW/yr	1	10	8	21	34	39	37	49
	ProRES	GW/yr	1	5	19	56	59	57	54	50
Learning rate	Reference	%	7%	7%	7%	7%	7%	7%	7%	7%
	High	%	10%	10%	10%	10%	10%	10%	10%	10%
	Low	%	4%	4%	4%	4%	4%	4%	4%	4%
Lifetime	-	Years	30	30	30	30	30	30	30	30

Table 16 and Table 17 present the investment cost trajectories of parabolic trough and solar tower systems, respectively. The cost reduction is graphically presented in Figure 15 and Figure 16 and is compared with literature estimates, next to a sensitivity analysis based on a range or learning rates. In Annex 3 a detailed description of the literature review on learning rates of solar thermal electricity plants is included.

3.3.1 Parabolic trough with storage

Table 16 Capital investment cost trajectories of parabolic trough with storage

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	6000	5650	5100	4530	4200
	Diversified	EUR/kW		4630	4040	3630	3420
	ProRES	EUR/kW		4920	3760	3430	3280
	Min	EUR/kW		4120	3040	2660	2490
	Max	EUR/kW		5800	5470	5120	4910
O&M costs	-	$\%_{CAPEX}$	1.7%	1.7%	1.7%	1.7%	1.7%

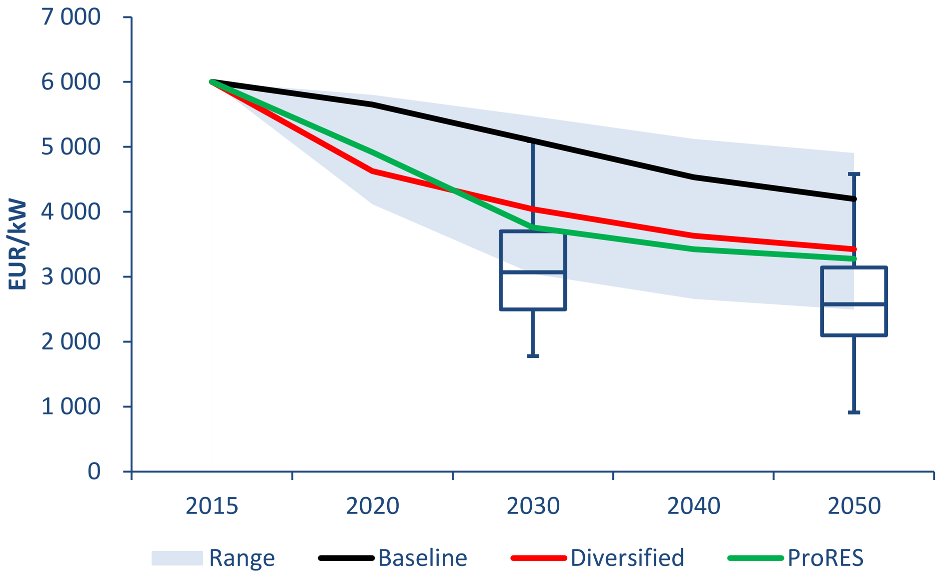

Figure 15 Capital investment cost trajectories of parabolic trough with storage under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include parabolic trough systems with and without storage)

3.3.2 Solar tower with storage

Table 17 Capital investment cost trajectories of solar tower with storage

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	5280	4970	4480	3990	3690
	Diversified	EUR/kW		4070	3560	3190	3010
	ProRES	EUR/kW		4330	3310	3010	2880
	Min	EUR/kW		3620	2680	2340	2190
	Max	EUR/kW		5110	4820	4510	4320
O&M costs	-	$\%_{CAPEX}$	1.7%	1.7%	1.7%	1.7%	1.7%

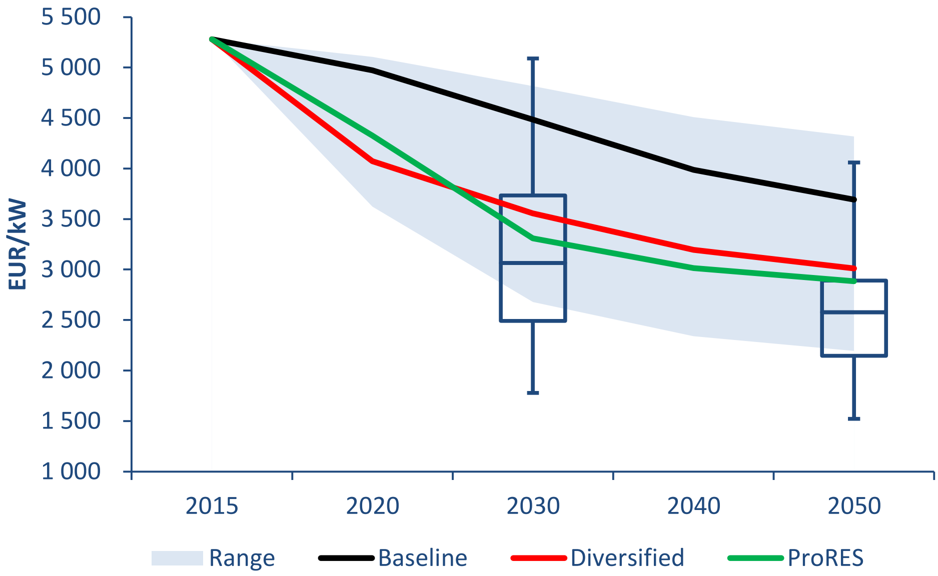

Figure 16 Capital investment cost trajectories of solar tower with storage under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include solar tower systems with and without storage)

3.4 Geothermal energy

Geothermal energy technologies are distinguished into three main subtechnologies, namely flash geothermal, Organic Rankine Cycle (ORC binary) geothermal and Enhanced Geothermal System (EGS). The capital investment costs of geothermal power plants depend highly on local sites. Therefore, the investment costs of 2015 may not be representative for all countries and locations. Table 18 presents global deployment and capacity additions based on three different growth scenarios. The table also presents the assumed technical lifetime and range of learning rates used to assess the investment cost trajectories. Technology costs include main equipment cost, drilling, and other costs components (e.g. balance of plant, installation, other indirect costs).

Table 18 Learning rate method input assumptions for geothermal energy

		Unit	2015	2020	2025	2030	2035	2040	2045	2050
Global installed capacity	Baseline	GW	12	18	23	28	36	44	55	65
	Diversified	GW	12	25	37	50	71	91	118	145
	ProRES	GW	12	28	82	137	231	325	405	485
Global capacity additions	Baseline	GW/yr	0.3	1	1	3	12	2	2	4
	Diversified	GW/yr	0.3	3	2	5	4	4	6	7
	ProRES	GW/yr	0.3	3	8	15	19	19	18	17
Learning rate	Reference	%	5%	5%	5%	5%	5%	5%	5%	5%
	High	%	10%	10%	10%	10%	10%	10%	10%	10%
	Low	%	2%	2%	2%	2%	2%	2%	2%	2%
Lifetime	-	Years	30	30	30	30	30	30	30	30

Capital investment cost trajectories and the share of O&M costs of the three different geothermal subtechnologies are presented in Table 19 - Table 21. The cost trajectories estimated based on the learning rate method are compared with literature estimates in Figure 17 - Figure 19. Detailed findings from the literature review on learning rates of geothermal energy technologies are presented in Annex 4.

3.4.1 Flash geothermal

Table 19 Capital investment cost trajectories of flash geothermal

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	3540	3430	3260	3160	3060
	Diversified	EUR/kW		3350	3150	3020	2910
	ProRES	EUR/kW		3320	2940	2760	2680
	Min	EUR/kW		3100	2420	2130	2000
	Max	EUR/kW		3500	3430	3390	3340
O&M costs	-	$\%_{CAPEX}$	2%	2%	2%	2%	2%

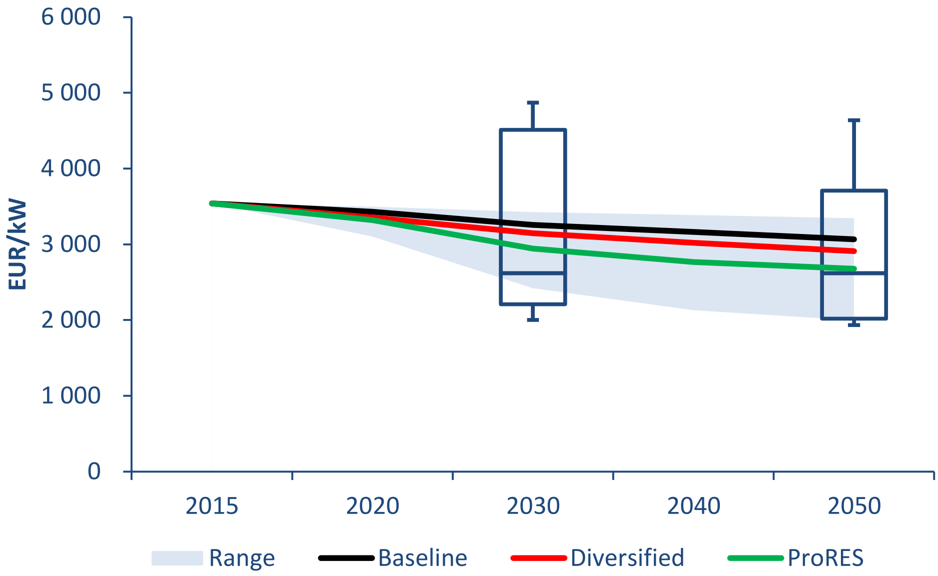

Figure 17 Capital investment cost trajectories of flash geothermal under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart)

3.4.2 Organic Rankine Cycle (binary)

Table 20 Capital investment cost trajectories of Organic Rankine Cycle (binary) geothermal

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	6970	6750	6410	6230	6030
	Diversified	EUR/kW		6600	6190	5950	5720
	ProRES	EUR/kW		6540	5790	5440	5270
	Min	EUR/kW		6110	4760	4190	3930
	Max	EUR/kW		6880	6740	6670	6580
O&M costs	-	$\%_{CAPEX}$	2%	2%	2%	2%	2%

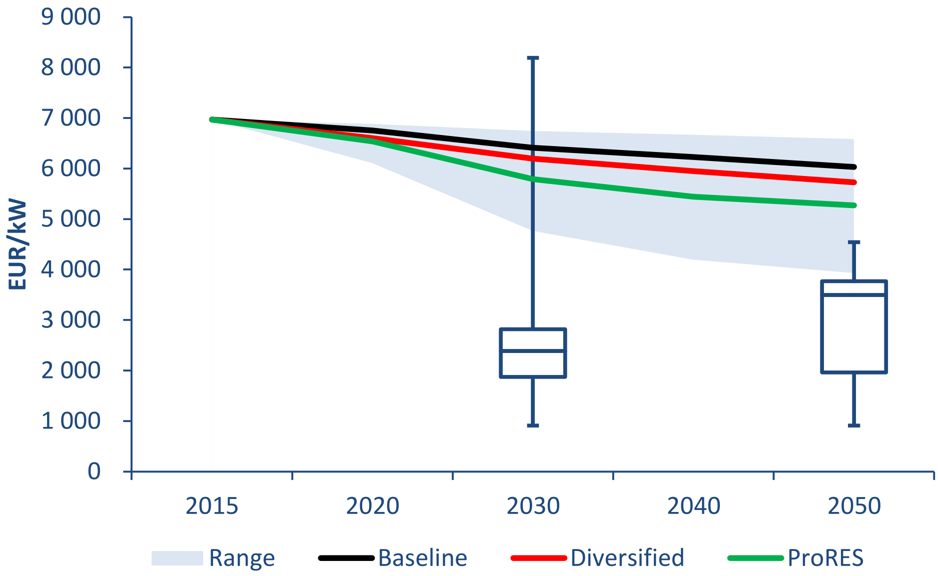

Figure 18 Capital investment cost trajectories of organic Rankine Cycle (binary) geothermal under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include all types of binary geothermal power plants)

3.4.3 Enhanced Geothermal system

Table 21 Capital investment cost trajectories of Enhanced Geothermal System

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	11790	11420	10840	10540	10200
	Diversified	EUR/kW		11170	10480	10060	9680
	ProRES	EUR/kW		11050	9800	9210	8920
	Min	EUR/kW		10330	8060	7090	6650
	Max	EUR/kW		11640	11410	11280	11140
O&M costs	-	$\%_{CAPEX}$	2%	2%	2%	2%	2%

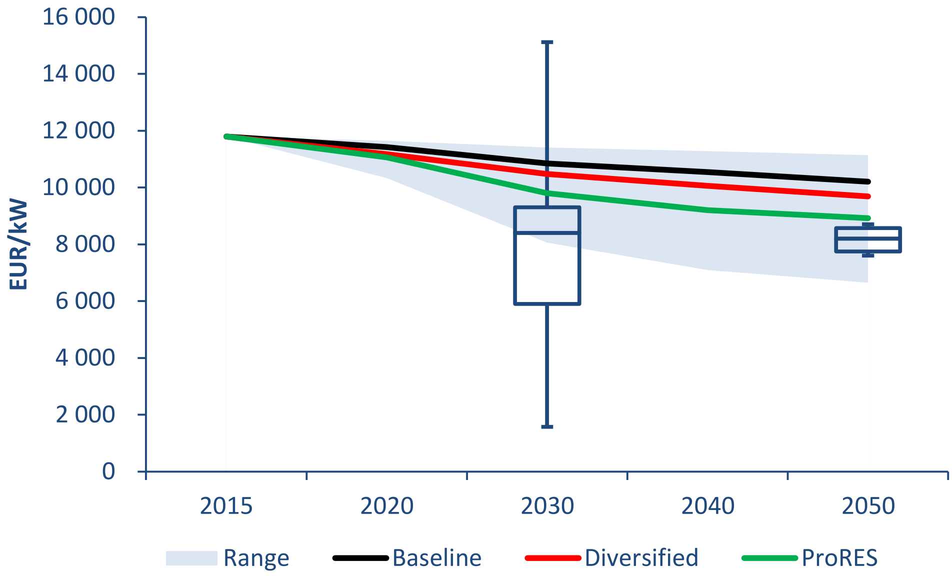

Figure 19 Capital investment cost trajectories of Enhanced Geothermal System under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart. Capital investment costs of EGS plants are highly dependent on local site conditions)

3.5 Ocean energy

The analysis on ocean energy technologies distinguishes three subtechnologies, namely tidal energy range, tidal energy stream and wave energy. Nearshore and offshore wave energy have similar capital investment costs. Differences, however, may be expected in the production costs of generating electricity due to different capacity factors. Table 22 presents the deployment and capacity additions based on three scenarios on growth of ocean energy globally to 2050. The table also presents the assumed technical lifetime and the range of learning rates used to assess the cost trajectories. The capital investment costs include all cost components such as equipment, balancing and interconnection costs.

