PROCEEDINGS OF ECOS 2022 - THE 35TH INTERNATIONAL CONFERENCE ON
EFFICIENCY, COST, OPTIMIZATION, SIMULATION AND ENVIRONMENTAL IMPACT OF ENERGY SYSTEMS
1-3 JULY, 2022, COPENHAGEN, DENMARK

Prospective study on the cost evolution for low-carbon technologies

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Abstract:

Drastic variations of energy costs are witnessed in past decades, especially for low-carbon technologies, where decreasing and increasing trends co-existed. Estimating the cost evolution in the future is hence essential in long-term energy planning. Despite a number of existing studies, the estimated costs show strong heterogeneity. Additionally, emerging technologies, such as electrolysis and CCUS (carbon capture, utilisation and storage), have gained limited attention. To improve the plausibility of the cost projection, we analysed the relationship between accumulated installation and the corresponding CAPEX for 14 low-carbon technologies, and applied 5-8 learning curves (LRs) via Non-Linear Optimization (NLP) for projecting the cost evolutions towards 2050. The LRs were carefully selected based upon the index of Coefficient of Determination, and calibrated by comparison to a bunch of existing literature. Based upon our results: (1) residential PV and onshore wind rank the highest and lowest respectively in terms of the decreasing potential; (2) the majority of energy technologies are promising to achieve 36% - 74% cost reduction in 2050 compared to 2020, with a mean value around 50%. This study can be helpful as benchmark for energy stakeholders in decision-making towards carbon neutrality.

Keywords:

Cost Projection, Learning Curve, Low-Carbon Technology, NLP Optimization.

1. Introduction

Energy transition is a key aspect in today's environmental crisis while having significant impacts on the social and economical dimensions. Long-term planning in order to achieve net-zero emissions by 2050 is therefore a necessary but very complex task. In order to facilitate decision making for a highly coupled energy system, where low carbon technologies are supposed to expand in large scale in the coming decades [26, 23], the Energy Center and IPESE group (Industrial Process and Energy Systems Engineering) of EPFL developed the Energyscope (ES) calculator. ES is an optimization bottom-up energy system model. It differs from other energy system models by its large modelling scope, i.e. electricity, heat, mobility, storage and CCUS, as well as its low computation time. Within the scope of ES, studying the prospective cost evolution of low carbon technologies by reliable predictions is crucial, as it is a key limiting factor for their large development.

Tsiropoulos et al. (2018) [32] have performed a prospective study on the cost of a large selection of low carbon technologies and sub-technologies. They have considered one single historic data point (2015) and applied constant learning rates, given a projected capacity growth until 2050. NREL (National Renewable Energy Laboratory) annually releases projections on both low and high carbon technology costs and performance data until 2050 through its ATB (Annual Technology Baseline) [27]. It is based on a set of economical input assumptions as well as different future capacity scenarios. However, it does not refer to learning curve theory. IEA proposes projections for capital costs for the main energy technologies per geographical region (US, EU, China, India) [8]. However, these are sparse results, i.e. milestone predictions for 2030 and 2050.

From an economic perspective, the energy technology costs are influenced by the installed quantities in market. It is thus essential for analyzing the bilateral relationship of the installed capacity and technological costs. In this study, we aim at exploring the possible cost evolution on 8 low carbon technologies, divided into 14 low carbon sub-technologies, between 2021 and 2050. Concretely, the objectives of the study lie in: 1) determining a modelling approach for analyzing the relationship between the installed capacity and investment cost of the main energy technologies; 2) validating the methodology in (1) by assessing historical data; and 3) applying the model in future years in order to generate the cost predictions for main energy technologies, and calibrating the results with other literature.

2. Methodology

2.1. Introduction

Cost is commonly regarded as a function of the commodity quantity [38, 31]. A typical methodology is the learning curve theory. Wright (1936) described the evolution of production costs resulting of the learning process in the aircraft industry [35]. Since then, learning curve models have been applied to several industries to explain cost reductions due to learning. In 1979, Yelle already accounted 90 articles that used learning curve theory [37]. The learning curve theory assumes that the cost of a technology decreases with time accordingly to the installed capacity thanks to the learning-by-doing process. They can be used for modelling the time to produce a single unit, number of units produced per time interval, or the percentage of non-conforming units. The present work focuses on cost-related learning curves.

Table 1 shows the learning curves selected for testing in our study. Among these expressions, Wright's, S-curve and Plateau's forms were historically used a lot to model learning-by-doing processes [1]. Other candidates such as Standford-B and DeJong's are very close to the aforementioned ones. Boone's form [2] is a more recent learning curve form, that has been chosen for its decreasing learning rate (LR) property, the LR being the observed cost reduction after doubling the cumulative capacity (see Eq. 3). The parametric Sigmoid (also known as S-curve, but mathematically different than the here called S-curve) is an input from authors. It has been included in order to fit the case of piecewise dynamics, e.g. a strong cost decrease period followed by a stabilizing cost period. Linear, logarithmic, exponential and 2^{nd} order polylogarithmic forms are more usual regression expressions which are *a priori* not related to the learning curve theory. However, they were kept on comparison purpose. In these formulations, y is the investment cost [USD_{2018}/kW], x is the cumulative capacity [GW] and a, b, c, d and M are technology-specific parameters to identify.

