Semester Project

Prospective study on the cost evolution for key energy technologies

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Abstract

Energy technologies are subject to dramatic cost changes. Indeed, the recent trend in investment costs (expressed in [USD/kW]) for the main renewable energy technologies showed an important cost reduction (e.g. solar PV and wind) or increase (e.g. hydro-power, geothermal energy) during the last decade. Taking these cost variations into account within the scope of a prospective energy system model such as Energyscope is therefore very important. While data concerning well-known energy technologies like solar PV and wind is widely available, emerging technologies such as electrolysis and CCUS (carbon capture, utilization and storage) have very few reliable data. Predicting their future cost is therefore a challenging task. To this end, the learning curve theory has been used. It has been widely used to model the cost reduction achieved in the industry via the learning-by-doing process, and can easily be transposed to energy technologies. The assessment of carefully selected learning curve functions applied to energy technologies historical data results in important cost changes until 2050. Indeed, the cost reduction between 2020 and 2050 of the cost-decreasing technologies under study are between 36% (onshore wind) and 74% (residential solar PV), with a mean over the studied technologies that equals 50%.

Acknowledgments

I am very grateful to Pr. François Maréchal, Xiang Li and Jonas Schnidrig, who gave me the opportunity to work on this subject at IPESE. Indeed, the topic of this semester project was challenging and very interesting. I have learnt a lot, both in terms of knowledge and scientific methods.
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A special thank to Xiang, who spent a lot of time with me, to improve our work and also to make me feel comfortable at the lab.
This nice experience also comforted my wish to pursue my studies with a PhD. Indeed, the atmosphere and working themes at the lab made me feel at the right place.

Again, thanks a lot to all IPESE members, and I wish you the very best for your ongoing and future work !

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Acronyms

EPFL	Ecole Polytechnique Fédérale de Lausanne
IEA	International Energy Agency
IRENA	International Renewable Energy Agency
IEA-NZ-2050	IEA Net-Zero by 2050 Energy Roadmap [13]
ES	EnergyScope
IPESE	Industrial Processes and Energy Systems Engineering
PV	Photovoltaics
HP	Heat Pumps
GSHP	Ground-Source Heat Pumps
DHP	Decentralized Heat Pumps
ALK	Alkaline (Electrolysis)
PEM	Polymer Electrolyte Membrane (Electrolysis)
SOEC	Solid Oxide Electrolyzer Cell
CSP	Concentrated Solar Power
CCUS	Carbon capture, utilization and storage

Nomenclature

Symbol	Quantity	Unit
y_t	Inflation-adjusted unit cost of a technology at year t	[USD_{2018}/kW]
q_t	Installed capacity during year t	[GW]
x_t	Cumulative installed capacity at yeat t	[GW]
LR	Learning rate	[-]
R^2	Coefficient of determination	[-]
C_1	Initial cost (starting year)	[USD_{2018}]
B	Number of unit of prior experience	[-]
M	Incompressibility factor	[-]

1 Introduction

1.1 Description of the Problem

The Energy Center and IPESE group of EPFL have developed the Swiss-Energyscope calculator. This interactive platform has been created with the aim to enable Swiss citizen to understand the challenges of the energy transition. The Calculator of ES is a tool that allows to create your own energy scenario and discover its implications for Switzerland.
Within the scope of this project, studying the costs of renewable energy source and have good predictions of future costs is crucial, as cost is a key limiting factor for their large development. Therefore, there is a need for analyzing the bilateral relationship of the installed capacity and technological costs, and quantifying the cost uncertainty ranges for energy technologies in the future.

1.2 Objectives

The objectives of this work are the following:

1. Determine a modelling approach for analyzing the relationship between the installed capacity and investment cost of the main energy technologies,
2. Collecting historical data in order to test and compare modellings in terms of outcome and performance,
3. Apply the model in future years in order to generate the cost uncertainty ranges for energy main technologies, and validating the obtained results by comparing them to other prediction results found in the literature.

The technologies under study are:

- Residential Solar PV
- Utility-scale Solar PV
- Commercial Solar PV
- Decentralized Solar thermal (CSP)
- Offshore and Onshore Wind
- Total Hydro-power[1]
- Geothermal energy
- Centralized and Decentralized Heat Pumps
- ALK, PEM and SOEC Electrolysis
- CO_2 capture

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

2 Methods

2.1 Introduction to Learning Curves

The learning curve theory is commonly used to estimate the relationship between the technology cost and the cumulative installed capacity of this same technology. It assumes that the cost of a technology decreases with time according to the installed capacity thanks to learning-by-doing. The present work is only focusing on cost-related learning curves, but they may also model the time to produce a single unit, number of units produced per time interval, or the percentage of non-conforming units.
The main univariate cost-related learning curve models are summarised in what follows [1].

2.1.1 Log-linear model and modifications

$$\text{Log-linear (i.e. Wright)} : y = C_1 x^b \tag{1}$$

$$\text{Stanford-B} : y = C_1 (x + B)^b \tag{2}$$

$$\text{DeJong's} : y = C_1 [M + (1 - M) x^b] \tag{3}$$

$$\text{S-curve} : y = C_1 [M + (1 - M)(x + B)^b] \tag{4}$$

$$\text{Plateau} : y = C + C_1 x^b \tag{5}$$

$$\text{Knecht} : y = \frac{C_1 x^{b+1}}{1 + b} \tag{6}$$

where C_1 is the starting cost and b is the slope of the learning curve ($-1 < b < 0$). And historically, B is the number of units of prior experience, M ($0 \leq M \leq 1$) is the incompressibility factor that informs the fraction of the task executed by machines and C is describing the steady-state worker's performance.

Wright's (or log-linear) form (Eq. 1 and 13) is the most commonly used learning curve function. It assumes a constant learning rate LR over time. The LR is defined as the cost reduction factor occurring when the capacity is doubled. In the case of Wright's form, it can be expressed as:

$$\text{LR} = 1 - 2^b \tag{7}$$

2.1.2 Exponential model

$$\text{Knecht-2} : y = C_1 x^b \exp(cx) \tag{8}$$

where c is a constant to identify.

2.1.3 Other models

Moreover, less usual learning curve forms, such as the so-called Boone's form, which is a decreasing learning curve model [9], and the Sigmoid function, may also be interesting candidates within the scope of this study:

$$\text{Boone[3]} : y = C_1 x^{\frac{b}{1+\frac{x}{c}}} \tag{9}$$

$$\text{Sigmoid} : S(x) = \frac{1}{1+\exp(-x)} \tag{10}$$

Regarding the Sigmoid function, the following expression is actually considered, which differs from Eq. 10 by the addition of some parameters as well as an offset:

$$\text{Parametric Sigmoid} : y = \frac{a}{b+\exp(-cx)} + d \tag{11}$$

2.1.4 Assessing technological improvement

However, learning curve theory is not limited to these functions, and may therefore take various forms. For instance, six learning curve forms for assessing technological improvement were identified by Nagy et al. (Eq. 12 to 17) [30]. They are linking the specific investment y_t [USD/kW] of a technology at year t and the cumulative installed capacity x_t [GW] (or respectively q_t [GW], the yearly installed capacity during year t).

$$\text{Moore[29]} : \log(y_t) = a + bt + n(t) \tag{12}$$

$$\text{Wright[40]} : \log(y_t) = a + b\log(x_t) + n(t) \tag{13}$$

$$\text{Lagged Wright} : \log(y_t) = a + b\log(x_t - q_t) + n(t) \tag{14}$$

$$\text{Goddard[7]} : \log(y_t) = a + b\log(q_t) + n(t) \tag{15}$$

$$\text{SKC[35]} : \log(y_t) = a + b\log(x_t - q_t) + c\log(q_t) + n(t) \tag{16}$$

$$\text{Nordhaus[31]} : \log(y_t) = a + b\log(x_t) + ct + n(t) \tag{17}$$

where a, b and c are constants to identify and $n(t)$ is the noise term.
The term $x_t - q_t$ observable in Eq. 14 and Eq. 16 represents the cumulative capacity until year $t-1$. This is a way to emphasize the variable lag that may occur in the learning-by-doing process.