Table 22 Learning rate method input assumptions for ocean energy

		Unit	2015	2020	2025	2030	2035	2040	2045	2050
Global installed capacity	Baseline	GW	0.5	1	2	3	8	13	23	34
	Diversified	GW	0.5	2	5	7	25	42	112	182
	ProRES	GW	0.5	11	53	95	207	318	435	552
Global capacity additions	Baseline	GW/yr	0.05	0.1	0.2	0.4	0.9	1	2	3
	Diversified	GW/yr	0.05	0.4	0.2	0.8	2	5	10	19
	ProRES	GW/yr	0.05	2	5	12	22	25	30	33
Learning rate	Reference	%	10%	10%	10%	10%	10%	10%	10%	10%
	High	%	15%	15%	15%	15%	15%	15%	15%	15%
	Low	%	7%	7%	7%	7%	7%	7%	7%	7%
Lifetime	-	Years	20	20	20	20	20	20	20	20

Capital investment cost trajectories and the share of O&M costs of tidal range and tidal stream are presented in Table 23 and Table 24, respectively. The cost trajectories estimated based on the learning rate method are compared with literature estimates of ocean energy technologies in Figure 20 and Figure 21. Cost trajectories of wave energy are presented in Table 25 and Figure 22. Detailed findings from the literature review on learning rates of ocean energy technologies are presented in Annex 5.

3.5.1 Tidal energy

Table 23 Capital investment cost trajectories of tidal range

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	6160	5680	4630	3760	3230
	Diversified	EUR/kW		4920	4140	3150	2520
	ProRES	EUR/kW		3890	2800	2320	2090
	Min	EUR/kW		3030	1830	1370	1170
	Max	EUR/kW		5830	5060	4390	3950
O&M costs	-	$\%_{CAPEX}$	6.3%	6.5%	5.6%	6.3%	4.9%

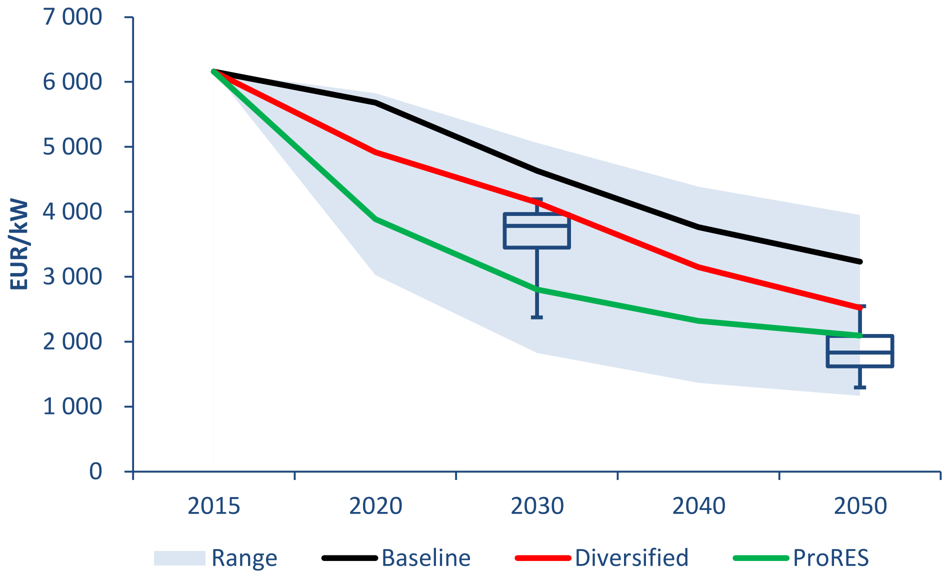

Figure 20 Capital investment cost trajectories of tidal range under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include both tidal and wave technologies)

Table 24 Capital investment cost trajectories of tidal stream

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	7840	7230	5900	4790	4120
	Diversified	EUR/kW		6260	5270	4000	3210
	ProRES	EUR/kW		4950	3560	2950	2660
	Min	EUR/kW		3850	2320	1740	1480
	Max	EUR/kW		7420	6440	5580	5030
O&M costs	-	$\%_{CAPEX}$	6.3%	6.5%	5.6%	6.3%	4.9%

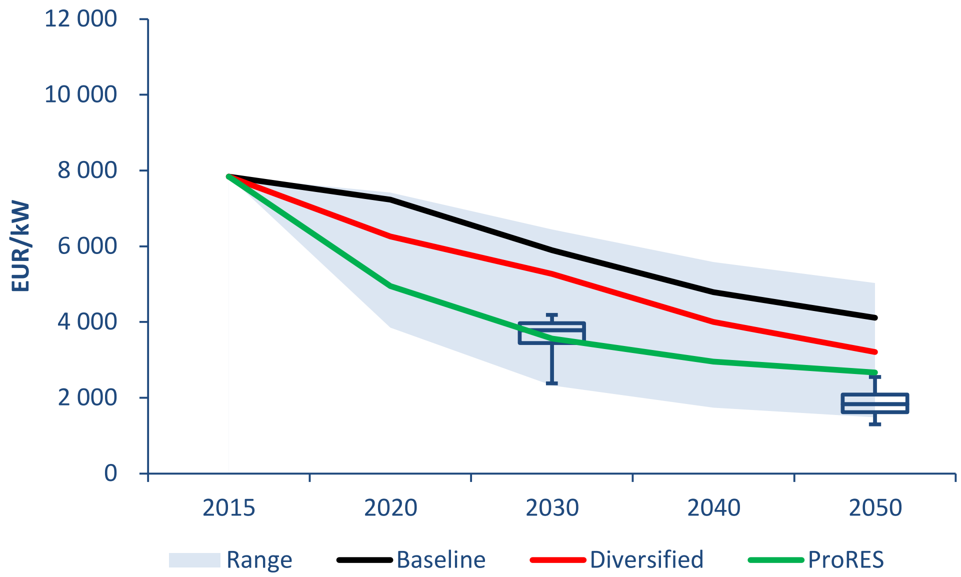

Figure 21 Capital investment cost trajectories of tidal stream under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include both tidal and wave technologies)

3.5.2 Wave energy

Table 25 Capital investment cost trajectories of wave energy

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	7910	7300	5950	4830	4150
	Diversified	EUR/kW		6310	5320	4040	3240
	ProRES	EUR/kW		4990	3600	2980	2690
	Min	EUR/kW		3890	2350	1750	1500
	Max	EUR/kW		7480	6500	5630	5070
O&M costs	-	$\%_{CAPEX}$	4%	4%	3.5%	4%	4%

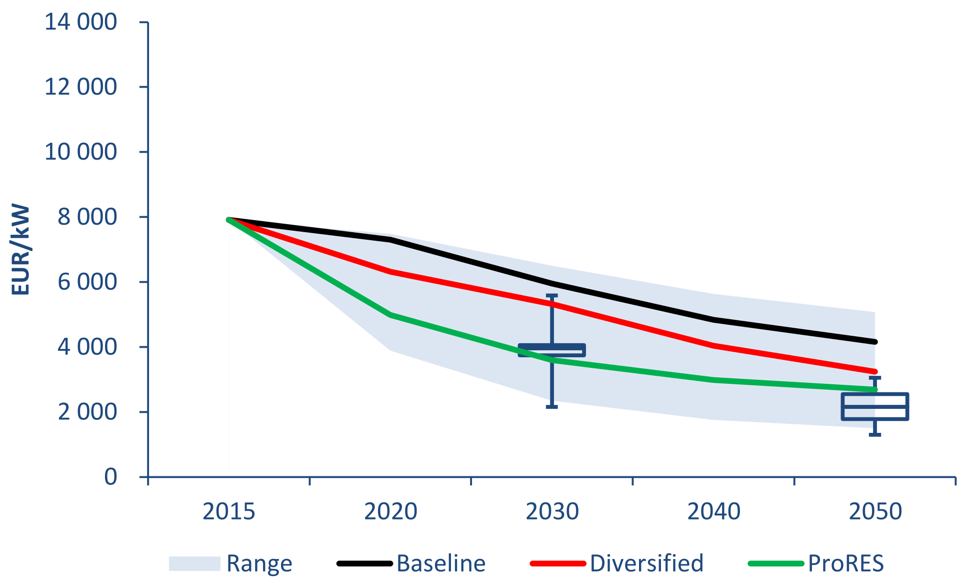

Figure 22 Capital investment cost trajectories of wave energy under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include both tidal and wave technologies)

3.6 Hydropower

Hydropower is a mature technology and global growth projections show that installed capacity may range from 1.5 to 2.2 TW by 2050. This entails that less than one doubling compared to 2015 may occur (Table 26). Based on these factors, no significant reduction in capital investment costs of hydropower plants is expected according to the learning curve method.

Total capital investment costs of hydropower plants include a range of activities, from construction of dams to electro-mechanical equipment. As such, specific costs of the total plant vary depending on the size but also the project conditions. This analysis identifies the range of capital investment costs (low-cost and high-cost hydropower) for three different plant sizes, namely large-scale (>10 MW), medium-scale (hydropower 1-10 MW) and small-scale (<1 MW). The analysis also includes costs of run-of-river plants. The costs include all components (e.g. civil and structural costs, electro-mechanical equipment, project development costs). While the learning rate method is applied, no significant differentiation between the three deployment scenarios and learning rate combinations is noticed (Table 27 - Table 33). For this reason, only the range between low-cost and high-cost hydropower plants is shown in Figure 23 - Figure 25 for the main subtechnologies. Annex 6 summarises the findings of the literature review on learning rates of hydropower plants.