Table 1: Learning curve expressions

Type	Expression
Linear	$y = a + bx$
Logarithmic	$y = a + b\log(x)$
Exponential	$\log(y) = a + bx$
Log-linear (Wright)	$\log(y) = a + b\log(x)$
2^{nd} Order Polylogarithmic	$\log(y) = a\log(x) + b\log(x)^2 + c$
S-curve	$y = a[M + (1 - M)(x + c)^b]$
Plateau	$y = ax^b + c$
Boone	$y = ax^{\frac{b}{1+\frac{x}{c}}}$
Parametric Sigmoid	$y = \frac{a}{b+\exp(-cx)} + d$

2.2. Parameters identification and assessment method

Given a set of data points, the parameters (a, b, c, d, M) of the learning curve expressions are found by solving linear/non-linear optimization problems (LP and NLP). It is achieved via the minimisation of squared errors between the learning curve function $\hat{f}$ and the discrete function f of real data points, illustrated by Eq. 1. In our study, all the technologies are tested via this process for the complete set of learning curves[1].

$$\operatorname*{argmin}_{a,b,c,d,M} SE = \{(a, b, c, d, M)|\min \sum_{x\in\mathcal{X}} (\hat{f}(x, a, b, c, d, M) - f(x))^2\} \tag{1}$$

In Eq. 2 we define the coefficient of determination R^2 minimising the residual error between real and predicted data. y_i represents the historic, i.e. real, data values and f_i the predicted data values.

$$R^2 = 1 - \frac{\sum_i (y_i - f_i)^2}{\sum_i (y_i - \overline{y})^2} \tag{2}$$

The acceptance of the learning curve depends on:

1. the plausibility analysis of the estimated cost in 2050;
2. the coefficient of determination.

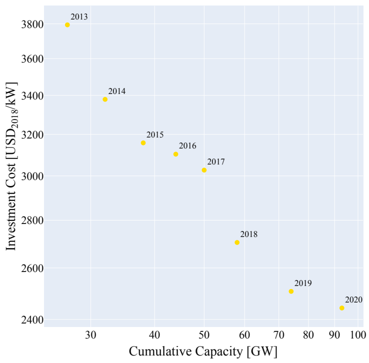
[1] The solving and visualisation files are available on this repository

The first requirement ensures a feasible cost for the 2021-2050 period, i.e. the function should be monotonic, non-negative and within a certain acceptable range estimated via literature results. The second requirement selects the learning curve that maximises the R^2, implying a low SE.

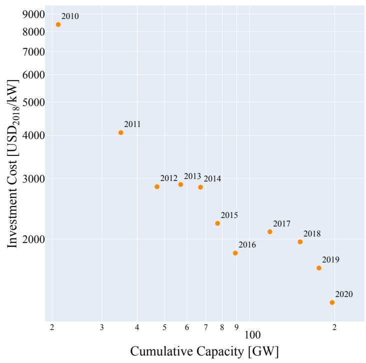
3. Data

3.1. Historical Data

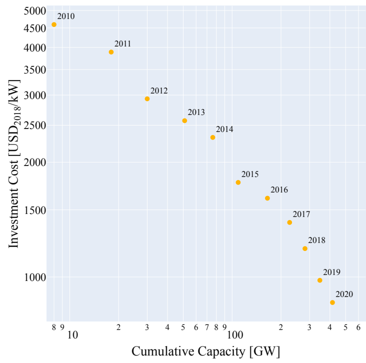
The technologies under study are: 1) Residential, utility-scale and commercial solar PV, 2) CSP (Concentrated Solar Power), 3) Offshore and Onshore Wind power, 4) Total Hydro-power[2], 5) Geothermal energy, 6) GSHP (Ground-Source Heat Pumps, approximated as decentralized heat pumps) and DHP (Decentralized Heat Pumps), 7) ALK (Alkaline), PEM (Polymer Electrolyte Membrane) and SOEC (Solid Oxide Electrolyzer Cell) Electrolysis, 8) CO_2 capture. Historical data that is collected from a variety of literature is represented in Figure 1. A data point is characterized by three dimensions: the date (year), the cumulative capacity [GW] and the weighted mean investment cost [USD_{2018}/kW]. The costs and capacities are considered on a global perspective. However, due to lack of data, national data may be used instead of global one. Moreover, due to limited data availability for technologies that have not yet been industrialized in large scale, i.e. ALK electrolysis, PEM electrolysis, SOEC electrolysis and carbon capture, we collected the values from specific applications, other than using the mean value as a basis for calculation. Data points for these four technologies are therefore aligned on the same vertical line when they belong to the same year.