2.2 Methodology

2.2.1 General Method

Learning curve forms and parameters were chosen for each technology by solving a non-dynamic estimation of the learning curve function parameters using GEKKO library (Python) or AMPL depending on the learning curve expression (see Table 7 for the ones solved with GEKKO and Table 8 for the ones solved with AMPL)[2]. The minimisation of squared errors between the learning curve function $\hat{f}$ and the discrete function f of real data points was therefore tested for various learning curve forms. It is illustrated by Eq. 18.

$$\underset{\alpha,\beta,...}{\text{argmin}}\, SE = \{(\alpha, \beta...)|\min \sum_{x\in\mathcal{X}} (\hat{f}(x, \alpha, \beta...) - f(x))^2\} \tag{18}$$

Furthermore, the acceptance of the learning curve depends on:

1. the plausibility analysis of the estimated cost in 2050;
2. the index R^2.

The first requirement was to ensure a feasible cost for the 2018-2050 period, meaning that the function should be non-zero and non-negative. Moreover, the shape of the curve should make sense. For instance, one could not accept a non-monotonic function, or a function that suddenly becomes constant. Then, the learning curve that maximised the coefficient of determination R^2, defined by Eq. 19, was selected.

$$R^2 = 1 - \frac{\sum_i (y_i - f_i)^2}{\sum_i (y_i - \overline{y})^2} \tag{19}$$

Here y_i represents the real data values and f_i the predicted data.

2.2.2 Important Assumptions and Remarks

Chronology of the study This study has begun with a first focus on a priori simple learning curve expressions. These are the linear, logarithmic, exponential, power law (i.e. Wright's form) and 2nd order polylogarithmic functions. There explicit expression is showed in Table 7. These regressions have been performed using the GEKKO library [2], and the calculation of R^2 has been done via SciPy library [4], using *scipy.stats*. At that point, these intermediary results were used for a first implementation in Energyscope.

Once these first results were assessed, some other learning curve functions were added to the analysis in order to improve the quality of the overall results. These are showed in Table 8. Regressions on these more complicated expressions could not be handled with GEKKO, therefore they have been performed by our own codes in

[2] The Python and AMPL files are available on this repository

AMPL language. Historical data of each technology are stored in separated data files, while each learning curve function has its own model file. The optimisation problem was squared errors minimisation exactly as formulated in Eq. 18.

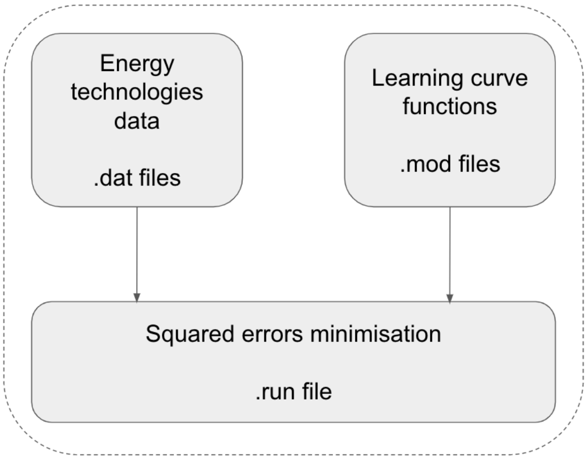

Figure 1: Structure of the AMPL files

Prospective Capacities The prospective capacities were chosen within the scope of the net-zero energy system objective by 2050. To this end, the main source comes from the Net-Zero by 2050 Roadmap from IEA [13]. The missing data are collected from a bunch of other literature given below. It is therefore important to understand that all the results that are given in this work strongly rely on the assumption that the energy technology installation pathway until 2050 should be close to the one predicted by IEA in its net-zero roadmap. This is the strong objective on which Energyscope is based.
Reports such as IEA's Net-Zero Roadmap often give milestones, typically in 2030 and 2050, and sometimes also in 2040. A linear interpolation between these milestones have been performed in order to estimate the yearly capacities between 2020 and 2050. In this work, learning curves are typically generated based upon the 1985-2020 data, especially 2010-2020 where the majority data are available (see Section 3.1) and then are applied to the 2021-2050 period with the interpolated capacities.

Cost Unit Regarding investment costs, they are all given in [USD_{2018}/kW]. Data from the literature have been converted to this unit by taking into account currency change rates and inflation rates between their publication date and 2018.

Assumptions

- Residential, Utility-scale and Commercial PV

The investment cost used for the learning curve of the residential PV cost is the one of the Swiss market [23], while the cost used for commercial PV is the one of the French market, due to lack of data concerning global or Swiss-market cost. Additionally, the learning curve of residential PV has been generated on the 2013-2020 period due to lack of data on older periods. The future installed capacities have been estimated by considering that the shares of residential, utility-scale and commercial solar PV would be constant: they have been set at 13.51%, 55.43% and 30.10% respectively (with respect to the total solar capacity). These ratios are the means over the 2015-2020 period. Note that these ratios do not sum up to 100%, the rest being indeed covered by off-grid PV. Capacity values are given in Table 1.

Year	Total PV Capacity [GW]	Residential PV Capacity [GW]	Utility-scale PV Capacity [GW]	Commercial PV Capacity [GW]
2030	4956	670	2747	1492
2040	10980	1484	6087	3305
2050	14458	1954	8014	4352

Table 1: Prospective capacities for Residential, Utility-scale and Commercial PV

- Onshore and Offshore Wind

Over the past 10 years, the share of offshore wind over total wind energy has increased from 1.7% to 4.7%. This increasing trend has been taken into account in the prospective study, since the cost of onshore and offshore wind farms are significantly different. IRENA's Future of Wind report [19] gives an estimation of the onshore and offshore wind capacities shares in 2030 and 2050, which are applied to IEA Net-Zero Roadmap total wind capacities, see Table 2.

Year	Share of Onshore Wind [%]	Share of Offshore Wind [%]	Total Wind Capacity [GW]	Onshore Wind Capacity [GW]	Offshore Wind Capacity [GW]
2030	88.68	11.32	3101	2750	351
2050	83.45	16.55	8265	6898	1367

Table 2: Prospective shares and capacities of onshore and offshore wind

- Thermal CSP

The decentralised thermal solar is approximated by thermal CSP in EnergyScope.

- Hydro-power

The total hydro-power capacity refers to the sum between run-of-river hydro-power and pumped-storage hydro-power. For instance, the future capacities have been estimated by summing the run-of-river capacity prediction from IEA [13] and the pumped-storage capacity prediction from IRENA [20].

- Ground-Source Heat Pumps

GSHP data is used to approximate centralized heat pumps in EnergyScope. GSHP learning curve was computed based on Swiss market capacities and costs over the period 1985-2008 [24] due to lack of better data. As these costs only included the heat pump purchase cost, they are multiplied by the bare module factor that is assumed to be 3.6 [36] in order to estimate the total investment, including the installation. The prospective GSHP capacity in 2050 has been estimated by IEA, reaching 739 GW_{th} in terms of the global GSHP capacity by 2050 [14]. The ratio of the Swiss GSHP capacity over the global one amounts to 3.26% [27] [28]. Therefore, the Swiss GSHP capacity in 2050 is estimated to 24 GW_{th}.

- Decentralized Heat Pumps

The same Wright's learning rate as GSHP has been applied to DHP. Swiss market data is also used for prospective capacities. The Swiss Energy Office (SFOE) estimated the DHP electricity consumption in Swiss buildings in 2000, 2019 and 2050 [33] at 0.6, 2.3 and 8.7 TWh_{el} respectively. Assuming a COP of 4.2 and a capacity factor of 0.17, this consumption can be converted to a power capacity of 6.49 and 24.54 GW_{th} in 2019 and 2050 respectively. 2018's capacity has been obtained by linear interpolation between years 2000 and 2019.

- CO_2 capture

The carbon capture learning curve has been computed with nine historical data points and one prospective data point in 2026 [17], estimated at 44 USD_{2018}/t_{CO_2}. The latter is added in order to increase the reliability of the result by compensating the large uncertainty of the few collected data.

- Electrolysis

As electrolysis is an emerging technology, very limited data are available at the time of the study. Therefore, we listed all the collected single costs of various plants instead of taking their annual arithmetic mean (see Section 3.1). Prospective shares [10] and capacities are given in Tables 3 and 4. Prospective data points in 2030 and 2050 have been taken from IEA's Net Zero Roadmap by 2050 [13] (see Table 6) and have also been added for the learning curve computation in order to get more reliable results.