Table 26 Learning rate method input assumptions for hydropower

		Unit	2015	2020	2025	2030	2035	2040	2045	2050
Global installed capacity	Baseline	GW	1208	1235	1297	1360	1436	1512	1584	1656
	Diversified	GW	1208	1246	1411	1577	1720	1863	2028	2193
	ProRES	GW	1208	1316	1356	1397	1421	1445	1474	1503
Global capacity additions	Baseline	GW/yr	37	5	12	13	14	17	15	13
	Diversified	GW/yr	37	8	34	33	23	35	34	32
	ProRES	GW/yr	37	22	10	6	5	4	5	6
Learning rate	Reference	%	1%	1%	1%	1%	1%	1%	1%	1%
	High	%	2%	2%	2%	2%	2%	2%	2%	2%
	Low	%	0%	0%	0%	0%	0%	0%	0%	0%
Lifetime	-	Years	60	60	60	60	60	60	60	60

3.6.1 Large-scale hydropower and dam

Table 27 Capital investment cost trajectories of large-scale low-cost hydropower and dam

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	1090	1090	1090	1090	1090
	Diversified	EUR/kW		1090	1090	1080	1080
	ProRES	EUR/kW		1090	1090	1090	1090
	Min	EUR/kW		1090	1080	1080	1070
	Max	EUR/kW		1090	1090	1090	1090
O&M costs	-	$\%_{CAPEX}$	0.5%	0.5%	0.5%	0.5%	0.5%

Table 28 Capital investment cost trajectories of large-scale high-cost hydropower and dam

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	3500	3500	3490	3490	3480
	Diversified	EUR/kW		3500	3490	3480	3470
	ProRES	EUR/kW		3500	3490	3490	3490
	Min	EUR/kW		3490	3470	3460	3440
	Max	EUR/kW		3500	3500	3500	3500
O&M costs	-	$\%_{CAPEX}$	0.5%	0.5%	0.5%	0.5%	0.5%

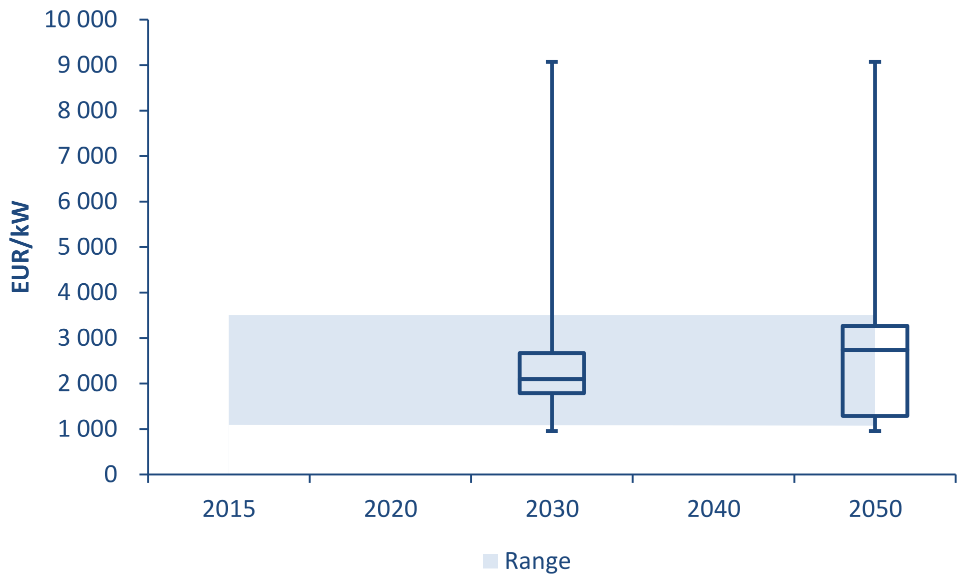

Figure 23 Capital investment cost trajectories of large hydro under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart)

3.6.2 Medium-scale hydropower and dam

Table 29 Capital investment cost trajectories of medium-scale low-cost hydropower and dam

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	1410	1410	1410	1410	1400
	Diversified	EUR/kW		1410	1400	1400	1400
	ProRES	EUR/kW		1410	1410	1410	1410
	Min	EUR/kW		1410	1400	1390	1390
	Max	EUR/kW		1410	1410	1410	1410
O&M costs	-	$\%_{CAPEX}$	0.5%	0.5%	0.5%	0.5%	0.5%

Table 30 Capital investment cost trajectories of medium-scale high-cost hydropower and dam

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	4000	4000	3990	3990	3980
	Diversified	EUR/kW		4000	3980	3970	3970
	ProRES	EUR/kW		4000	3990	3990	3990
	Min	EUR/kW		3990	3970	3950	3930
	Max	EUR/kW		4000	4000	4000	4000
O&M costs	-	$\%_{CAPEX}$	0.5%	0.5%	0.5%	0.5%	0.5%

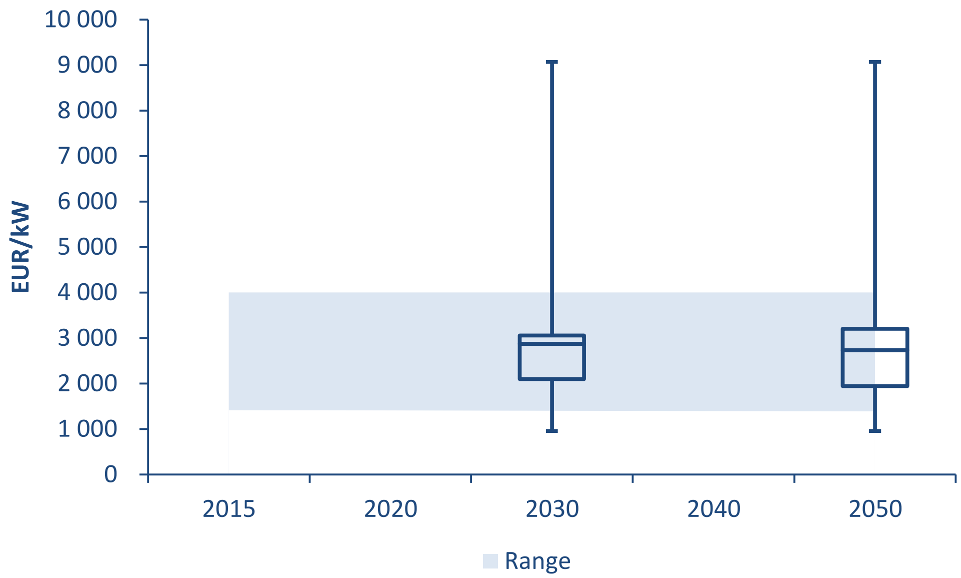

Figure 24 Capital investment cost trajectories of medium hydro under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart)

3.6.3 Small-scale hydropower and dam

Table 31 Capital investment cost trajectories of small-scale low-cost hydropower and dam

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	1740	1740	1740	1730	1730
	Diversified	EUR/kW		1740	1730	1730	1730
	ProRES	EUR/kW		1740	1740	1740	1730
	Min	EUR/kW		1740	1730	1720	1710
	Max	EUR/kW		1740	1740	1740	1740
O&M costs	-	$\%_{CAPEX}$	1%	1%	1%	1%	1%

Table 32 Capital investment cost trajectories of small-scale high-cost hydropower and dam

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	5000	5000	4990	4980	4980
	Diversified	EUR/kW		5000	4980	4970	4960
	ProRES	EUR/kW		4990	4990	4990	4980
	Min	EUR/kW		4990	4960	4940	4910
	Max	EUR/kW		5000	5000	5000	5000
O&M costs	-	$\%_{CAPEX}$	1%	1%	1%	1%	1%

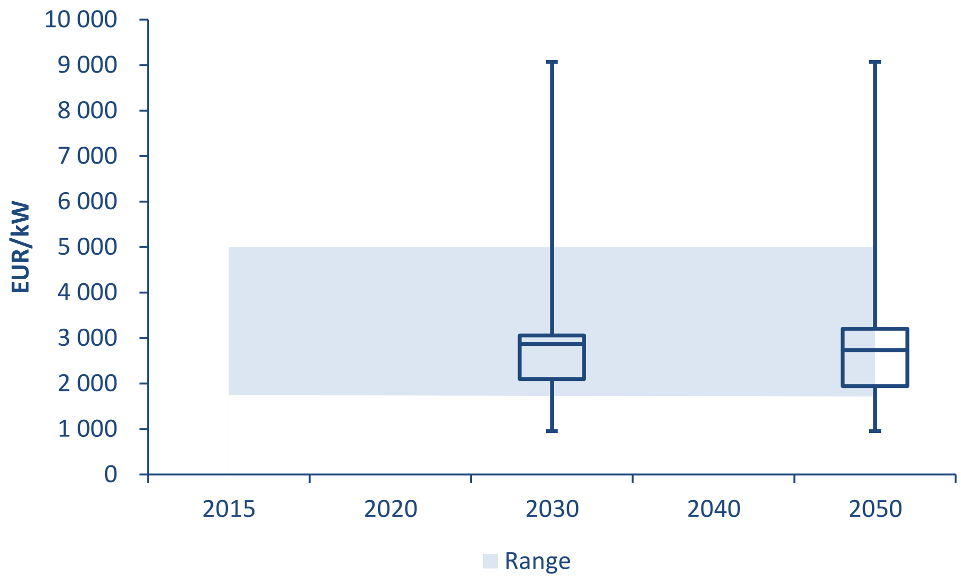

Figure 25 Capital investment cost trajectories of small hydro under different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart)

3.6.4 Run-of-river

Table 33 Capital investment cost trajectories of run-of-river plants

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	3000	3000	2990	2990	2990
	Diversified	EUR/kW		3000	2990	2980	2970
	ProRES	EUR/kW		3000	2990	2990	2990
	Min	EUR/kW		2990	2980	2960	2950
	Max	EUR/kW		3000	3000	3000	3000
O&M costs	-	$\%_{CAPEX}$	0.5%	0.5%	0.5%	0.5%	0.5%

3.7 Heat and power from biomass

The scope of biomass technologies covers a wide range of different processes, from anaerobic digestion coupled with gas engines to subcritical steam turbines. This analysis differentiates between four main biomass subtechnologies for combined heat and power generation, namely biomass subcritical steam turbine, gasified biomass, biomass-fired Organic Rankine Cycle and anaerobic digestion. Table 34 presents the global deployment and capacity additions based on three different scenarios on growth of biomass energy to 2050. The table also presents the assumed technical lifetime and range of learning rates used to assess the investment cost trajectories. Technology costs include main equipment and other cost components (e.g. balance of plant, installation, other indirect costs).

Table 34 Learning rate method input assumptions for heat and power from biomass

		Unit	2015	2020	2025	2030	2035	2040	2045	2050
Global installed capacity	Baseline	GW	84	182	204	226	250	275	312	350
	Diversified	GW	84	245	327	408	558	707	917	1126
	ProRES	GW	84	194	293	392	475	558	652	746
Global capacity additions	Baseline	GW/yr	5	20	11	5	7	12	27	19
	Diversified	GW/yr	5	32	25	15	29	40	79	62
	ProRES	GW/yr	5	22	24	24	20	22	42	41
Learning rate	Reference	%	5%	5%	5%	5%	5%	5%	5%	5%
	High	%	7%	7%	7%	7%	7%	7%	7%	7%
	Low	%	2%	2%	2%	2%	2%	2%	2%	2%
Lifetime	-	Years	25	25	25	25	25	25	25	25

Capital investment cost trajectories and O&M shares of biomass conversion technologies are presented in Table 35 - Table 38. The cost trajectories estimated based on the learning rate method are compared with literature estimates in Figure 26 - Figure 29. Values from literature do not differentiate on the technology subtype. In Annex 7, the findings from the literature review on learning rates of biomass heat and power technologies are presented.

3.7.1 Biomass subcritical steam turbine Combined Heat and Power

Table 35 Capital investment cost trajectories of biomass subcritical steam turbine CHP plant

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	3600	3400	3310	3230	3120
	Diversified	EUR/kW		3330	3180	3050	2910
	ProRES	EUR/kW		3380	3190	3100	2980
	Min	EUR/kW		3220	3020	2850	2660
	Max	EUR/kW		3520	3480	3450	3400
O&M costs	-	$\%_{CAPEX}$	2%	2%	2%	2%	2%

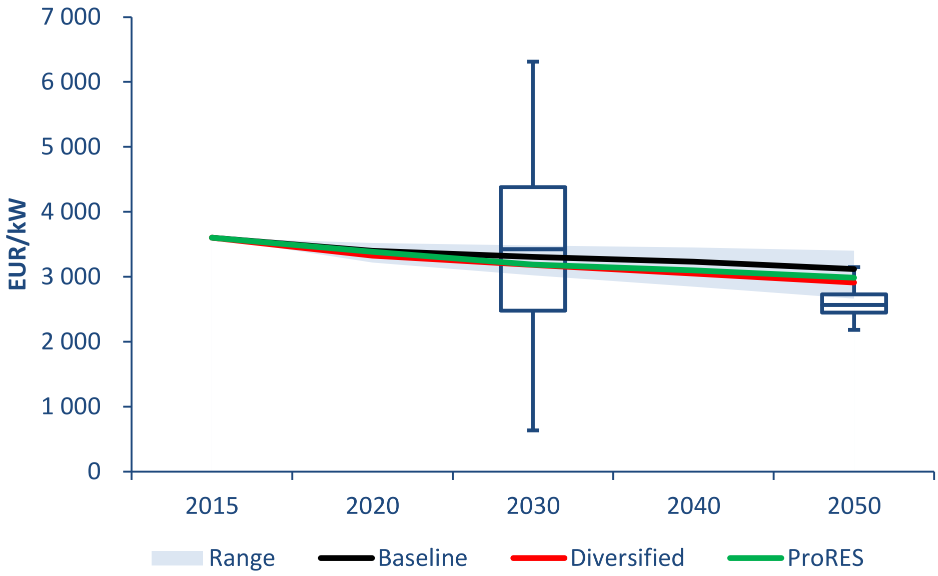

Figure 26 Capital investment cost trajectories of biomass subcritical steam turbine CHP in different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include all types of biomass CHP plants, i.e. steam turbine, gasification and ORC)

3.7.2 Gasified biomass Combined Heat and Power

Table 36 Capital investment cost trajectories of gasified biomass CHP plant

		Unit	2015	2020	2030	2040	2050
Capital investment costs ([1])	Baseline	EUR/kW	5300	5010	4870	4760	4590
	Diversified	EUR/kW		4900	4680	4490	4280
	ProRES	EUR/kW		4980	4700	4560	4390
	Min	EUR/kW		4740	4450	4190	3920
	Max	EUR/kW		5180	5130	5080	5010
O&M costs	-	$\%_{CAPEX}$	2%	2%	2%	2%	2%