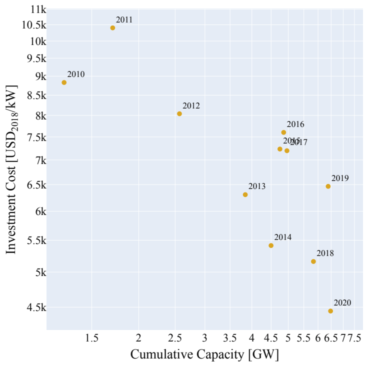
(a) Residential PV. Cost on Swiss market. [10] [19]



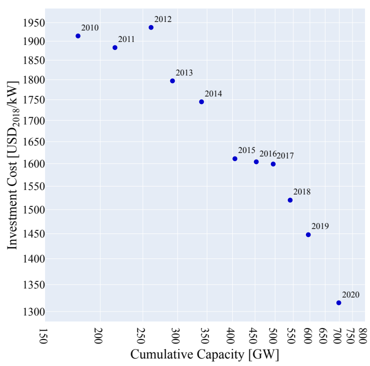
(b) Commercial PV. Cost on French market. [10] [19]



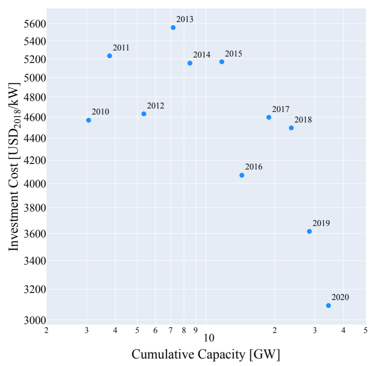
(c) Utility-scale PV [10] [19]



(d) CSP [18] [19]



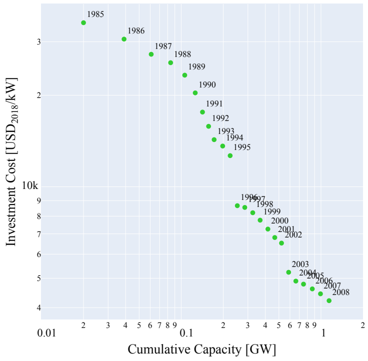
(e) Onshore wind [18] [19]



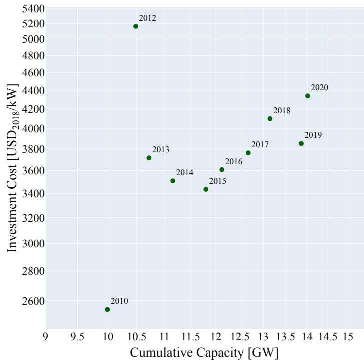
(f) Offshore wind [18] [19]

Figure 1: Historical data

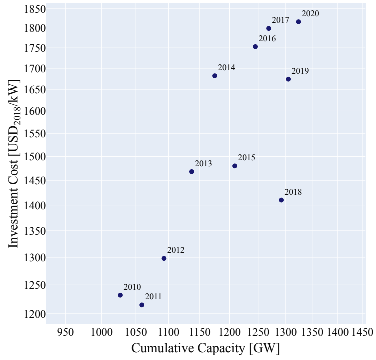
[2]Total hydro-power is defined as the sum between run-of-river hydro and pumped-storage hydro



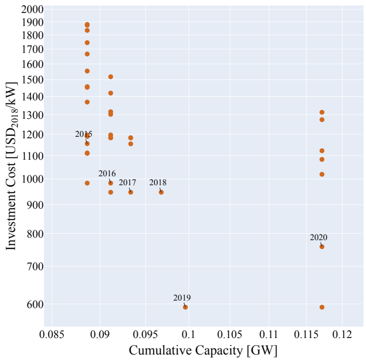
(g) GSHP. Cost on Swiss market[3], Swiss capacities. [20]



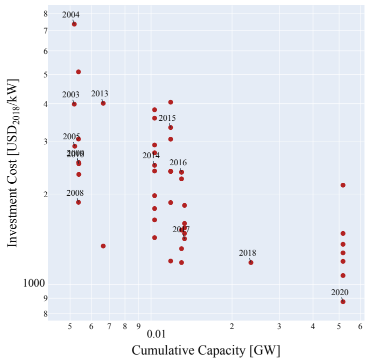
(h) Geothermal energy [18] [19]



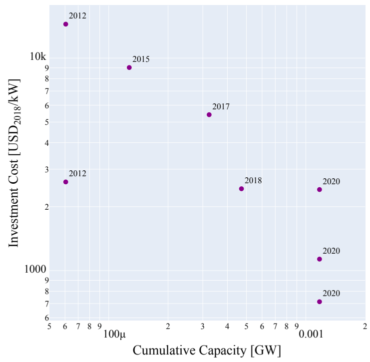
(i) Total hydro-power [10] [19]