Year	ALK Electrolysis Share [%]	PEM Electrolysis Share [%]	SOEC Electrolysis Share [%]
2030	35	23	13
2050	37	32	30

Table 3: Prospective shares of ALK, PEM and SOEC Electrolysis

Year	Total Electrolysis Capacity [GW_{el}]	ALK Electrolysis Capacity [GW_{el}]	PEM Electrolysis Capacity [GW_{el}]	SOEC Electrolysis Capacity [GW_{el}]
2030	850	297.5	195.5	110.5
2045	3000	1093	892.5	772.5

Table 4: Prospective capacities of ALK, PEM and SOEC Electrolysis

Finally, the power-to-hydrogen efficiencies used in order to convert electrical power into thermal power are given in Table 5 [16].

Electrolysis Technology	Efficiency [%]
ALK	66.5
SOEC	77.5
PEM	58.0

Table 5: Power to hydrogen efficiencies of ALK, PEM and SOEC Electrolysis

3 Data

3.1 Historical Data

The historical data that has been used is represented on the following figures (one figure per technology). The data sources are given in the corresponding figure caption. Future capacities predictions have been collected in the literature and are shown in Table 6.

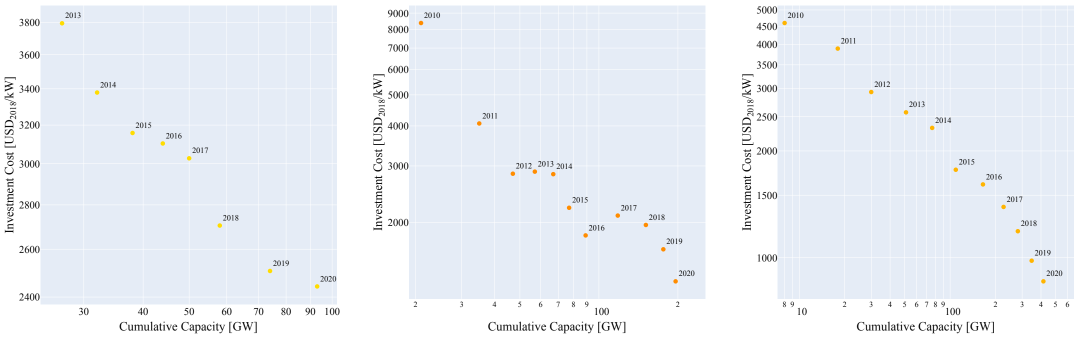

Figure 2: Historical data of residential PV (left) [15] [23], commercial PV (middle) [15] [23] and utility-scale PV (right) [15] [23]

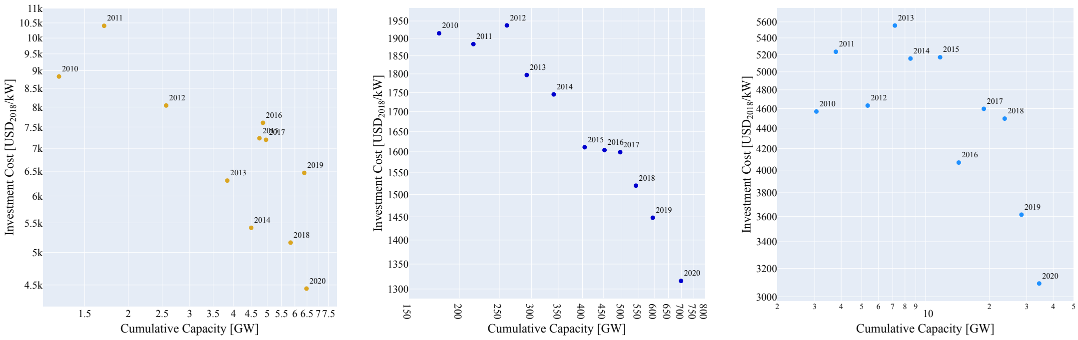

Figure 3: Historical data of CSP (left) [22] [23] onshore wind (middle) [22] [23] and offshore wind (right) [22] [23]

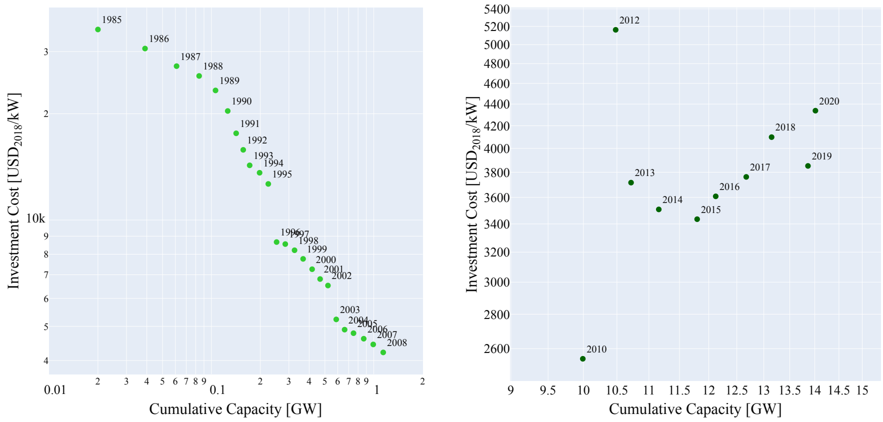

Figure 4: Historical data of GSHP (left) [24] and geothermal energy (right) [22] [23]

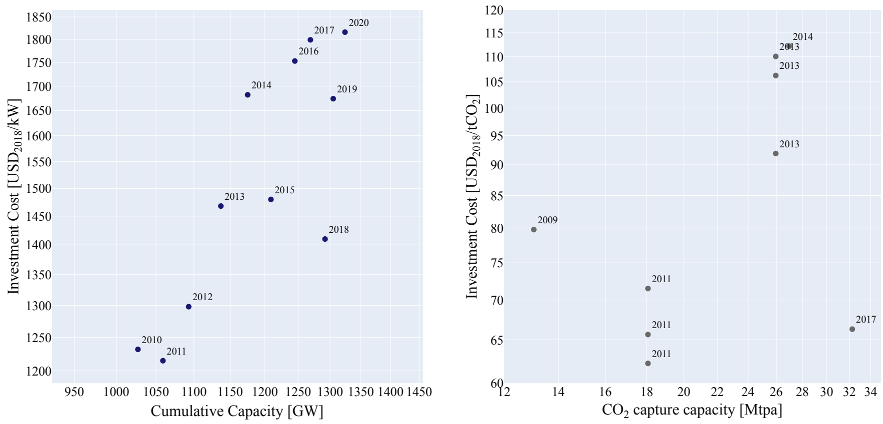

Figure 5: Historical data of total hydro-power (left) [15] [23] and carbon capture (right) [18] [17]. Mtpa: Million tonne per annum.

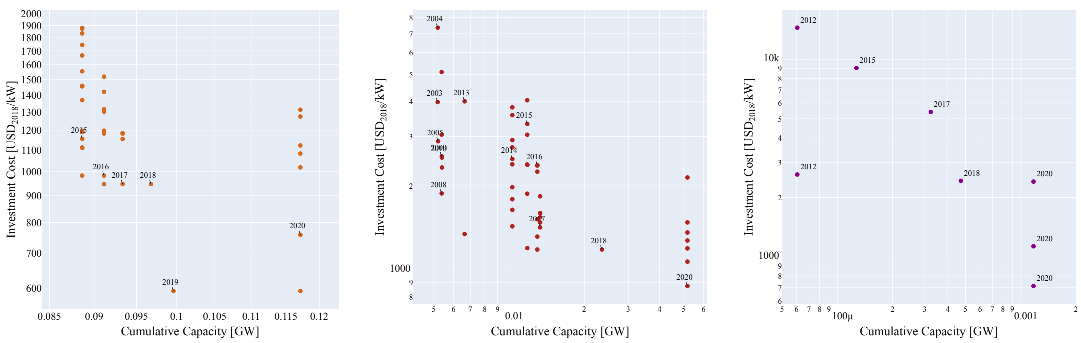

Figure 6: Historical data of ALK Electrolysis (left) [11] [6] PEM Electrolysis (middle) [12] [6] and SOEC Electrolysis (right) [12] [6]

For ALK electrolysis, PEM electrolysis, SOEC and carbon capture, the very low amount of data allows us to represent each data point rather than the mean (as it is the case of other technologies, where each yearly data point is actually the mean of a several hundreds or thousands of collected data). Note that the data points of these four technologies are therefore aligned on the same vertical line when they belong to the same year (as for a fixed year the cumulative capacity is fixed too).