([1]) Using waste as a feedstock could increase capital investment costs by 10-15 %

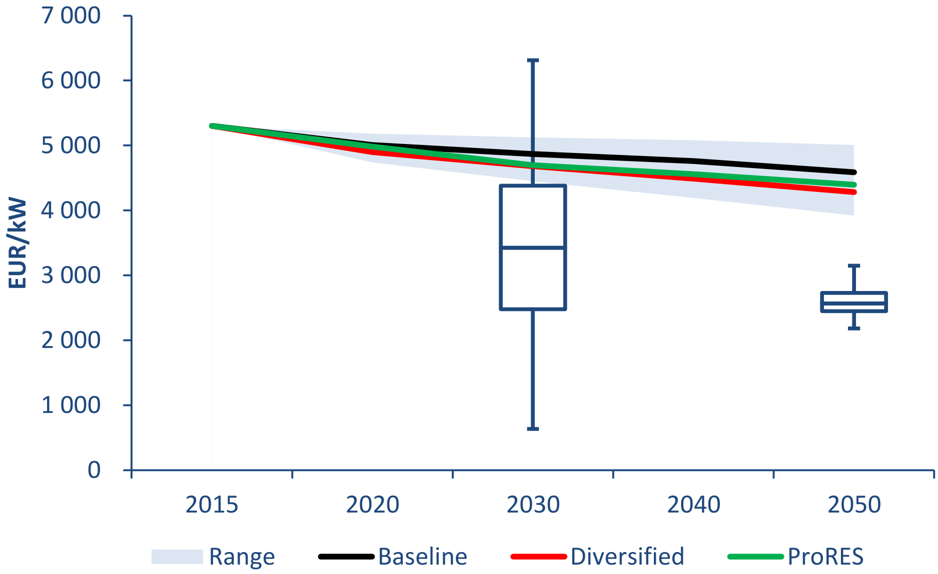

Figure 27 Capital investment cost trajectories of gasified biomass CHP in different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include all types of biomass CHP plants, i.e. steam turbine, gasification and ORC)

3.7.3 Biomass-fired Organic Rankine Cycle

Table 37 Capital investment cost trajectories of biomass-fired Organic Rankine Cycle

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	4700	4440	4320	4220	4070
	Diversified	EUR/kW		4340	4150	3980	3800
	ProRES	EUR/kW		4420	4160	4040	3900
	Min	EUR/kW		4200	3950	3720	3480
	Max	EUR/kW		4600	4540	4510	4440
O&M costs	-	$\%_{CAPEX}$	2%	2%	2%	2%	2%

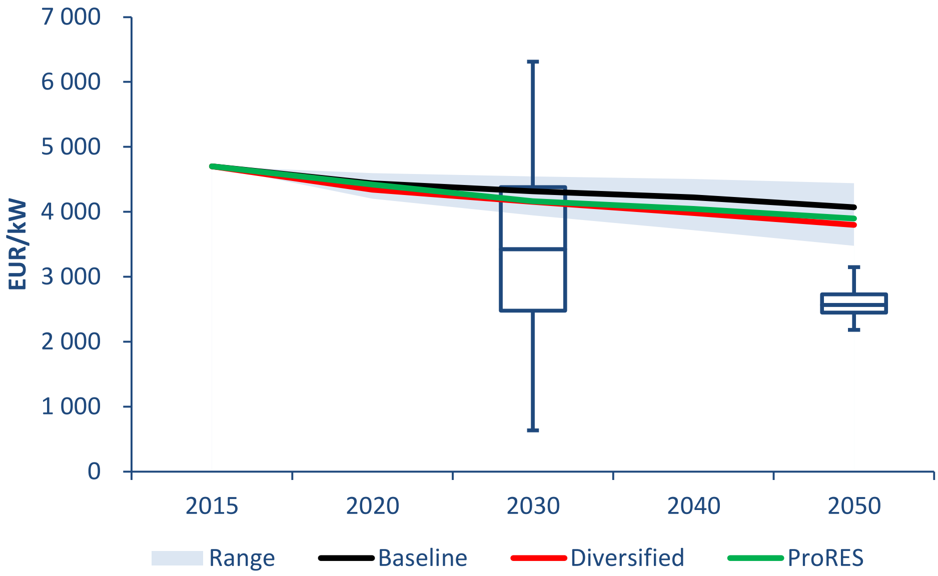

Figure 28 Capital investment cost trajectories of gasified biomass CHP in different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include all types of biomass CHP plants, i.e. steam turbine, gasification and ORC)

3.7.4 Anaerobic digestion

Table 38 Capital investment cost trajectories of anaerobic digestion plants

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	3100	2930	2850	2780	2680
	Diversified	EUR/kW		2860	2740	2630	2510
	ProRES	EUR/kW		2910	2750	2670	2570
	Min	EUR/kW		2770	2600	2450	2290
	Max	EUR/kW		3030	3000	2970	2930
O&M costs	-	$\%_{CAPEX}$	4%	4%	4%	4%	4%

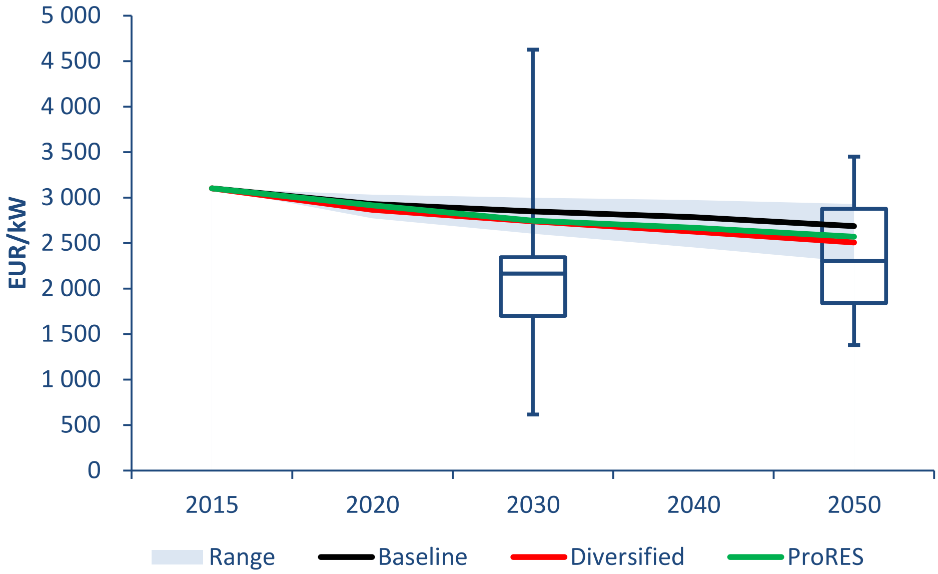

Figure 29 Capital investment cost trajectories of anaerobic digestion in different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include from digestion only plants to biogas engines)

3.8 Carbon Capture and Storage

This report analyses potential cost trajectories of six power generation technologies with carbon capture. These are:

- Pulverised coal supercritical power plant with post-combustion CCS (PC)
- Pulverised coal supercritical power plant with oxyfuel CCS
- Lignite Integrated Gasification and Combined Cycle (IGCC) power plant with pre-combustion CCS
- Coal Integrated Gasification and Combined Cycle power plant with pre-combustion CCS
- Natural Gas Combined Cycle power plant with post-combustion CCS (NGCC)
- Biomass Integrated Gasification and Combined Cycle power plant with pre-combustion CCS (BIGCC)

Global growth trajectories are distinguished for carbon capture in coal-based power generation (sections 3.8.1 - 3.8.4), gas-based power generation (section 3.8.5) and biomass-based power generation (section 3.8.6). The growth trajectories per subtechnology, the assumed plant lifetime, the range of learning rates and the reduction in capital investment costs over time are presented in the respective sections. In the "ProRES" scenario, CCS is not part of the technology portfolio and as such capital investment cost trajectories are estimated only for the "Baseline" and the "Diversified" scenario. The capital investment cost trajectories presented in this analysis are relevant for total costs of greenfield plants, excluding CO_2 transport and storage. Figure 30 to Figure 35 present capital cost trajectories of CCS technologies for a range of scenarios and learning rates and are compared with literature estimates. A detailed description of the literature review on learning rates of CCS technologies is presented in Annex 8.

3.8.1 Pulverised coal supercritical, CCS post-combustion

Table 39 Learning rate method input assumptions for pulverised coal plants with CCS, post-combustion

		Unit	2015	2020	2025	2030	2035	2040	2045	2050
Global installed capacity	Baseline	GW	0	0	0.2	1	2	3	5	11
	Diversified	GW	0	0	6	42	137	267	346	284
Global capacity additions	Baseline	GW/yr	0	0	0.04	0.2	0.2	0.2	0.4	1
	Diversified	GW/yr	0	0	1	7	19	26	16	0
Learning rate	Reference	%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%	2.1%
	High	%	3.5%	3.5%	3.5%	3.5%	3.5%	3.5%	3.5%	3.5%
	Low	%	1.1%	1.1%	1.1%	1.1%	1.1%	1.1%	1.1%	1.1%
Lifetime	-	Years	40	40	40	40	40	40	40	40

Table 40 Capital investment cost trajectories of pulverised coal plants with CCS, post-combustion

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	-	-	2760	2680	2580
	Diversified	EUR/kW		-	2740	2590	2570
	Min	EUR/kW		-	2630	2400	2360
	Max	EUR/kW		-	2830	2790	2740
O&M costs	-	$\%_{CAPEX}$	2.1%	2.1%	2.1%	2.1%	2.1%

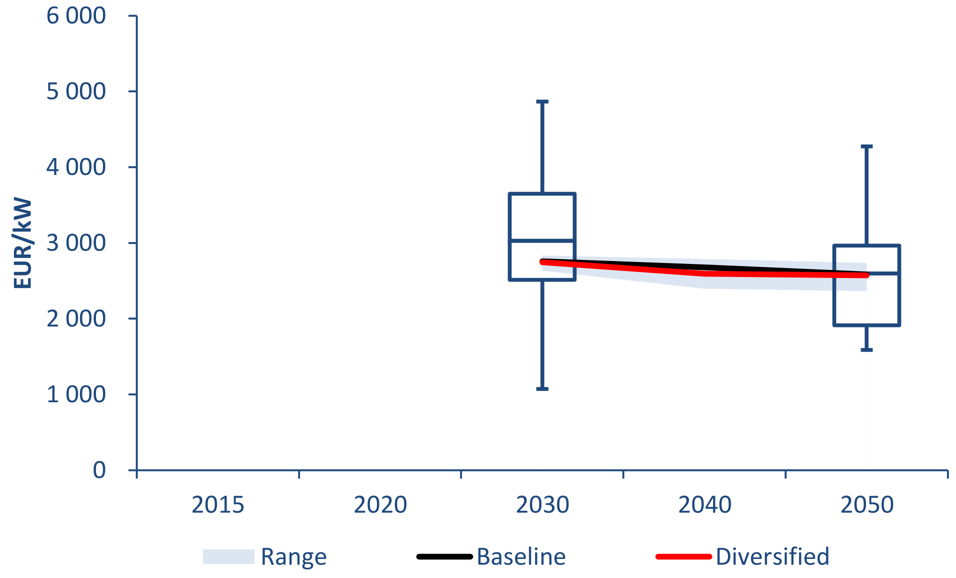

Figure 30 Capital investment cost trajectories of PC coal plants with CCS in different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart)

3.8.2 Pulverised coal supercritical, CCS oxyfuel

Table 41 Learning rate method input assumptions for pulverised coal plants with CCS, oxyfuel

		Unit	2015	2020	2025	2030	2035	2040	2045	2050
Global installed capacity	Baseline	GW	0	0	0.2	1	2	3	5	11
	Diversified	GW	0	0	6	42	137	267	346	284
Global capacity additions	Baseline	GW/yr	0	0	0.04	0.2	0.2	0.2	0.4	1
	Diversified	GW/yr	0	0	1	7	19	26	16	0
Learning rate	Reference	%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%
	High	%	4.4%	4.4%	4.4%	4.4%	4.4%	4.4%	4.4%	4.4%
	Low	%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%
Lifetime	-	Years	40	40	40	40	40	40	40	40

Table 42 Capital investment cost trajectories of pulverised coal plants with CCS, oxyfuel

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	-	-	2710	2600	2480
	Diversified	EUR/kW		-	2690	2490	2470
	Min	EUR/kW		-	2560	2270	2240
	Max	EUR/kW		-	2810	2750	2690
O&M costs	-	$\%_{CAPEX}$	2.3%	2.3%	2.3%	2.3%	2.3%