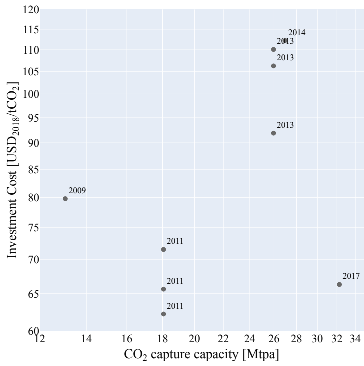
(j) ALK electrolysis [6] [4]



(k) PEM Electrolysis [7] [4]



(l) SOEC Electrolysis [7] [4]



(m) Carbon capture [14] [13]. Mtpa: Million tonne per annum.

Figure 1: Historical data *(continued from previous page)*

3.2. Future Capacities

Future capacity predictions have been collected in the literature and are given in Table 2. They were chosen within the scope of the target of a net-zero energy system by 2050. One of the major sources is the Net-Zero by 2050 Roadmap from IEA [8].
These predictions are given under the form of milestones, often one per decade, e.g. 2030, 2040 and 2050. The complete prediction for the capacities has been achieved via linear interpolation between these milestones.

[3]Purchase cost turned into investment cost with Bare module factor of 3.6 [30]

Table 2: Future Capacities or yearly productions found in the literature

Technology	Year	Region	Predicted Capacity or Production	Unit	Source
Total PV	2030	Global	4956	[GW]	IEA-NZ-2050 [8]
Total PV	2040	Global	10980	[GW]	
Total PV	2050	Global	14458	[GW]	
CSP	2030	Global	73	[GW]	IEA-NZ-2050 [8]
CSP	2040	Global	281	[GW]	
CSP	2050	Global	426	[GW]	
Total Wind	2030	Global	3101	[GW]	IEA-NZ-2050 [8]
Total Wind	2040	Global	6525	[GW]	
Total Wind	2050	Global	8265	[GW]	
Total Electrolysis	2030	Global	850	[GW][4]	IEA-NZ-2050 [8]
Total Electrolysis	2040	Global	2400	[GW][4]	
Total Electrolysis	2050	Global	3000	[GW][4]	
GSHP	2050	Global	739[5]	[GW_{th}]	IEA [9]
Geothermal	2030	Global	52	[GW]	IEA-NZ-2050 [8]
Geothermal	2040	Global	98	[GW]	
Geothermal	2050	Global	126	[GW]	
HP in buildings	2050	Switzerland	8.7[6]	[TWh_{el}/year]	OFEN [28]
Carbon capture	2030	Global	1670	[Mtpa]	IEA-NZ-2050 [8]
Carbon capture	2050	Global	7600	[Mtpa]	
Hydro (excl. pumped storage)	2030	Global	1804	[GW]	IEA-NZ-2050 [8]
Hydro (excl. pumped storage)	2040	Global	2282	[GW]	
Hydro (excl. pumped storage)	2050	Global	2599	[GW]	
Pumped hydro storage	2030	Global	225	[GW]	IRENA [16]
Pumped hydro storage	2050	Global	325	[GW]	

These capacities are then shared among the different sub-categories of technologies (e.g. onshore and off-shore for wind or residential, commercial and utility-scale for solar PV) according to milestones given in Table 3. Years in-between are deduced via linear interpolation.

Table 3: Capacity shares [%] of wind power, solar PV and electrolysis

Year	2030	2050
Onshore wind	88.68 [15]	83.45 [15]
Offshore wind	11.32 [15]	16.55 [15]
Residential PV	13.51[7]	13.51[7]
Commercial PV	30.10[7]	30.10[7]
Utility-scale PV	55.43[7]	55.43[7]
ALK electrolysis	35 [12]	37 [12]
PEM electrolysis	23 [12]	32 [12]
SOEC electrolysis	13 [12]	30 [12]

4. Results and discussion

4.1. Learning curves visualisation

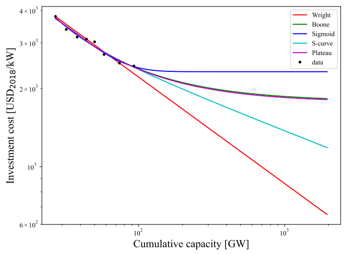
For each technology, the different learning curves (Wright, Boone, Sigmoid, S-curve and Plateau) obtained after parameter identification are plotted in Figure 2. Historical data is also represented, and the curves' ending points are coinciding with the corresponding predicted capacities for 2050 (on the x-axis).

[4][GW] later converted to [GW_{th}] using power-to-hydrogen efficiencies: ALK: 66.5%, PEM: 58.0%, SOEC: 77.5% [11].