3.2 Future Capacities Predictions

Future capacities predictions have been collected in the literature and are shown in Table 6.

Technology	Year	Region	Predicted Capacity or Production	Unit	Source
Total PV	2030	Global	4956	[GW]	
Total PV	2040	Global	10980	[GW]	IEA-NZ-2050 [13]
Total PV	2050	Global	14458	[GW]	
CSP	2030	Global	73	[GW]	
CSP	2040	Global	281	[GW]	IEA-NZ-2050 [13]
CSP	2050	Global	426	[GW]	
Total Wind	2030	Global	3101	[GW]	
Total Wind	2040	Global	6525	[GW]	IEA-NZ-2050 [13]
Total Wind	2050	Global	8265	[GW]	
Total Electrolysis	2030	Global	850	[GW]	
Total Electrolysis	2040	Global	2400	[GW]	IEA-NZ-2050 [13]
Total Electrolysis	2050	Global	3000	[GW]	
GSHP	2050	Global	739	[GW_{th}]	IEA [14]
Geothermal	2030	Global	52	[GW]	
Geothermal	2040	Global	98	[GW]	IEA-NZ-2050 [13]
Geothermal	2050	Global	126	[GW]	
HP in buildings	2050	Switzerland	8.7	[TWh_{el}/year]	OFEN [33]
Carbon capture	2030	Global	1670	[Mtpa]	IEA-NZ-2050 [13]
Carbon capture	2050	Global	7600	[Mtpa]	
Hydro (excl. pumped storage)	2030	Global	1804	[GW]	
Hydro (excl. pumped storage)	2040	Global	2282	[GW]	IEA-NZ-2050 [13]
Hydro (excl. pumped storage)	2050	Global	2599	[GW]	
Pumped hydro storage	2030	Global	225	[GW]	IRENA [20]
Pumped hydro storage	2050	Global	325	[GW]	

Table 6: Future Capacities or Yearly Productions found in the literature

As explained in the assumptions, it was decided to linearly interpolate these milestones. This means that between two milestones (e.g. between 2020 and 2030, and then between 2030 and 2050) the annual capacity addition is constant.

4 Results and Calibration

4.1 Preliminary Learning Curve Choice

Even if the usual learning curve forms are known, some other very usual regression expressions were tested in order to test the accuracy of learning curve theory. The tested expressions are listed in Table 7.

Type	Expression
Linear	$y = \alpha + \beta x$
Logarithmic	$y = \alpha + \beta \log(x)$
Exponential	$\log(y) = \alpha + \beta x$
Log-linear (Wright)	$\log(y) = \alpha + \beta \log(x)$
2^{nd} Order Polylogarithmic	$\log(y) = \alpha \log(x) + \beta \log(x)^2 + \gamma$

Table 7: Expressions of preliminary regressions

The results in terms of R^2 and corresponding projected costs in 2050 of all expressions for each technology for are given in the Appendix as Table 13. Regressions that are considered as being the better fit are showed in bold. More details on the literature results given in Table 13 ("cost in 2050" column) are showed in Table 12.

4.2 Assessment of more complex learning curve models

In addition to the ones presented in Table 7, the models presented in Table 8 are assessed in what follows. The study is restricted to these four additional learning curve forms (not counting Wright that has already been treated in Section 4.1) for the sake of simplicity. Indeed, after some tests to observe which models were fitting well the data under study, the choice of the four candidates has been motivated by the variety of expressions, in order to get a rich set of results.

Type	Expression
Log-linear (Wright)	$y = C_1 x^b$
S-curve	$y = C_1[M + (1 - M)(x + B)^b]$
Plateau	$y = C + C_1 x^b$
Boone	$y = C_1 x^{\frac{b}{1+\frac{x}{c}}}$
Parametric Sigmoid	$y = \frac{a}{b+\exp(-cx)} + d$

Table 8: Learning curve models

The Table containing the results in terms of R^2 and cost in 2050 is available as Appendix 14, where the learning curve functions that are considered as being the better choice are showed in bold, and the information about the parameters of all learning curve functions presented in Table 8 is available as Appendix 15.

4.2.1 Learning curves visualisation

For each technology, all the learning curves predicted by the expressions of Table 8 are plotted in this section. The historical data is represented by black dots, and the curves ending point is coinciding with the predicted capacity for 2050 (on the x-axis).

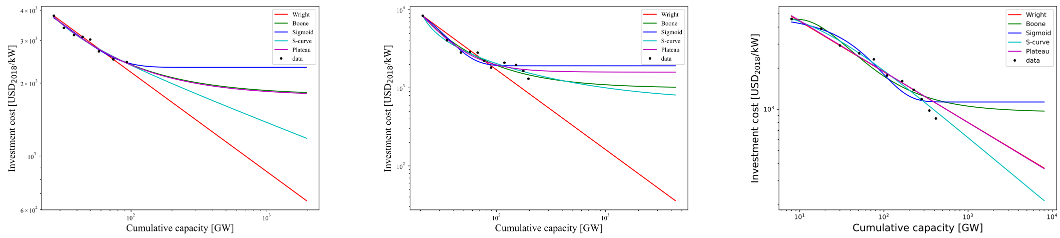

Figure 7: Learning curves visualisation for residential PV (left), commercial PV (middle) and utility-scale PV (right)

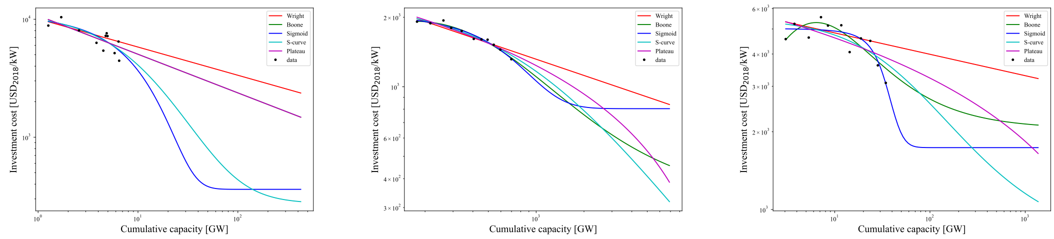

Figure 8: Learning curves visualisation for CSP (left), onshore wind (middle) and offshore wind (right)

Note: for CSP, Boone's and Plateau curves are coinciding.

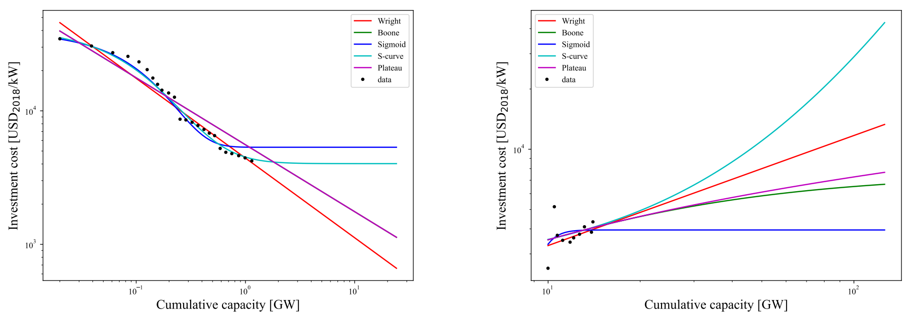

Figure 9: Learning curves visualisation for GSHP (left) and geothermal energy (right)

Note: for GSHP, Boone's and Sigmoid curves are coinciding.