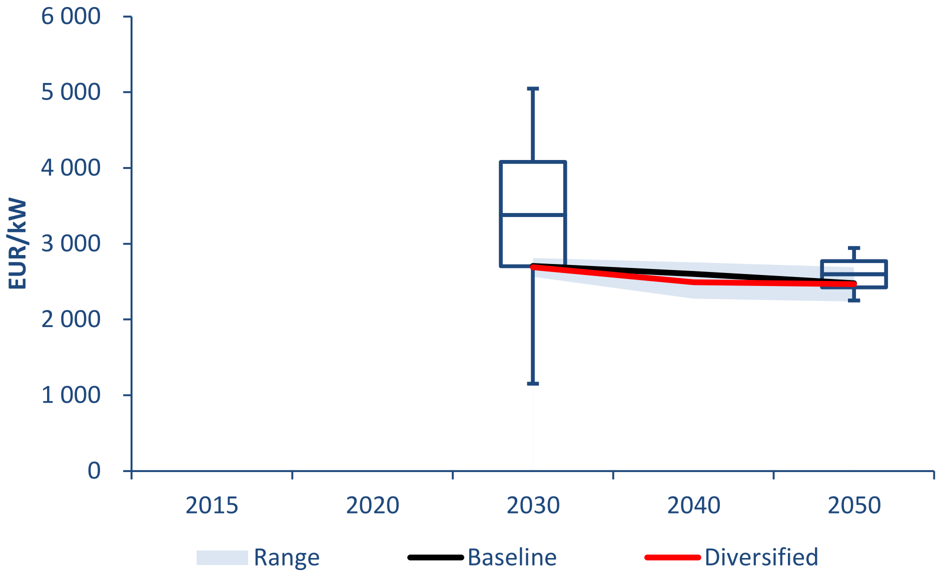

Figure 31 Capital investment cost trajectories of PC coal plants oxyfuel with CCS in different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart)

3.8.3 Lignite integrated gasification and combined cycle, CCS pre-combustion

Table 43 Learning rate method input assumptions for lignite integrated gasification and combined cycle plants with CCS, pre-combustion

		Unit	2015	2020	2025	2030	2035	2040	2045	2050
Global installed capacity	Baseline	GW	0	0	0.2	1	2	3	5	11
	Diversified	GW	0	0	6	42	137	267	346	284
Global capacity additions	Baseline	GW/yr	0	0	0.04	0.2	0.2	0.2	0.4	1
	Diversified	GW/yr	0	0	1	7	19	26	16	0
Learning rate	Reference	%	5%	5%	5%	5%	5%	5%	5%	5%
	High	%	7.6%	7.6%	7.6%	7.6%	7.6%	7.6%	7.6%	7.6%
	Low	%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%
Lifetime	-	Years	40	40	40	40	40	40	40	40

Table 44 Capital investment cost trajectories of lignite integrated gasification and combined cycle plants with CCS, pre-combustion

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	-	-	3920	3640	3340
	Diversified	EUR/kW		-	3870	3380	3310
	Min	EUR/kW		-	3570	2900	2810
	Max	EUR/kW		-	4200	4040	3880
O&M costs	-	$\%_{CAPEX}$	2.2%	2.2%	2.2%	2.2%	2.2%

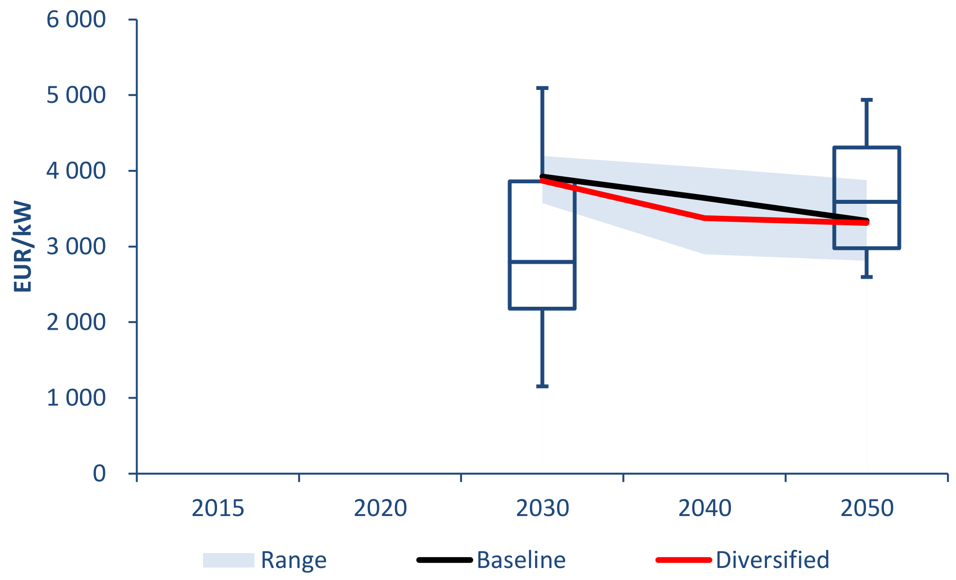

Figure 32 Capital investment cost trajectories of lignite IGCC plants with CCS in different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include both coal and lignite IGCC with CCS)

3.8.4 Coal integrated gasification and combined cycle, CCS pre-combustion

Table 45 Learning rate method input assumptions for coal integrated gasification and combined cycle with CCS, pre-combustion

		Unit	2015	2020	2025	2030	2035	2040	2045	2050
Global installed capacity	Baseline	GW	0	0	0.2	1	2	3	5	11
	Diversified	GW	0	0	6	42	137	267	346	284
Global capacity additions	Baseline	GW/yr	0	0	0.04	0.2	0.2	0.2	0.4	1
	Diversified	GW/yr	0	0	1	7	19	26	16	0
Learning rate	Reference	%	5%	5%	5%	5%	5%	5%	5%	5%
	High	%	7.6%	7.6%	7.6%	7.6%	7.6%	7.6%	7.6%	7.6%
	Low	%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%
Lifetime	-	Years	40	40	40	40	40	40	40	40

Table 46 Capital investment cost trajectories of coal integrated gasification and combined cycle plants with CCS, pre-combustion

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	-	-	2580	2390	2200
	Diversified	EUR/kW		-	2540	2220	2180
	Min	EUR/kW		-	2350	1900	1850
	Max	EUR/kW		-	2760	2660	2550
O&M costs	-	$\%_{CAPEX}$	3%	3%	3%	3%	3%

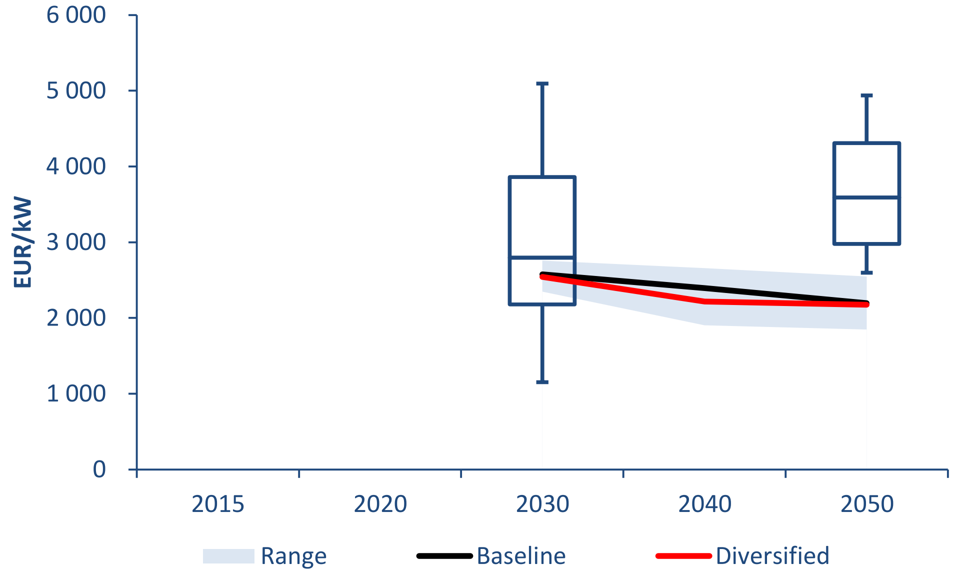

Figure 33 Capital investment cost trajectories of coal IGCC plants with CCS in different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart and include both coal and lignite IGCC with CCS)

3.8.5 Natural gas combined cycle, CCS post-combustion

Table 47 Learning rate method input assumptions for natural gas combined cycle plants with CCS, post-combustion

		Unit	2015	2020	2025	2030	2035	2040	2045	2050
Global installed capacity	Baseline	GW	0	0	0	0	0	0	0	0
	Diversified	GW	0	0	2	22	72	146	225	286
Global capacity additions	Baseline	GW/yr	0	0	0	0	0	0	0	0
	Diversified	GW/yr	0	0	0.4	4	10	15	16	12
Learning rate	Reference	%	2.2%	2.2%	2.2%	2.2%	2.2%	2.2%	2.2%	2.2%
	High	%	3.6%	3.6%	3.6%	3.6%	3.6%	3.6%	3.6%	3.6%
	Low	%	1.2%	1.2%	1.2%	1.2%	1.2%	1.2%	1.2%	1.2%
Lifetime	-	Years	30	30	30	30	30	30	30	30

Table 48 Capital investment cost trajectories of natural gas combined cycle plants with CCS, post-combustion

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	-	-	1510	1510	1510
	Diversified	EUR/kW		-	1390	1310	1280
	Min	EUR/kW		-	1320	1190	1150
	Max	EUR/kW		-	1510	1510	1510
O&M costs	-	$\%_{CAPEX}$	2.5%	2.5%	2.5%	2.5%	2.5%

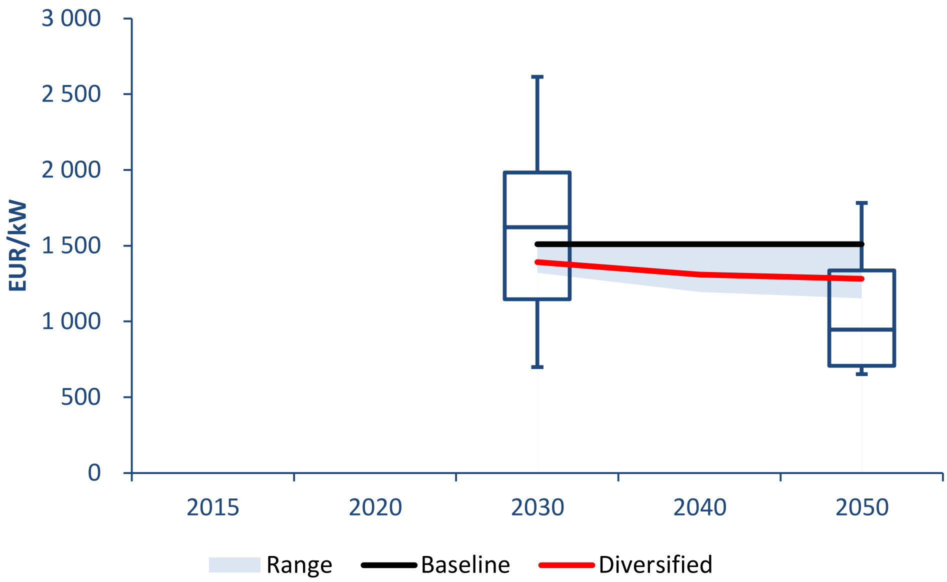

Figure 34 Capital investment cost trajectories of NGCC plants with CCS in different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart)

3.8.6 Biomass integrated gasification and combined cycle, CCS pre-combustion

Table 49 Learning rate method input assumptions for biomass integrated gasification and combined cycle plants with CCS, pre-combustion

		Unit	2015	2020	2025	2030	2035	2040	2045	2050
Global installed capacity	Baseline	GW	0	0	0	0	0	0	0	0
	Diversified	GW	0	0	1	2	9	34	100	162
Global capacity additions	Baseline	GW/yr	0	0	0	0	0	0	0	0
	Diversified	GW/yr	0	0	0.1	0.2	2	5	13	13
Learning rate	Reference	%	5%	5%	5%	5%	5%	5%	5%	5%
	High	%	7.6%	7.6%	7.6%	7.6%	7.6%	7.6%	7.6%	7.6%
	Low	%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%
Lifetime	-	Years	25	25	25	25	25	25	25	25

Table 50 Capital investment cost trajectories of biomass integrated gasification and combined cycle plants with CCS, pre-combustion

		Unit	2015	2020	2030	2040	2050
Capital investment costs	Baseline	EUR/kW	-	-	5800	5800	5800
	Diversified	EUR/kW		-	5380	4310	3840
	Min	EUR/kW		-	5160	3680	3070
	Max	EUR/kW		-	5800	5800	5800
O&M costs	-	$\%_{CAPEX}$	2.3%	2.3%	2.3%	2.3%	2.3%