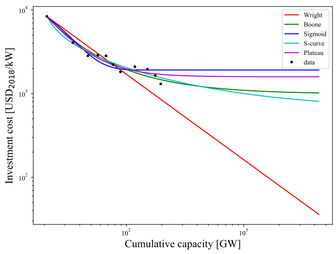
[5]The ratio of the Swiss GSHP capacity over the global one amounts to 3.26% [24] [25], thus the Swiss GSHP capacity in 2050 is estimated to 24 GW_{th}.

[6]Assuming a COP of 4.2 and a capacity factor of 0.17, this consumption can be converted to a heating capacity of 24.54 GW_{th}.

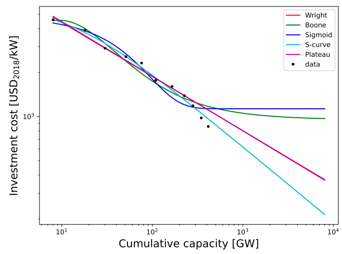
[7]PV shares assumed to be constant and equals their means over the 2015-2020 period.



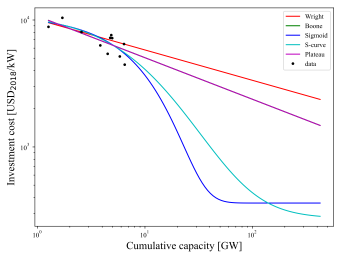
(a) Residential PV



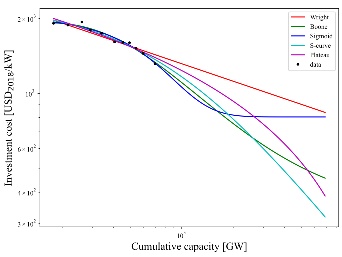
(b) Commercial PV



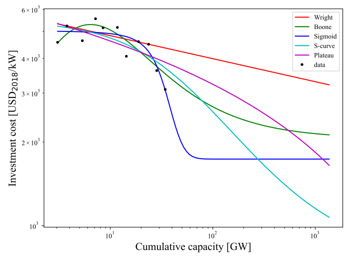
(c) Utility-scale PV



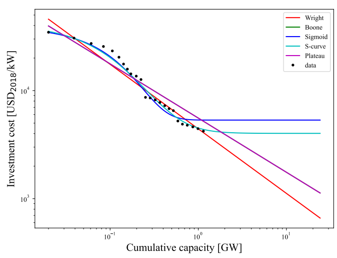
(d) CSP[8]



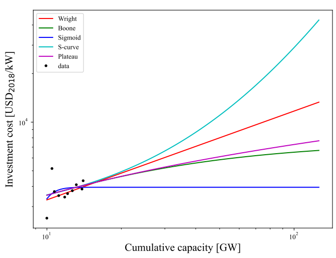
(e) Onshore wind



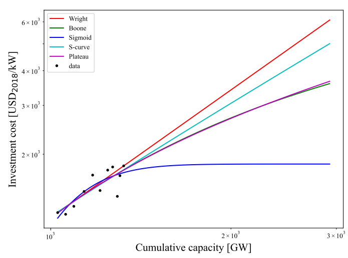
(f) Offshore wind



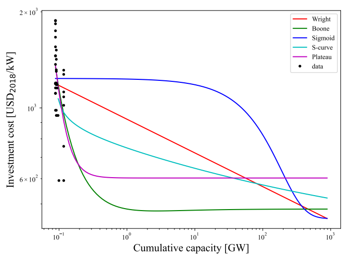
(g) GSHP[8]



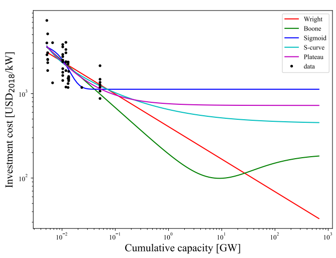
(h) Geothermal energy



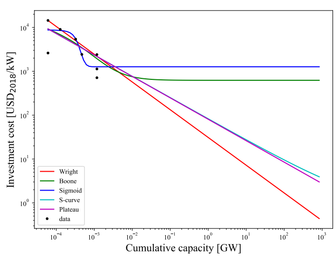
(i) Total hydro-power



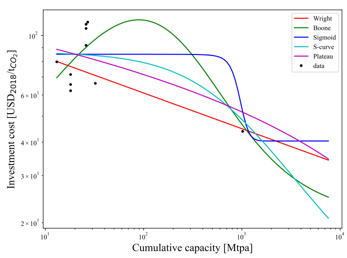
(j) ALK electrolysis[9]



(k) PEM electrolysis[9]



(l) SOEC electrolysis[9]



(m) Carbon capture[10]. Mtpa: Million tonne per annum.