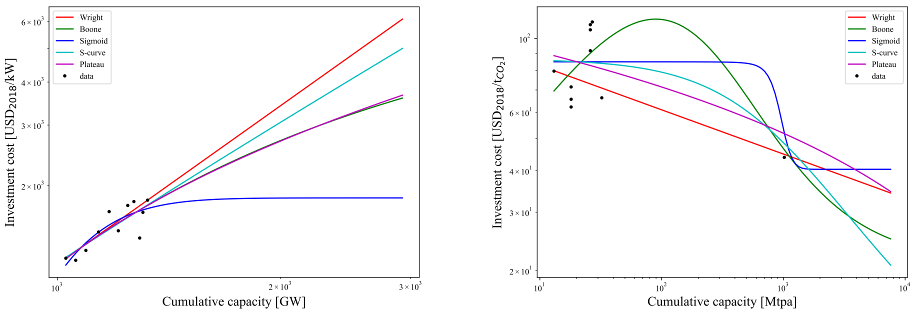

Figure 10: Learning curves visualisation for total hydro-power (left) and carbon capture (right)

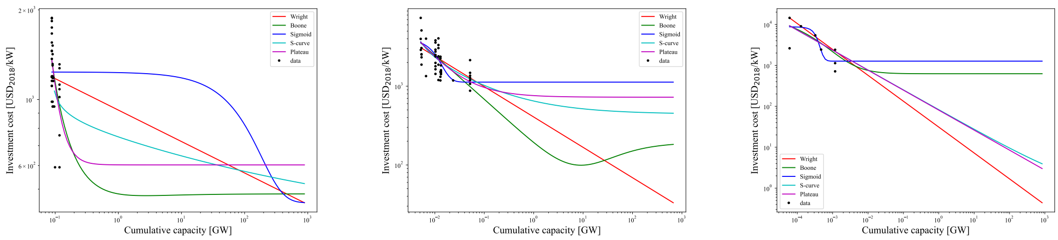

Figure 11: Learning curves visualisation for ALK electrolysis (left), PEM electrolysis (middle) and SOEC electrolysis (right)

One can observe an interesting variety of curves for each technology. As explained earlier, non-monotonic and partly constant curves cannot be kept for further analysis. The final choice of the learning curve is given in Table 9 and a justification of why some learning curve could not be chosen is given in Table 14.

4.2.2 Learning rates visualisation

The learning rates, which are defined as the cost reduction observed when the capacity is doubled, are plotted in this section for each learning curve expression for all technologies. As seen previously, Wright's form as a constant learning rate, whereas other functions may have varying learning rates over time. A positive learning rate is associated to a cost reduction. Here, we stick to the mathematical definition and allow negative learning rates to illustrate a cost increase.

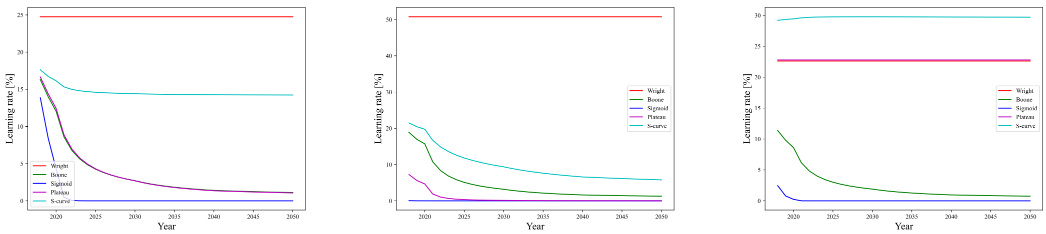

Figure 12: Learning rates visualisation for residential PV (left), commercial PV (middle) and utility-scale PV (right)

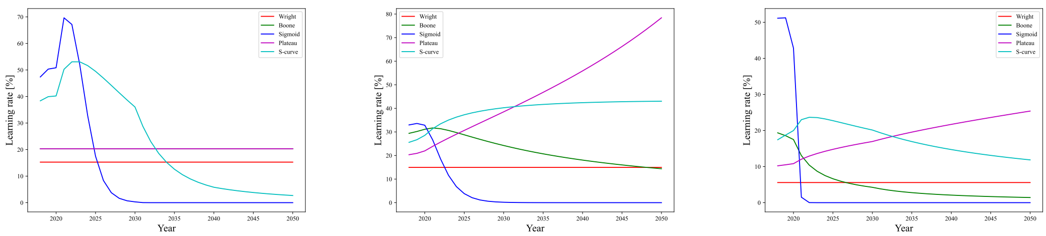

Figure 13: Learning rates visualisation for CSP (left), onshore wind (middle) and offshore wind (right)

Note: for CSP, Boone's and Plateau curves are coinciding.

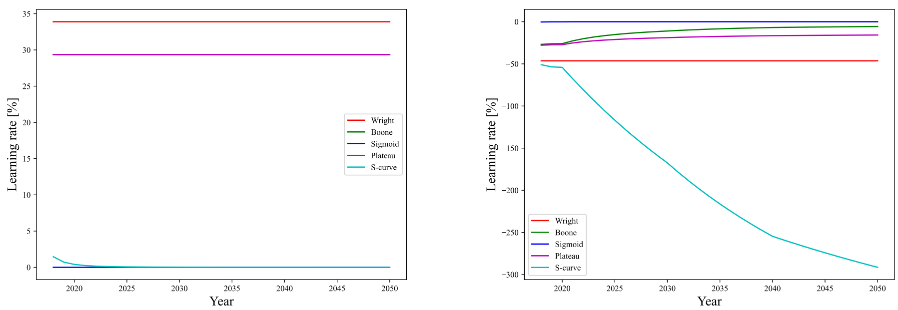

Figure 14: Learning rates visualisation for GSHP (left) and geothermal energy (right)

Note: for GSHP, Boone's and Sigmoid curves are coinciding.

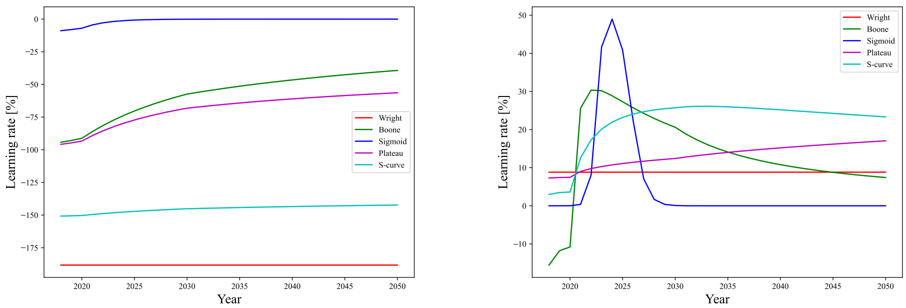

Figure 15: Learning rates visualisation for total hydro-power (left) and carbon capture (right)

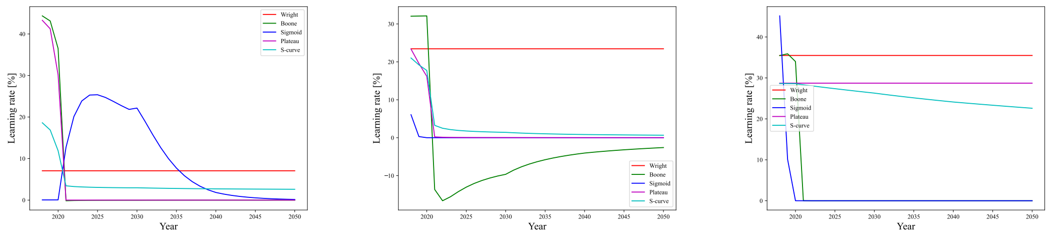

Figure 16: Learning rates visualisation for ALK electrolysis (left), PEM electrolysis (middle) and SOEC electrolysis (right)

4.3 Final Learning Curves Parameters Values and Validity Ranges

After analysing a large variety of candidates for each technology, the expressions and parameters that are finally selected as well as their respective validity ranges are summarised in Table 9. A justification of this choice can be found in Table 14.

Technology	Model	Expression	Parameters	Validity range [GW]
Onshore Wind	Wright	$\log(c) = \alpha + \beta \log(Q)$	α = 8.7969 β = -0.2337	178 - 6898
Offshore Wind	Plateau	$c = \alpha + \gamma Q^{\beta}$	α = -2849200 β = -0.000211753 γ = 2855210	3 - 1368
Residential PV	Wright	$\log(c) = \alpha + \beta \log(Q)$	α = 9.5926 β = -0.4103	27 - 1954
Utility-scale PV	Wright	$\log(c) = \alpha + \beta \log(Q)$	α = 9.2414956077 β = -0.36978581295	8 - 8014
Commercial PV	S-curve	$c = \gamma[\delta + (1-\delta)(Q+\alpha)^{\beta}]$	α = -16.8468 β = -0.574336 γ = 18146.3 δ = 0.0368012	21 - 4352
CSP	Wright	$\log(c) = \alpha + \beta \log(Q)$	α = 9.2176319436 β = -0.23914138084	1.3 - 426
GSHP	Boone	$c = \alpha Q^{\frac{\beta}{1+\frac{Q}{\gamma}}}$	α = 5571.67 β = -0.501507 γ = 10094400	0.020 - 24.1
Decentralized HP	Wright	$\log(c) = \alpha + \beta \log(Q)$	α = 7.8974 β = -0.5972	6.22 - 24.5
Geothermal	Boone	$c = \alpha Q^{\frac{\beta}{1+\frac{Q}{\gamma}}}$	α = 7597.11 β = -81.6475 γ = 0.0409338	10 - 126
SOEC Electrolysis	Logarithmic	$c = \alpha + \beta \log(Q)$	α = 1577.406647 β = -122.94632644	6.05e-4 - 837
PEM Electrolysis	S-curve	$c = \gamma[\delta + (1-\delta)(Q+\alpha)^{\beta}]$	α = -0.0031024 β = -0.446522 γ = 648.199 δ = 0.682924	5.18e-3 - 668
ALK Electrolysis	S-curve	$c = \gamma[\delta + (1-\delta)(Q+\alpha)^{\beta}]$	α = -0.0886337 β = -0.129458 γ = 744.529 δ = 0.488405	88.6e-3 - 886
Carbon Capture	Plateau	$c = \alpha + \gamma Q^{\beta}$	α = -44898.2 β = -0.000189357 γ = 45008.9	13 - 7600 [Mtpa]
Total hydropower	Plateau	$c = \alpha + \gamma Q^{\beta}$	α = -5750.07 β = 0.286223 γ = 958.715	1027 - 2924