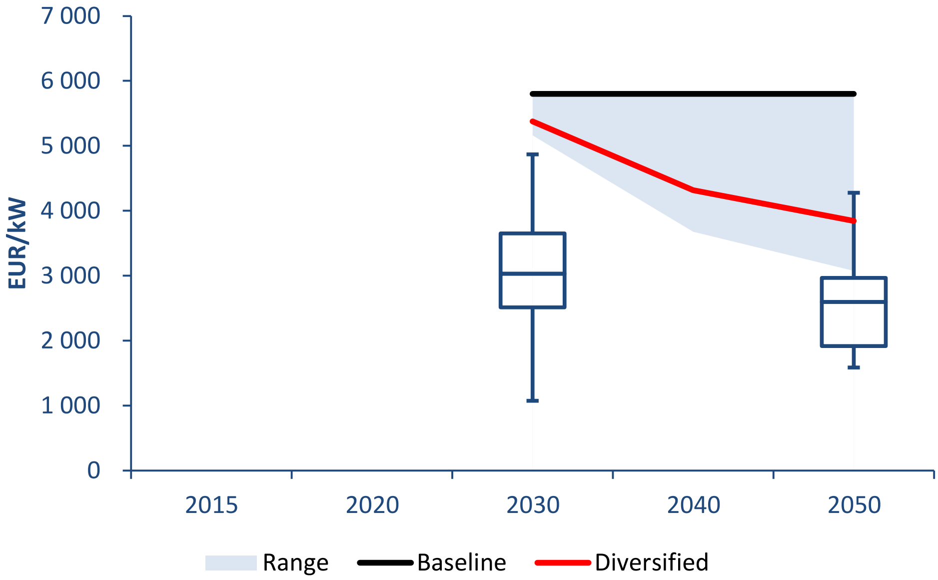

Figure 35 Capital investment cost trajectories of biomass IGCC plants with CCS in different global growth scenarios and varying learning rates (Note: literature estimates are represented by the boxplot chart. Due to lack of sufficient literature projections includes coal and lignite IGCC plants with CCS)

4 Conclusions

This report presents internally consistent trajectories of capital investment and O&M costs across eight low carbon energy technologies to 2050. To do so, it combines global scenario projections on technology deployment with the one-factor learning rate method. Three global scenarios are used in order to identify a cost reduction range based on different deployment pathways. One scenario is in line with baseline (business as usual) assumptions and two scenarios are in line with long-term deep decarbonisation pathways, which differ in their technology portfolio and deployment levels. A sensitivity analysis is performed based on a range of learning rates to assess their influence on the reference cost trajectories. The results are compared with literature projections. The reduction in capital investment costs that could be achieved by 2030 and 2050 compared to 2015 is summarised in Figure 36.

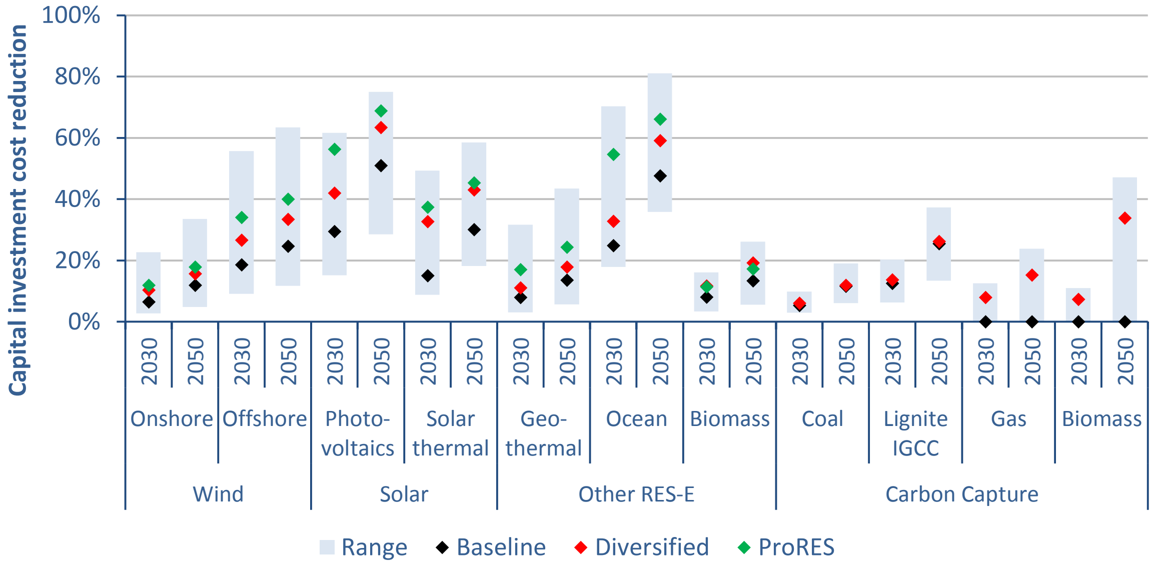

Figure 36 Reduction in capital investment costs of selected low carbon energy technologies under different global growth scenarios and learning rates by 2030 and 2050 compared to 2015 (Note: excluding hydropower for which capital investment costs are estimated to decrease by 2 % in 2050 compared to 2015)

In the long term (2050), global deployment levels may influence considerably the cost reduction potential of technologies when these are estimated with the learning rate method. A difference higher than 10 % percent points between the lowest ("Baseline") and the highest ("ProRES") estimate is found for offshore wind turbines (15 %), photovoltaics (18 %), solar thermal electricity (15 %), ocean energy (19 %) and biomass with CCS (34 %). Depending on the technology, such a range could translate from about 100 €/kW (e.g. for photovoltaics) to more than 1,000 €/kW (e.g. for ocean energy) or 2,000 €/kW for biomass CCS. For most technologies, the influence of the decarbonisation pathways (between "Diversified" and "ProRES") is less pronounced, with the exception of photovoltaics and ocean energy in the mid-term (2030).

Across all scenarios, moderate reduction in capital investment costs is estimated for onshore wind turbines, geothermal energy, biomass CHPs and CCS technologies. For these technologies costs may decrease up to about 15 % in 2030 compared to 2015. Towards 2050, an additional 5 % to 7 % reduction may be achieved in onshore wind turbines, geothermal energy, biomass CHPs, coal and gas plants with CCS. For lignite IGCC plants with CCS the additional reduction is somewhat higher (about 12 %) due to the different learning rates assumed for CCS technologies.

A steep cost reduction is noticed for offshore wind turbines (16-34 %), photovoltaics (29-56 %), solar thermal electricity (15-37 %) and ocean energy (25-55 %) in all global deployment scenarios by 2030. From then onwards, capital investment costs continue to reduce sharply for photovoltaics and ocean energy due to the additional deployed capacity projected by global scenarios. Between 2030 and 2050, costs of these technologies reduce by an additional 13-20 % for photovoltaics and 12-26 % for ocean energy. The cost reduction of offshore wind turbines and solar thermal electricity slows down between 2030 and 2050; the additional reduction is estimated at about 6-7 % for offshore wind turbines and 8-15 % for solar thermal electricity. For these technologies, however, the influence of learning rate and global growth scenario projections can be significant, as the range in cost reduction by 2050 between the highest and the lowest estimate is more than 50 %. Costs of biomass IGCC plants decrease by about 40 % in 2050 compared to their first year of large-scale deployment (2025), however, only based on the "Diversified" scenario. In the other two scenarios biomass IGCC with CCS is not deployed.

The approach followed in this report addresses limitations of previous work published on techno-economic projections [15], which did not take into account the competition of RES technologies in the energy system and their costs dependence based on global dynamics. However, although an improvement of existing projections, the approach that this report follows has limitations.

Firstly, with the exception of wind energy and partly of CCS, the deployment projections at a technology level are applied on all subtechnologies assuming that perfect spillover learning takes place. This may overestimate the deployed capacity and the related cost reduction. This assumption may hold true, for example, for PV modules, and therefore there needs to be no differentiation based on the size and application of photovoltaics. However, it may not be representative for other technologies such as ocean energy, where tidal and wave energy are distinct. This limitation could be addressed if the global projected deployment of technologies is distributed to subtechnologies in line with selected criteria (e.g. resource potential).

Secondly, a one-factor rate is applied on each subtechnology, assuming that learning may take place in all capital cost-components of the technology. However, not all components may improve due to learning or with the same rate. For such technologies the component-based learning rate method would be preferable. While results of component-based approaches would be more precise, it is expected that they would still fall in the range that this report identifies. Other improvements call for estimating other cost components such as the O&M costs of CCS using the learning rate method, or incorporate bottom-up techno-economic developments on cost-components that are not subjected to learning such as the BOS costs of PV systems.

Finally, a critical aspect that deserves further attention is the role and contribution of raw material prices in the cost structure of technologies. While overall the technology costs may improve due to learning the price dynamics of raw materials may influence the investments and stimulate or impede further reduction.

Future research may address these limitations, and in particular apply decomposed learning rates on the part of the technology's cost-structure that may benefit from learning complemented by other bottom-up methods on those components for which learning does not apply. Similarly, other long-term cost drivers such as raw material prices or potential disruptions due to material substitution could be addressed by further research to complement the insights into the future cost trajectories of low carbon energy technologies.

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List of abbreviations and definitions

BIGCC	Biomass Integrated Gasification and Combined Cycle
BNEF	Bloomberg New Energy Finance
BOS	Balance of System
CAPEX	Capital Expenditures
CHP	Combined Heat and Power
CCS	Carbon Capture and Storage
EGS	Enhanced Geothermal System
IEA	International Energy Agency
IGCC	Integrated Gasification and Combined Cycle
LCOE	Levelised Cost of Electricity
LR	Learning Rate
NGCC	Natural Gag Combined Cycle
ORC	Organic Rankine Cycle
O&M	Operation and Maintenance
PC	Pulverised Coal
PV	Photovoltaic
R&D	Research and Development
RES	Renewable Energy Supply
RES-E	Renewable Energy Supply - Electricity

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Annexes

Different studies that report on the development of technology costs diverge in results depending on the method used to assess future cost reduction (e.g. learning curves, bottom-up engineering assessments or expert expectations), existing geographical differences, different times of reporting or system boundaries. Similar variability also applies to learning rates reported in the public domain, which are a key parameter in this report as they are used to estimate cost developments of low carbon energy technologies. Differences consist of particular technologies (e.g. onshore vs offshore wind), time periods during which the learning rates were estimated, geographic location, technology boundaries (e.g. including or excluding grid connection costs), but also the performance or experience parameter used. This Annex summarises the findings of the literature review on learning rates of low carbon energy technologies.

Annex 1. Wind energy

Wind power plants have been widely assessed using the learning curve method. The capital investment costs of wind power are comprised of turbine costs, hub/base costs and BOS costs. The latter include costs that are not directly related to the technology (mounting, interconnection, land preparation, etc.) and other costs related with system design, financing, permits and so forth. In particular, for offshore wind power plants interconnection costs may constitute a substantial part.

The majority of literature on learning rates of wind energy that was reviewed for this analysis either assesses onshore wind turbines or does not provide any details on the subtechnology (Figure 37). Studies indicate a range in learning rates from negative values up to 33 %. Negative learning rates are found in studies with limited regional and temporal coverage. Examples are the case of wind power in Germany, where based on a sample between 1991 and 1999 a -3 % learning rate was derived and wind power in Taiwan, where based on a sample between 2001 and 2010 even lower learning rates were found [16–18]. A clear pattern could not be observed for learning rates that belong to the higher end of literature estimates. These relate with the 32 % learning rate observed for the US between 1985 and 1995 (onshore wind parks) and with the 30 % rate observed at a global level between 1981 and 1995 (onshore turbines) [4].

Only a few studies assess learning rates of separate wind power plant components, other than turbines. Reported values on learning rates of separate components tend to be higher than those related with the total wind park or turbine. For example, a 38 % learning rate for offshore HVDC cables is reported and a 77 % rate for the installation time of offshore wind turbines [4].

Recent wind energy auctions could suggest even higher learning rates, especially for offshore turbines. However, the capital investment costs of such projects may only be inferred based on announced electricity prices, and until these projects become operational the capital investment costs remain uncertain and are thus excluded from the present analysis. In wind power generation, besides capital investment costs, significant learning takes place on capacity factors [19]. However, these improvements are not included in this report.

Figure 37 shows the reported learning rates of wind turbines, power plants and farms based on publications from 1995 to 2016. The majority of data is distributed between 5 % and 20 %. This range may be a result of different system boundaries (turbine, power plant, wind farm), different sample size or period, geographical coverage and so forth.