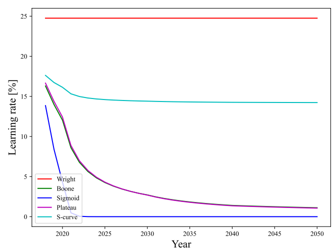
Figure 2: Learning curves for 13 low-carbon technologies.

4.2. Learning rates visualisation

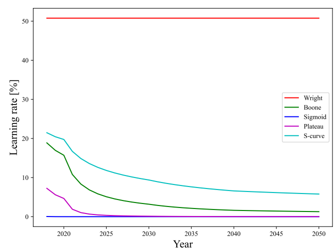
The learning rate (LR) is defined as the cost reduction observed when the cumulative capacity is doubled. It translates into 3, where x is the cumulative capacity and y is the learning curve function.

$$LR(x) = 1 - \frac{y(2x)}{y(x)} \tag{3}$$

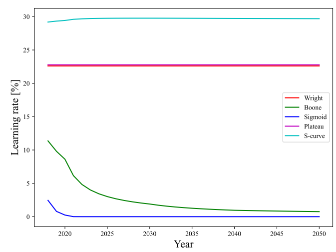
In the case of Wright's form, the learning rate is constant and equals $1-2^b$. On the other hand, Boone, Sigmoid, Plateau and S-curve forms have time-varying learning rates, thus they have been plotted as a discrete curve using Eq. 3. A positive learning rate is associated to a cost reduction. Moreover, we stick to the mathematical definition and allow negative learning rates to illustrate a cost increase. This can happen for certain relative mature renewable technologies, such as hydro power plant. The results of the learning rates are presented in Figure 3, where a high positive LR implies a quick cost reduction. Different curves show heterogeneous behaviors.



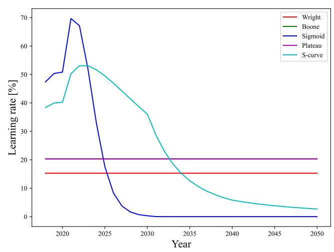
(a) Residential PV



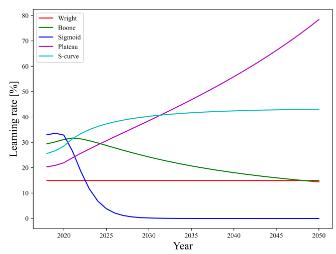
(b) Commercial PV



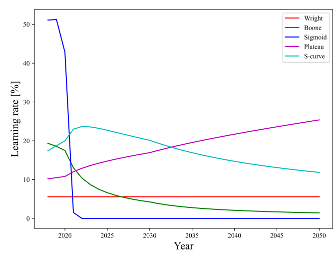
(c) Utility-scale PV



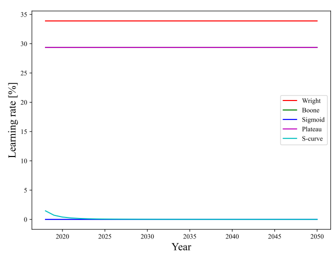
(d) CSP[11]



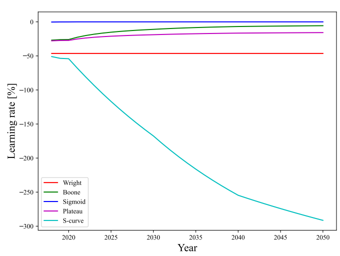
(e) Onshore wind



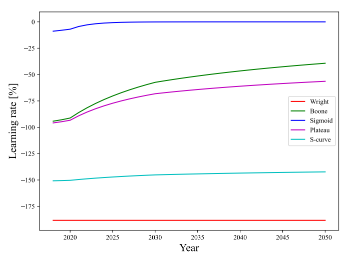
(f) Offshore wind



(g) GSHP[11]



(h) Geothermal energy



(i) Total hydro-power

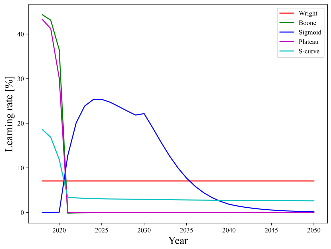
Figure 3: Learning rates for 13 low-carbon technologies.