Table 9: Learning curves parameters, expressions and validity ranges

4.4 Summary Graph of Prospective Costs

Figure 17 shows the historical and prospective costs, as well as the learning curve, for all technologies that are under study.
In order not to overload Figure 17, only the first and last years of historical data are labelled. Except for electrolysis technologies and carbon capture, which have several points per year (showed due to the low amount of data). These four technologies (ALK, PEM, SOEC and carbon capture) have one label per year. Note that the data points of these technologies which belong to the same year are therefore aligned on the same vertical line (as for a fixed year the cumulative capacity is also fixed). The right y-axis and the top x-axis are relative to carbon capture only, while the left y-axis and the bottom x-axis are relative to other technologies.

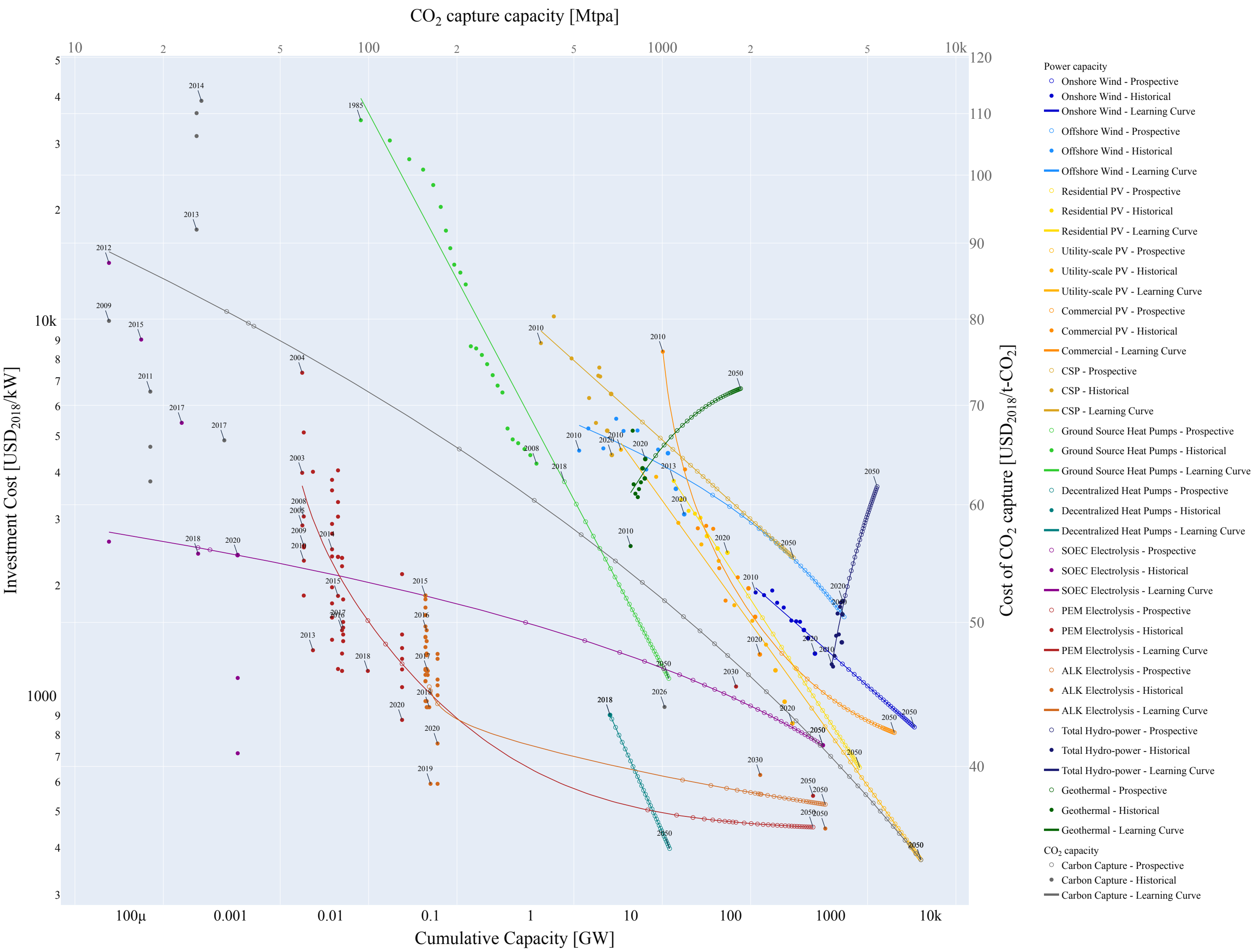

Figure 17: Summary Graph of the Results

4.5 Cost reduction between 2020 and 2050

Cost reductions (or rise in the specific cases of geothermal energy and total hydro-power) between 2020 and 2050 are summarised in Table 10.

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[1]	1129	61.77
ALK Electrolysis	865[2]	522	39.67
SOEC Electrolysis	1178[2]	750	36.33
PEM Electrolysis	1035[2]	454	56.14
Total hydro-power	1816	3663	-101.71
Geothermal	4338	6683	-54.05
CO_2 capture	79[1]	35	55.70

Table 10: Cost reduction between 2020 and 2050

Excepting total hydro-power and geothermal energy, which actually have an increasing trend, the cost reduction mean between 2020 and 2050 of these 11 technologies is 49.77%. The higher cost reduction is achieved by residential PV with 73.21%, whereas the lowest one is achieved by onshore wind with 36.32%.

[1]Estimation via our learning curve due to lack of data
[2]Mean between the 2020's data points

5 Discussion of the Results

5.1 Comparison with Literature Results

The results of this study have been compared to the ones from the literature according to two main results: the technologies learning rates [%] and the investment costs [USD_{2018}/kW] in 2050. This comparison is shown in Tables 11 and 12. Some technologies may be missing from one of these tables due to lack of reliable result in the literature. However, each technology is at least present in one of these two tables.

Technology	This report	Learning rates from literature [%]			
Res. PV	24.75	23.8[3][38]	20[3] [37]	23[3] [34]	11 - 24[3] [26]
Utility-scale PV	22.61	34 [23]			
CSP	15.28	22 [23]	7 [37]	10 - 23 [26]	
Onshore Wind	14.96	17 [23]	5 [37]	12 [34]	
Offshore Wind	10.22 - 25.39	9 [23]	5 - 11 [37]	12 [34]	
ALK Electrolysis	2.6 - 18.61	9 [5]			
SOEC Electrolysis	3.4 - 11.4	15 - 25 [8]			
PEM Electrolysis	0.66 - 21.02	13 [5]			
GSHP	29.36	35 [25]	5 - 17 [26]		
Dec. HP	33.89	35 [25]	5 - 17 [26]		
Geothermal	-26.86 - -5.65	5 [37]			
Carbon capture	7.29 - 17.04	2.1 - 5.0 [37]	6.45 - 11.35 [39]		
Hydropower	-95.85 - -56.39	1 [37]	1.4 [34]		