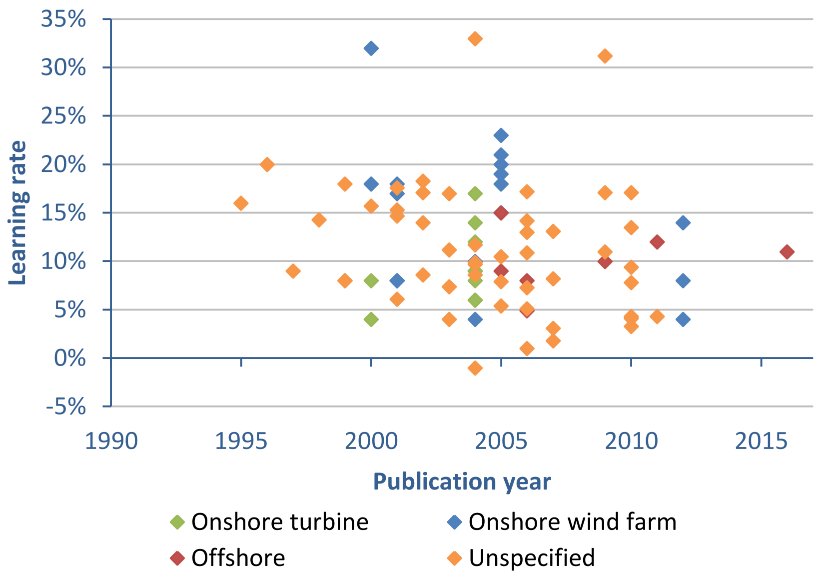

Figure 37 Learning rates of wind power as observed in literature

In this analysis, a *reference* 5 % rate for onshore wind power plants, and a sensitivity range from a *low learning rate* of 2 % to a *high learning rate* of 10 % are used. The *reference rate* for offshore wind power plants in 2015 is set to 11 % decreasing gradually to 8 % in 2025 and remaining at 5 % from 2030 onwards. As such it is assumed that steep learning will continue for offshore wind turbines in the short-term for projects that are largely in the pipeline, while beyond 2030 the learning rates of onshore and offshore wind turbines will converge. A sensitivity analysis on offshore wind is performed based on the following *ranges*: 5 % and 20 % in 2015-2020; 5 % and 15 % in 2025, 2 % and 10 % from 2030 onwards.

Annex 2. Photovoltaics

Photovoltaics, either small-scale (residential systems) or large-scale (utility systems), have been widely assessed using the learning curve method. The capital investment costs of PV systems are comprised of PV module costs, inverter costs and other BOS costs. The latter include non-technology related costs (e.g. mounting, wiring, tracking systems, land preparation) and other costs related with system design, financing, permits and so forth. The main findings follow:

- **Modules:** More than two thirds of the studies reviewed, use PV module sales price as performance indicator and cumulative capacity as experience indicator. Learning rates range from 7 % to 47 %, primarily due to different regional and temporal coverage and the period in which the data are fitted to curves. The price of raw materials has also been associated with temporal variability of module prices from learning curve estimates. For instance, the price increase of silicon and silver between 1998 and 2006, was met by an increase in PV module price in contrast to a price reduction, which was expected based on learning curves and due to decrease in silver use (substitution effect) in PV production [20]. Based on industry experts, Fraunhofer ISE [21] mentions that at module prices below 0.2 €/W_p material costs could dominate. This may occur at a global cumulative production capacity higher than 10 TW and steep learning rates. For PV modules, other literature suggests learning rates between 18 % and 22 % [22], with an average of about 21 % [21]. Current PV module prices range from 450 to 650 €/kW_p depending on the region [22]. According to literature, historical learning rates will be maintained in the future due to technological developments in monocrystalline and multicrystalline module costs across the supply chain [21–24].

- **Inverters:** There are few studies that assess learning rates of inverters despite the great drop in their price over time. Most studies mention that learning rates of inverters are similar with those of PV modules. Along these lines, Fraunhofer ISE [21] use a learning rate of 18.9 %, which lies within the range of 18 % to 20 % reported by IRENA [22]. An exception is the study of ECN which estimates a much lower range from 7 % to 9 % [25]. Depending on the region and the scale of the PV system, the inverter price in the global market is around 125 €/kW$_p$ for central inverters (>100 kW$_p$, typically used in centralised systems), 160 €/kW$_p$ for string inverters (<100 kW$_p$, typical for residential systems) and 350 €/kW$_p$ for micro-inverters [22]. Lower costs from the Chinese market have also been reported (i.e. 25-45 €/kW$_p$ for central and 55-75 €/kW$_p$ for string inverters, respectively) [22]. Next to scale effects, inverters may enter commodity markets and, therefore, historical learning rates are expected to continue.
- **BOS:** While the price reduction of modules and inverters is associated with the experience gained globally, the remainder of BOS costs are dependent on local parameters (e.g. raw material prices, labour costs, land prices) and show regional variability [21, 22, 25]. For instance, IRENA [22] shows a range of BOS costs between 450 and 1,550 €/kW$_p$ (excluding inverters). For selected EU countries the range is somewhat narrower from about 450 to 1,200 €/kW$_p$. In Germany, utility-scale BOS costs of 350 €/kW$_p$ (excluding inverters) are reported [21]. BOS costs of residential systems could be higher on a W$_p$ basis. Cost reduction potentials are either associated with material improvements (thus reducing the effect of raw material prices on BOS costs) or with efficiency improvements of PV modules. The large variation in BOS costs suggests that it is difficult to obtain an average global price for PV systems.

Figure 38 shows reported learning rates of photovoltaic systems based on publications from 1992 to 2016. The data cloud tends to concentrate around the range of 15-20 % which is in line with recent reporting; however due to significant variations this range is rather indicative than representative. The studies vary in the performance and experience indicator they assess. Most commonly the price of the PV system is used as a performance indicator (23 studies), whilst 10 studies use production costs. The rest of the studies do not specify the performance indicator. Regarding the experience indicator, most studies use cumulative capacity figures (in MW). These may refer to shipments, installed capacity, sales or production.

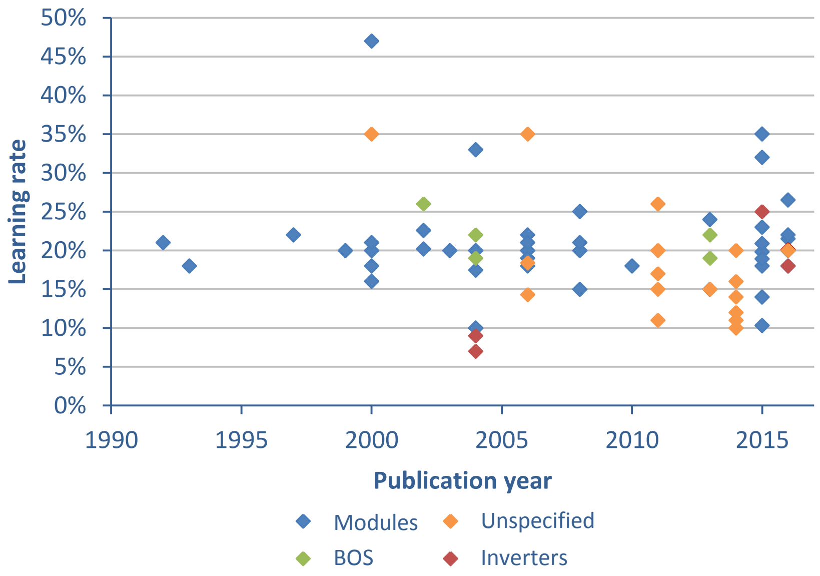

Figure 38 Learning rates of photovoltaics as observed in literature

Overall, PV module and inverter costs are expected to follow historical learning rates and as such a *reference learning rate* of 20 % is used in this report. This learning rate lies within the range reported in literature (from 18 % to 22 %). A *high learning rate* of 23 % is also used as sensitivity analysis. Due to the large contribution of other BOS on PV system costs and their independence from global experience, the overall system could have much slower learning than what has been observed for PV modules and inverters. To capture this uncertainty a *low learning rate* of 10 % is used. From the reviewed literature, there is no clear evidence to suggest that commercial and residential PV modules or inverters would follow different learning rates. Other factors, however, which relate primarily with current investment costs, are expected. For example, residential PV systems may have different cost drivers with large regional difference compared to utility-scale PVs.

Current fixed O&M costs of utility-scale PV systems are about 20 €/kW$_p$ (or 2 % of investment costs) and are expected to drop to 10 €/kW$_p$ by 2050 [21]. Based on levelised costs of electricity (LCOE) estimated by BNEF, the fixed O&M of four European countries are 2.3-2.5 % of their average capital investment costs [26]. As investment costs decline, the contribution of O&M costs in the LCOE of photovoltaic power may increase over time. However, in this report, O&M costs are assumed as a fixed share of capital investment costs over the lifetime of the PV system.

Technical system lifetime is currently around 25 years and may reach up to 30 years in 2050. Inverter lifetime is 15 years, however this is not taken into account in this analysis.

Typical efficiencies of PV modules are around 15 % today and may climb up to 35 % (scenario based) in 2050 [21]. BNEF reports higher average current efficiencies of 18.2 % for multicrystalline and 19.8 % for monocrystalline silicon cells [6].

Capacity factors range from 10 % to 25 % for fixed tilt systems; again these are region specific. According to BNEF the capacity factors of four European countries range from 10 % to 17 % [26].

Annex 3. Solar thermal electricity

Solar thermal electricity is still at early stages in terms of global deployment (with global installed capacity at about 5 GW [14]). Consequently, learning rates have not yet been established based on a large volume of historical evidence, similar to those of wind energy and PV systems. The subtechnology with the highest market share is parabolic trough (about 85 % of global cumulative installed capacity), second are solar tower systems (about 10 % of global cumulative installed capacity) and the remainder is Linear Fresnel reflectors. From the 1.3 GW of solar thermal power that is under construction about 55 % is parabolic trough systems and 32 % solar towers [27]. While parabolic troughs and solar tower systems have several differences, current and near-term capital investment costs are similar [22].

Despite the early stage of technology deployment in terms of global installed capacity, there are several studies that report or incorporate learning rates for future cost estimates. Although not explicitly stated across all studies, historical learning rates have been primarily based on solar thermal electricity plants (parabolic trough systems) built in California in the 1980s and Spain in the 2000s. Some studies report only a learning rate (or progress ratio) without further details as they are neither explicit about the period or region of coverage nor about the experience and performance indicator they assess. A small number of studies base their cost trajectories on plausible future scenarios and policy assumptions. The range of learning rates found in literature for solar thermal power systems is from 5 % to 20 %, with most studies referring to a rate of around 10 % (Figure 39).

The three key components of solar thermal electricity systems are the solar field (comprised of mirrors, tracking systems, heating fluid, support structures), the storage systems (comprised of heat exchangers, storage tanks) ([4]) and the power block (conventional steam turbines). Viebahn *et al.* [28], Trieb *et al.* [29] and DLR (in Junginger *et al.* [5]), report learning rate ranges for these three components separately. Namely, 10 % to 12 % for the solar field, 8 % to 12 % for the storage system and 2 % to 6 % for the power block (Figure 39).

Most studies conclude that there are significant future prospects for reducing the technology's investment costs enabled by improved materials and material designs in the solar field and innovative heat transfer fluids (e.g. molten salts in parabolic trough systems). These may improve the systems' heat transfer and storage capability and through increased capacity factors and steam cycle efficiency will improve the overall efficiency [22, 27, 30]. Today's efficiency of 15-17 % may increase to 18-20 % within the next decade [27]. IRENA mentions that the efficiency of parabolic trough systems from about 15 % today, may reach 17 % in 2025 and of solar towers from about 16 % to 18 % [22].

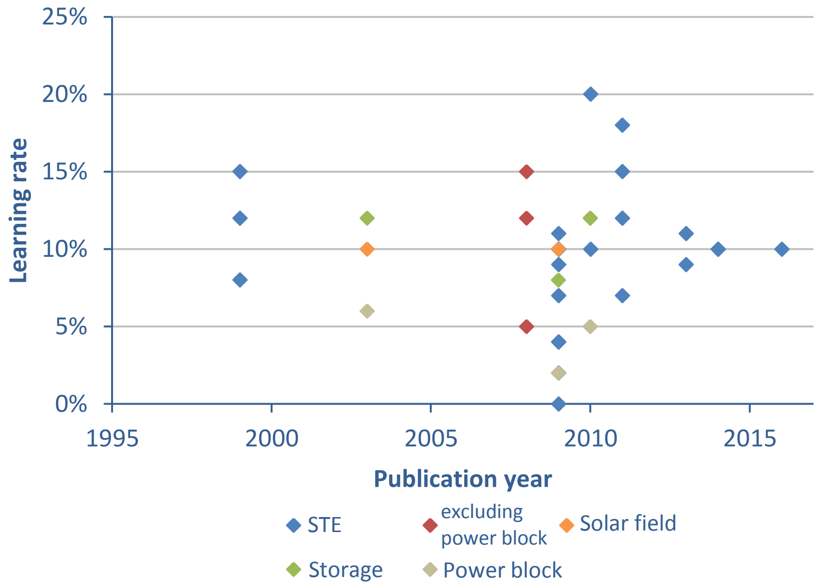

Figure 39 Learning rates of solar thermal electricity as observed in literature

Next to R&D improvements, economies of scale can also improve future costs of solar thermal plants (see e.g. Arvizu *et al.* [30]). These led several studies to conduct bottom-up (engineering) estimations on near-future cost reduction potentials (e.g. IRENA in [22]). Nonetheless, for solar thermal power, learning effects may still be important in reducing future system costs also in the mid-term.