[8] Boone and Plateau curves are coinciding

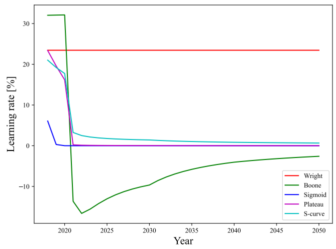
[9] Prospective data point in 2050 used during training necessary to get acceptable results: 450 USD_{2018}/kW for ALK, 550 USD_{2018}/kW for PEM and 750 USD_{2018}/kW for SOEC

[10] Prospective data point in 2026 [13] at 44 USD_{2018}/t_{CO_2} used during training necessary to get acceptable results

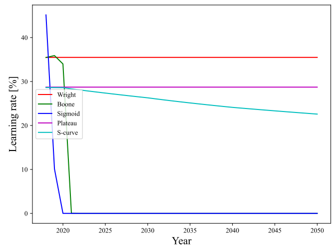
[11] Boone's and Plateau curves are coinciding



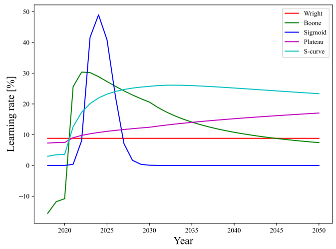
(j) ALK electrolysis



(k) PEM electrolysis



(l) SOEC electrolysis



(m) Carbon capture

Figure 3: Learning rates *(continued from previous page)*

4.3. Final Learning Curves Parameters Values and Validity Ranges

Following the selection process described in Section 2.2., the learning curve expressions that were kept for the study results part are given in Table 4. Particularly, non-monotonic and partly constant learning curves were excluded, and the plausibility of the cost achieved in 2050 was assessed by comparison with literature results, given in Table 7.

Table 4: Learning curves parameters, expressions and validity ranges

Technology	Model	Expression	Parameters	Validity range [GW]
Onshore Wind	Wright	$\log(y) = \alpha + \beta \log(x)$	α = 8.7969 β = -2.3370e-1	178 - 6898
Offshore Wind	Plateau	$y = \alpha + \gamma x^{\beta}$	α = -2.8492e6 β = -2.1175e-4 γ = 2.8552e6	3 - 1368
Residential PV	Wright	$\log(y) = \alpha + \beta \log(x)$	α = 9.5926 β = -4.1030e-1	27 - 1954
Utility-scale PV	Wright	$\log(y) = \alpha + \beta \log(x)$	α = 9.2415 β = -3.6979e-1	8 - 8014
Commercial PV	S-curve	$y = \gamma[\delta + (1 - \delta)(x + \alpha)^{\beta}]$	α = -1.6847e1 β = -5.7434e-1 γ = 1.8146e4 δ = 3.6801e-2	21 - 4352
CSP	Wright	$\log(y) = \alpha + \beta \log(x)$	α = 9.2176 β = -2.3914e-1	1.3 - 426
GSHP	Boone	$y = \alpha x^{\frac{\beta}{1+\frac{x}{\gamma}}}$	α = 5.5717e3 β = -5.0151e-1 γ = 1.0094e7	0.020 - 24.1
Decentralized HP[12]	Wright	$\log(y) = \alpha + \beta \log(x)$	α = 7.8974 β = -5.9720e-1	6.22 - 24.5
Geothermal	Boone	$y = \alpha x^{\frac{\beta}{1+\frac{x}{\gamma}}}$	α = 7.5971e3 β = -8.1648e1 γ = 4.0934e-2	10 - 126

SOEC Electrolysis	Logarithmic	$y = \alpha + \beta \log(x)$	α = 1.5774e3 β = -1.2295e2	6.05e-4 - 837
PEM Electrolysis	S-curve	$y = \gamma[\delta + (1-\delta)(x+\alpha)^{\beta}]$	α = -3.1024e-3 β = -4.4652e-1 γ = 6.4820e2 δ = 6.8292e-1	5.18e-3 - 668
ALK Electrolysis	S-curve	$y = \gamma[\delta + (1-\delta)(x+\alpha)^{\beta}]$	α = -8.8634e-2 β = -1.2946e-1 γ = 7.4453e2 δ = 4.8841e-1	88.6e-3 - 886
Carbon Capture	Plateau	$y = \alpha + \gamma x^{\beta}$	α = -4.4898e4 β = -1.8936e-4 γ = 4.5009e4	13 - 7600 [Mtpa]
Total hydropower	Plateau	$y = \alpha + \gamma x^{\beta}$	α = -5.7501e3 β = 2.8622e-1 γ = 9.5872e2	1027 - 2924

4.4. Discussion

From the cost estimation results summarised in Table 5, hydro-power and geothermal energy have an increasing trend in the future, extended from their cost growth witnessed in the past decade. Their cost increase between 2020 and 2050 is estimated at 101% and 54% respectively. This ”astonishing” discovery against the common understanding that renewables will be cheaper in the future, can however, be explained from two aspects: (1) the technical maturity of these technologies, and (2) large-scale hydro projects and places to drill for geothermal are supposed to be increasingly difficult to find, since historical projects have already occupied the techno-economically advantageous locations. In constant, the investment costs for all other studied low-carbon technologies (Solar, Wind, HP, Electrolysis, CO_2 capture) are expected to decrease considerably in future years. From our results, the mean cost reduction for these technologies reaches approx. 50%. The most impressive cost decrease lies in Residential PV, with 73% drop between 2020 and 2050 (from 2443 USD_{2018}/kW to 654 USD_{2018}/kW), whereas onshore wind is of the lowest reduction potential around 36% (from 1316 USD_{2018}/kW to 838 USD_{2018}/kW).