Table 11: Learning rates found in the literature

Technology	This report	Investment costs results from literature [USD_{2018}/kW]			
Res. PV	654.48	340[3] [13]	300 - 1600[3] [41]	533 - 984 [32]	396 - 1096 [37]
Utility-scale PV	371.48	472 - 761 [32]	294 - 904 [37]		
Commercial PV	810.26	510 - 894 [32]	328 - 1096 [37]		
CSP	2367.91	2689 - 6648 [32]	2475 - 5548 [37]	1600 - 5225 [41]	
Onshore Wind	838.08	1300 [13]	514 - 882 [32]	825 - 1989 [37]	1000 - 1700 [41]
Offshore Wind	1647.52	1420 [13]	1494 - 2660 [32]	1446 - 5481 [37]	1525 - 3610 [41]
ALK Electrolysis	521.85	200 - 700 [16]	$<$ 200 [21]		
SOEC Electrolysis	750	500 - 1000 [16]	$<$ 300 [21]		
PEM Electrolysis	453.93	200 - 900 [16]	$<$ 200 [21]		
Hydropower	3663.01	2141 - 2478 [32]	1209 - 3955 [37]		
Geothermal	6682.74	4240 - 5592 [32]	2260 - 12588 [37]		

Table 12: Investment costs in 2050 found in the literature

Note: In Tables 11 and 12, the notation "Value 1 - Value 2" corresponds the the minimum and maximum values. When it concerns the "This report" data, it is due to the fact that some learning curves have varying learning rates. When it concerns literature results, it means that authors have mentioned different sub-categories of the considered technology.

Obviously, some of these results may not be in line with literature results. Even if these have been taken into account during the final learning curve step choice, the

[3]Total PV

set of learning curves functions, the assumptions that we have made and the fact that we use the most recent data may induce major differences with other literature results. One should be aware that the uncertainty on all of these results may be very important, as the cost of a technology depends on so many parameters that may know dramatic modifications until 2050. For example, the impact of Swiss subsides on these technologies cost until 2050 would be a very interesting topic to further continue this work.

5.2 Limitations and further possible improvements

In order to further improve the limitations of the conducted work, following ideas could be addressed:

- Propose a different interpolation method than the linear one to compute prospective capacities

  By taking the example of electrolysis (both ALK, PEM and SOEC), one can see on Figure 17 that the gap between the 2020 and 2021 points is really huge. This is due to the fact that IEA's predictions in terms of electrolysis capacities are really massive with respect to the current ones. The linear interpolation there generates a very unrealistic capacity evolution that starts in 2020 (order of magnitude: the capacity addition in 2020 is 10'000 larger than the ones of 2019, and the installed capacity is multiplied by a factor between 100 and 1000 within a year depending on the electrolysis technology). Consequently, a S-curve interpolation may be much more relevant, but it is also much more complicated to choose its parameters (it could be a whole study in itself, especially regarding very uncertain technologies like electrolysis).

- Add some missing technologies as data becomes more widely available

  Originally, this study included some additional technologies that are expected to play a major role in future energy systems, but for which data is currently very difficult to find. These technologies were the followings: CO_2 sequestration, natural gas storage, wood gasification, cogeneration, methanation and H_2 storage. A further improvement would be to include these technologies as soon as reliable data can be found.

- Enrich the learning curve functions set thanks to machine learning

  Even if this method may look very non-standard, it may be interesting to try some machine learning regression methods on our data. Indeed, one could use methods like SVR (support vector regression) or GMR (Gaussian mixture regression) to generate additional regression functions that may be interesting candidates. However, it looked much safer to focus on learning curve theory, this is why it has not been done in this work.

- Update data and see how the model is performing

In some years, this model will probably have to be updated, it will be the occasion to assess its performances and see if some learning curve functions may be further kept, by adding the new historical points.

- Perform an uncertainty analysis on the obtained results

  An interesting complement to our result would be to have the 95% confidence range (e.g. in terms of cost in 2050 or learning rate). In our case, the original data does not always present a confidence interval, thus making such an analysis more difficult.

- Perform a train/test analysis

  With longer time series (e.g. 30 years with data), the data could be split into a training set (e.g. 15 first years) and a testing set (e.g. 15 last years). The model could then be trained on the training set and tested on the testing set in order to verify its accuracy.

6 Conclusions

To conclude, the dramatic predicted cost variation between 2020 and 2050 show the relevance of including varying investment costs into Energyscope. Moreover, the variety of selected learning curve forms show that considering a large set of functions is necessary to ensure good predictive performances.
The investment cost of hydro-power and geothermal energy is expected to increase. Indeed, hydro-power cost is doubling between 2020 and 2050 (from 1816 USD/kW to 3663 USD/kW), while geothermal energy cost increase is more than 50% (from 4338 USD/kW to 6683 USD/kW). This can be explained by the fact that water streams and places to drill are more and more difficult to find, and therefore the associated cost should increase. On the other hand, all other studied technologies investment costs (Solar, Wind, HP, Electrolysis, CO_2 capture) are expected to decrease a lot in future years. The mean cost reduction between these technologies being 50%. The most impressive cost increase is achieved by Residential PV, with 73% cost reduction between 2020 and 2050 (from 2443 USD/kW to 654 USD/kW).
However, these results are estimation that were subject to several assumptions, thus leading to important uncertainties. This work can therefore be used as a starting point in future years, when new data points are available and can be compared to the obtained results.

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7 Appendices

Technology	Expression	Cost in 2050 [USD_{2018}/kW]	R^2	Cost in 2050 from literature [USD_{2018}/kW]
Onshore Wind	Linear	-5885.81	0.962	
Onshore Wind	Logarithmic	365.92	0.922	
Onshore Wind	Exponential	16.51	0.959	514 - 1989
Onshore Wind	**Wright**	**838.08**	**0.902**	
Onshore Wind	2nd order polylogarithmic	191.53	0.966	
Offshore Wind	Linear	-112'911	0.724	
Offshore Wind	Logarithmic	-1329.59	0.600	
Offshore Wind	Exponential	1.500E-7	0.698	1420 - 5481
Offshore Wind	**Wright**	**1156.54**	**0.549**	
Offshore Wind	2nd order polylogarithmic	1.86	0.620	
Residential PV	Linear	-36'525	0.861	
Residential PV	Logarithmic	-228.53	0.946	
Residential PV	Exponential	3.996E-3	0.899	340 - 1600
Residential PV	**Wright**	**654.48**	**0.965**	
Residential PV	2nd order polylogarithmic	9019.92	0.965	
Utility-scale PV	Linear	-45314.27	0.736	
Utility-scale PV	Logarithmic	-1796.64	0.984	
Utility-scale PV	Exponential	1.81e-10	0.851	294 - 904
Utility-scale PV	**Wright**	**371.48**	**0.977**	
Utility-scale PV	2nd order polylogarithmic	134.25	0.991	
Commercial PV	Linear	-45657.12	0.463	
Commercial PV	Logarithmic	-3078.04	0.720	
Commercial PV	Exponential	2.19e-8	0.563	328 - 1096
Commercial PV	Wright	35.95	0.940	
Commercial PV	2nd order polylogarithmic	28975.16	0.981	
CSP	Linear	-249079	0.673	
CSP	Logarithmic	-791.30	0.660	
CSP	Exponential	4.54E-10	0.677	1600 - 6648
CSP	**Wright**	**2367.91**	**0.647**	
CSP	2nd order polylogarithmic	575.76	0.678	
ALK Electrolysis	Linear	450.00	0.170	
ALK Electrolysis	Logarithmic	450.00	0.229	
ALK Electrolysis	Exponential	450.00	0.183	$<$ 200 - 700
ALK Electrolysis	**Wright**	**450.00**	**0.238**	