In the absence of an established learning rate for solar thermal plants and in view of clearly distinct system components a component-based learning method seems more appropriate. This way, the costs of mature technology components such as steam turbines will not be affected by the steeper learning that may occur in other parts of the system. However, as the learning rates for solar fields and storage systems are not yet established a component-based approach could give a false sense of certainty. As such, a one-factor method is applied for a *reference learning rate* of 7 %. *High* and *low learning rates* of 10 % and 4 % are used as sensitivity parameters.

This report assesses solar thermal electricity technologies that include storage components. Whilst differences on investment costs between parabolic trough and solar tower systems are not substantial, both subtechnologies are reported due to different

([4]) Not all solar thermal electricity plants have storage capacity. Energy storage systems increase the investment costs of solar thermal electricity plants but offer higher capacity factors, dispatchability and demonstrate lower LCOE.

capacity factors. The investment costs for 2015, the share of O&M costs over investment costs (1.7 % constant over time), the lifetime of the subtechnologies, and the capacity factors are based on JRC expert opinion and Kic InnoEnergy [31].

Annex 4. Geothermal energy

Geothermal power technologies differ from the other low carbon energy technologies assessed in this report in that there are limited geothermal power plant installations, yet two of the main technology components are well-established: (a) exploration and drilling, which is similar with developments in the oil and gas industry and (b) power and heat production, which is similar with conventional power plants. Due to the limited penetration of the technology, the majority of learning occurs in other sectors, mainly conventional/renewable heat and power, oil drilling and gas fracking. As such, component-based learning methods would be preferable over a one-factor learning rate.

Only a few literature sources look into learning rates of geothermal energy. Rubin *et al.* [34] conclude that studies which report cost reduction of geothermal technologies do not incorporate or include learning rates. A comparison of historical costs of geothermal energy technologies is complicated due site-specific drilling and operating conditions such as depth and available temperature. Some studies suggest a 5 % learning rate [15, 32]. Literature shows that a 13 % learning rate for gas hydraulic fracturing is attainable and it could provide an indication on the future investment cost reduction of EGS [33]. However, such a high learning rate cannot be considered representative for all components of the EGS technology or more generally for other geothermal energy technologies.

In this report a *reference rate* of 5 % is used and a sensitivity range from a *low learning rate* of 2 % to a *high learning rate* of 10 %.

Annex 5. Ocean energy

Ocean energy technologies are at early stages of development and deployment and there is little empirical evidence to establish learning rates. Most studies that use the learning rate method for future cost estimates rely on expert judgments, expectations and assumptions. The findings of the literature review are summarised below and presented graphically in Figure 40:

- For tidal energy, the reported learning rates range from 3 % to 15 %. The lower rate is reported in the JRC's ETRI report and was based on expert judgment [15], while the higher rate is used as a sensitivity case by SI Ocean [34].
- For wave energy, learning rates range from 9 % to 30 %. The lowest rate is used in a sensitivity scenario by Dalton *et al.* [35] and the highest rate is based on technology developer expectations for large-scale projects (>1 MW) and projects at technology readiness level higher than 6 [36].
- Studies that are not explicit on the subtechnology, report or use a learning rate range between 6 % and 15 %, which includes ranges used for sensitivity analysis [37]. Lewis *et al.* [38] estimate an overall learning rate of 11 %, based on wind market analysis used for preliminary cost projections.
- Other studies (e.g. IRENA in [39]) report cost reduction of wave energy due to learning rates and economies of scale, however, do not disclose their assumptions.

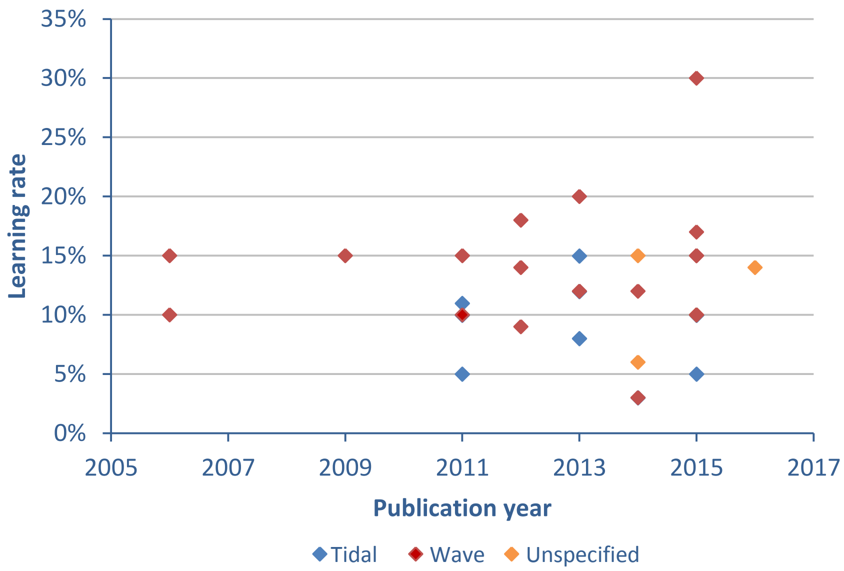

Figure 40 Learning rates of ocean energy as observed in literature

Besides one-factor learning rates, the Carbon Trust [40] reports component-based learning rates for tidal and wave energy technologies (Table 51).

Table 51 Component-based learning rates of ocean energy based on Carbon Trust [40]

Component	Tidal	Wave
Structure and prime mover	12%	9%
Power take off	13%	7%
Station keeping	12%	12%
Connection	2%	1%
Installation	15%	8%
O&M	17%	12%

As ocean energy is in early stage of deployment, the cost development over time and performance of units and farms are shown to differ widely (Figure 1). Investment costs and performance in 2015 is based on expert judgment. The values reported in Figure 40 are either based on engineering expectations, expert judgments, or are scenario-based assumptions applied to estimate future costs of ocean energy. The spread of reported learning rates for ocean energy is wide, also at a subtechnology level. To capture the reported range this study applies the same learning rate to all ocean subtechnologies. A value of 10 % is used as *reference learning rate*. As an optimistic case a *high learning rate* of 15 % is chosen and a pessimistic estimate is based on a *low learning rate* of 7 %, similar to offshore wind turbines.

Annex 6. Hydropower

Capital investment costs of hydropower plants have been extensively reported in literature. The main subtechnologies are size-dependent and ultimately the variation in investment costs depends on the local site and conditions that determine the civil work required. Such costs are typically reflected on an energy basis (€/kWh) and costs of mature electro-mechanical equipment on a power basis (€/kW). As such, the specific costs of the electro-mechanical components have very limited learning opportunities, which is reflected by the limited available studies on learning rates of hydropower. Typical values reported in Rubin *et al.* [4] range from 1.4 % one-factor learning to a 1.96 % for a learning-by-doing and 2.6 % learning-by-researching for large-scale hydropower plants. In this report a *reference rate* of 1 % is used and a sensitivity range from a *low learning rate* of 0 % (no cost reduction) to a *high learning rate* of 2 %.

Given the potentially wide variation in investment costs of hydropower projects, the subtechnologies are defined based on a range of expensive and low cost projects.

Annex 7. Heat and power from biomass

Capital investment costs of different biomass-based power generation technologies have been extensively reported in literature (e.g. [6, 15, 32, 41–43]). There is a wide range of subtechnologies that depend on the process and the feedstock used such as waste incineration, biomass co-firing, anaerobic digestion and gasification.

Only a limited number of studies is available on learning rates of biomass heat and power technologies. Rubin *et al.* [34] report a range from 0 % to 24 % for one-factor learning rate based on 2 data sets that cover a period from 1976 to 2005. Grosse *et al.* [44] observe that the majority of biomass heat and power technologies is well established and no substantial improvements are expected based on learning. Similarly, Rubin *et al.* [34] conclude that there are limited learning opportunities on the conversion side. However, they point towards a substantially higher potential for cost reduction based on learning in biomass production, preparation and pre-treatment. For these steps the reported one-factor learning rates range from 20 % to 45 %. This report, however, focuses only on capital investment costs of conversion technologies and not on biomass production, preparation and pre-treatment. A *reference rate* of 5 % is used and a sensitivity range from a *low learning rate* of 2 % to a *high learning rate* of 7 %.

Annex 8. Carbon Capture and Storage

This report assesses the CCS system that includes the fossil fuel or biomass-based power plant and the capture component. Transport and storage of CO_2 is not included in the system boundaries.

The technology is at an early stage of development and there are no long-term historically observed one-factor learning rates in literature. A significant body of literature, however, applies component-based learning rate methods as more suitable, assuming learning rates from similar well-established technologies [5, 45–48]. For example, the acid gas removal section of the CCS plant bares strong similarities with flue gas desulfurisation. Learning rates of the latter technology are frequently used for CO_2 removal systems (e.g. amine systems) or as even proxies for the whole CCS plant.

Given the large uncertainty of component-based learning rates on CCS technologies literature usually performs sensitivity analysis using a range of values for these components. Figure 41 shows the range of values used in studies that assess future cost reduction of CCS in the power sector for pulverised coal, oxyfuel, integrated gasification and combined cycle plants. Next to component-based rates, Rubin *et al.* [4, 45] and Junginger *et al.* [5] estimate a combined rate for the total plant based on different approaches. Lohwasser and Madlener [49], apply a two-factor learning rate method and obtain learning-by-doing and learning-by-researching rates for CCS.

This report applies one-factor learning rates on four CCS subtechnologies (pulverised coal, oxyfuel, integrated gasification, natural gas combined cycle plants), which were derived by a component-based approach in Rubin *et al.* [45]. The same source also reports ranges, which are incorporated as sensitivity analysis in the present study. For integrated gasification of biomass combined with CCS, the same learning rates with IGCC plants are used. Studies also report learning in O&M costs of CCS plants. These, however, were not taken into account in this report, which applies a fixed share over investment costs over time, in line with expert judgment. Finally, for CO_2 transport and storage technologies, Lohwasser and Madlener [49] mention that O&M costs could decline at a learning rate of 3 % assuming similar developments with the oil and gas industry. These however are out of the technology boundaries of this report.

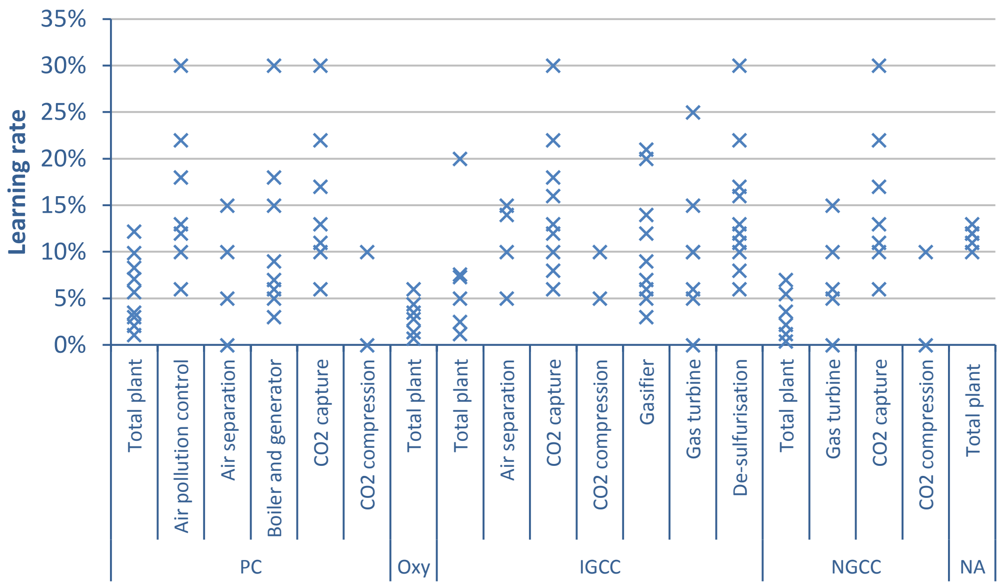

Figure 41 Learning rates of CCS technology components used in literature (Note: NA refers to unspecified technologies)

Table 52 Assumed start year costs and reference learning rates and ranges used in this report on Carbon Capture and Storage subtechnologies based on Rubin *et al.* [45]

Subtechnology	Start year capital investment costs (1)	Reference learning rate	High learning rate	Low learning rate
NGCC	1510	2.2%	3.6%	1.2%
PC	2920	2.1%	3.5%	1.1%
Coal IGCC	2945	5%	2.5%	7.6%
Lignite IGCC	4480	5%	2.5%	7.6%
Oxyfuel	2920	2.8%	4.4%	1.4%
Biomass IGCC	5800	5%	2.5%	7.6%

(1) Assumed for the year 2025

Based on the method applied in this report, one factor that influences the estimated capital investment cost trajectories of biomass IGCC with CCS is the initial capital costs. Few literature sources suggest that biomass IGCC with CCS may cost from 2,300 to 2,600 €/kW in 2025-30 [50, 51]. This range, however, is far below on indications based on other sources that mention specific capital investment costs of biomass IGCC plants without CCS at about 5,000 €/kW. This report uses estimates of biomass IGCC plants without CCS based on Grosse *et al.* [44] (section 3.7.2) and adds as CCS cost component 500 €/kW, based on IEAGHG [51].

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