Table 5: Cost reduction between 2020 and 2050

Technology	Cost in 2020 [USD_{2018}/kW]	Cost in 2050 [USD_{2018}/kW]	Cost reduction [%]
Residential PV	2443	654	73.21
Utility-scale PV	857	371	56.71
Commercial PV	1309	810	38.10
CSP	4448	2368	46.76
Onshore Wind	1316	838	36.32
Offshore Wind	3092	1648	46.72
GSHP	2954[13]	1129	61.77
ALK Electrolysis	865[14]	522	39.67
SOEC Electrolysis	1178[14]	750	36.33
PEM Electrolysis	1035[14]	454	56.14
Total hydro-power	1816	3663	-101.71
Geothermal	4338	6683	-54.05
CO_2 capture	79[13]	35	55.70

The results of this study have been compared to the ones from the literature according to two main properties: the technologies learning rates [%] and the investment costs in 2050 [USD_{2018}/kW]. This comparison is given in Tables 6 and 7. It shows that all our results are in a reasonable range compared to other literature, except the two increasing cost technologies. The positive values given in [32] and [29] result probably from the lack of realistic consideration in their approaches on the historical cost evolution or from the consideration of older data.

[12] Due to lack of historical data on DHP, GSHP's Wright learning curve has been applied to DHP
[13] Estimation via our learning curve due to lack of data
[14] Mean between the 2020's data points

Table 6: Learning rates found in the literature. Two values are given, i.e. min - max, for emphasizing varying learning rates ("this report") or a range of values due to consideration of different sub-categories ("literature").

Technology	This report	Learning rates from literature [%]			
Res. PV	24.75	23.8[15] [33]	20[15] [32]	23[15] [29]	11 - 24[15] [22]
Utility-scale PV	22.61	34 [19]			
CSP	15.28	22 [19]	7 [32]	10 - 23 [22]	
Onshore Wind	14.96	17 [19]	5 [32]	12 [29]	
Offshore Wind	10.22 - 25.39	9 [19]	5 - 11 [32]	12 [29]	
ALK Electrolysis	2.6 - 18.61	9 [3]			
SOEC Electrolysis	3.4 - 11.4	15 - 25 [5]			
PEM Electrolysis	0.66 - 21.02	13 [3]			
GSHP	29.36	35 [21]	5 - 17 [22]		
Dec. HP	33.89	35 [21]	5 - 17 [22]		
Geothermal	-26.86 - -5.65	5 [32]			
Carbon capture	7.29 - 17.04	2.1 - 5.0 [32]	6.45 - 11.35 [34]		
Hydropower	-95.85 - -56.39	1 [32]	1.4 [29]		

Table 7: Investment costs in 2050 found in the literature. Two values are given, i.e. min – max, for emphasizing range of values due to consideration of different sub-categories in literature references.

Technology	This report	Investment costs results from literature [USD_{2018}/kW]			
Res. PV	654.48	340[15] [8]	300 - 1600[15] [36]	533 - 984 [27]	396 - 1096 [32]
Utility-scale PV	371.48	472 - 761 [27]	294 - 904 [32]		
Commercial PV	810.26	510 - 894 [27]	328 - 1096 [32]		
CSP	2367.91	2689 - 6648 [27]	2475 - 5548 [32]	1600 - 5225 [36]	
Onshore Wind	838.08	1300 [8]	514 - 882 [27]	825 - 1989 [32]	1000 - 1700 [36]
Offshore Wind	1647.52	1420 [8]	1494 - 2660 [27]	1446 - 5481 [32]	1525 - 3610 [36]
ALK Electrolysis	521.85	200 - 700 [11]	$\leq$ 200 [17]		
SOEC Electrolysis	750	500 - 1000 [11]	$\leq$ 300 [17]		
PEM Electrolysis	453.93	200 - 900 [11]	$\leq$ 200 [17]		
Hydropower	3663.01	2141 - 2478 [27]	1209 - 3955 [32]		
Geothermal	6682.74	4240 - 5592 [27]	2260 - 12588 [32]		

5. Conclusion

To conclude, the estimated dramatic cost variation between 2020 and 2050 shows the importance of including varying investment costs into energy planning models, which are commonly treated, however, as constants, or based upon simple assumptions according to the researchers' experience. Moreover, the variety of selected learning curve forms allows both horizontal and vertical identification and verification from a large set of functions, in order to improve the plausibility of the prospective results.

The validity of our research depend significantly on the plausibility of input data, which are however difficult to evaluate due to the heterogeneous assumptions. Therefore, uncertainty analysis is envisioned in future studies. Possible research topics include the analysis of cost evolution under different inputs, e.g. the installed capacities. A detailed paper is under preparation.

[15] Total PV

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