ALK Electrolysis	2nd order polylogarithmic	inf	0.271	
PEM Electrolysis	Linear	550.00	0.051	
PEM Electrolysis	**Logarithmic**	**550.00**	**0.176**	
PEM Electrolysis	Exponential	550.00	0.056	$<$ 200 - 900
PEM Electrolysis	Wright	33.12	0.373	
PEM Electrolysis	2nd order polylogarithmic	-	-	
SOEC Electrolysis	Linear	-	-	
SOEC Electrolysis	**Logarithmic**	**750.00**	**0.196**	
SOEC Electrolysis	Exponential	750.00	0.084	$<$ 300 - 1000
SOEC Electrolysis	Wright	0.44	0.501	
SOEC Electrolysis	2nd order polylogarithmic	-	-	
GSHP	Linear	-	-	
GSHP	Logarithmic	-26863.20	0.941	
GSHP	Exponential	-	-	-
GSHP	**Wright**	**661.89**	**0.875**	
GSHP	2nd order polylogarithmic	36.81	0.982	
Geothermal	Linear	22787.40	0.075	
Geothermal	**Logarithmic**	**8350.43**	**0.075**	
Geothermal	Exponential	706998.77	0.076	2260 - 12588
Geothermal	Wright	13299.89	0.075	
Geothermal	2nd order polylogarithmic	2.107e12	0.053	
Carbon capture	Linear	-157.52	0.310	
Carbon capture	Logarithmic	28.95	0.223	
Carbon capture	Exponential	1.55	0.308	-
Carbon capture	**Wright**	**34.27**	**0.197**	
Carbon capture	2nd order polylogarithmic	3.30	0.414	
Total hydro	Linear	4962.13	0.650	
Total hydro	**Logarithmic**	**3637.54**	**0.659**	
Total hydro	Exponential	3.802e9	0.634	1209 - 3955
Total hydro	Wright	6091.12	0.645	
Total hydro	2nd order polylogarithmic	79.37	0.681	

Table 13: Results in terms of R^2 and 2050's cost of the preliminary regressions

Technology	Form	Cost in 2050 [USD_{2018}/kW]	R^2	Remark for assessment	Cost in 2050 from literature [USD_{2018}/kW]
Onshore Wind	**Wright**	**838.08**	**0.902**		
Onshore Wind	S-curve	302.78	0.949	2050 cost not in range	
Onshore Wind	Plateau	386.39	0.921	2050 cost not in range	514 - 1989
Onshore Wind	Boone	455.98	0.966	2050 cost not in range	
Onshore Wind	Sigmoid	803.90	0.963	too rapidly constant	
Offshore Wind	Wright	1156.54	0.549	2050 cost not in range	
Offshore Wind	S-curve	1072.61	0.581	2050 cost not in range	
Offshore Wind	**Plateau**	**1647.52**	**0.448**		1420 - 5481
Offshore Wind	Boone	2122.72	0.716	non-monotonic	
Offshore Wind	Sigmoid	1736.24	0.731	too rapidly constant	
Residential PV	**Wright**	**654.48**	**0.965**		
Residential PV	S-curve	1184.62	0.974		
Residential PV	Plateau	1813.22	0.972	2050 cost not in range	300 - 1600
Residential PV	Boone	1829.78	0.972	2050 cost not in range	
Residential PV	Sigmoid	2322.71	0.969	2050 cost not in range	
Utility-scale PV	**Wright**	**371.48**	**0.977**		
Utility-scale PV	S-curve	214.72	0.991	2050 cost not in range	
Utility-scale PV	Plateau	368.06	0.977		294 - 904
Utility-scale PV	Boone	970.59	0.972	2050 cost not in range	
Utility-scale PV	Sigmoid	1131.86	0.967	too rapidly constant	
Commercial PV	Wright	35.95	0.940	2050 cost not in range	
Commercial PV	**S-curve**	**810.26**	**0.987**		
Commercial PV	Plateau	1591.59	0.983	2050 cost not in range	328 - 1096
Commercial PV	Boone	1019.36	0.981		
Commercial PV	Sigmoid	1915.71	0.967	too rapidly constant	
CSP Solar	**Wright**	**2367.91**	**0.647**		
CSP Solar	S-curve	284.23	0.676	2050 cost not in range	
CSP Solar	Plateau	1477.36	0.641	2050 cost not in range	1600 - 6648
CSP Solar	Boone	1477.36	0.641	2050 cost not in range	
CSP Solar	Sigmoid	361.49	0.677	2050 cost not in range	
ALK Electrolysis	Wright	450.00	0.238		
ALK Electrolysis	**S-curve**	**521.85**	**0.471**		
ALK Electrolysis	Plateau	602.94	0.387	too rapidly constant	<200 - 700
ALK Electrolysis	Boone	481.86	0.384	too rapidly constant	
ALK Electrolysis	Sigmoid	450.51	0.210	unrealistic curvature	
PEM Electrolysis	Wright	33.12	0.373	2050 cost not in range	
PEM Electrolysis	**S-curve**	**453.93**	**0.426**		
PEM Electrolysis	Plateau	725.14	0.424		<200 - 900
PEM Electrolysis	Boone	182.37	0.409	non-monotonic	

PEM Electrolysis	Sigmoid	1127.01	0.422	too rapidly constant	
SOEC Electrolysis	Wright	0.44	0.501	2050 cost not in range	
SOEC Electrolysis	S-curve	3.94	0.509	2050 cost not in range	
SOEC Electrolysis	Plateau	3.01	0.51	2050 cost not in range	<300 - 1000
SOEC Electrolysis	Boone	624.38	0.533	too rapidly constant	
SOEC Electrolysis	Sigmoid	1269.68	0.58	too rapidly constant	
GSHP	Wright	661.89	0.875		
GSHP	S-curve	4021.80	0.983	too rapidly constant	
GSHP	Plateau	1129.29	0.904		-
GSHP	**Boone**	**1129.29**	**0.904**		
GSHP	Sigmoid	5336.81	0.986	too rapidly constant	
Geothermal	Wright	13299.89	0.075	2050 cost not in range	
Geothermal	S-curve	42897.97	0.0754	2050 cost not in range	
Geothermal	Plateau	7667.05	0.0754		2260 - 12588
Geothermal	**Boone**	**6682.74**	**0.0751**		
Geothermal	Sigmoid	3951.18	0.106	too rapidly constant	
Carbon capture	Wright	34.27	0.197		
Carbon capture	S-curve	20.78	0.301	LR strongly increasing	
Carbon capture	**Plateau**	**34.61**	**0.224**		-
Carbon capture	Boone	24.93	0.452	non-monotonic	
Carbon capture	Sigmoid	40.38	0.316	unrealistic curvature	
Total hydropower	Wright	6091.12	0.645	2050 cost not in range	
Total hydropower	S-curve	5007.17	0.647	2050 cost not in range	
Total hydropower	**Plateau**	**3663.01**	**0.656**		1209 - 3955
Total hydropower	Boone	3593.08	0.654		
Total hydropower	Sigmoid	1843.58	0.680	too rapidly constant	

Table 14: Results in terms of R^2 and 2050's cost of the learning curve models

Technology	Form	a	b	c	d	m
Onshore Wind	Wright	8.797E+00	-2.337E-01			
Onshore Wind	S-curve	9.250E+02	-9.521E-01	1.542E+06		1.000E-05
Onshore Wind	Plateau	-9.379E+04	-4.648E-03	9.813E+04		
Onshore Wind	Boone	3.189E+02	4.333E-01	7.106E+02		
Onshore Wind	Sigmoid	-4.029E+02	2.486E-01	3.068E-03	2.425E+03	
Offshore Wind	Wright	8.673E+00	-8.278E-02			
Offshore Wind	S-curve	3.904E+01	-7.534E-01	7.551E+04		1.000E-02
Offshore Wind	Plateau	-2.543E+06	-2.372E-04	2.549E+06		
Offshore Wind	Boone	5.701E+04	-3.148E+05	5.486E+00		
Offshore Wind	Sigmoid	-4.147E+01	1.245E-02	1.394E-01	1.157E+06	
Residential PV	Wright	9.593E+00	-4.103E-01			
Residential PV	S-curve	-1.673E+01	-2.213E-01	1.607E+06		1.000E-03
Residential PV	Plateau	1.772E+03	-9.017E-01	3.849E+04		
Residential PV	Boone	1.785E+03	5.160E+00	1.231E+00		
Residential PV	Sigmoid	-2.461E+05	7.627E+00	3.944E-02	3.459E+04	
Utility-scale PV	Wright	9.241E+00	-3.698E-01			
Utility-scale PV	S-curve	1.113E+06	-5.151E-01	2.182E+04		1.000E-04
Utility-scale PV	Plateau	1.000E-03	-3.729E-01	1.051E+04		
Utility-scale PV	Boone	9.548E+02	2.601E+05	1.593E+06		
Utility-scale PV	Sigmoid	-1.762E+06	2.136E+01	1.745E-02	8.360E+04	
Commercial PV	Wright	1.215E+01	-1.022E+00			
Commercial PV	S-curve	-1.685E+01	-5.743E-01	1.815E+04		3.680E-02
Commercial PV	Plateau	1.591E+03	-1.843E+00	1.847E+06		
Commercial PV	Boone	9.911E+02	6.763E+03	2.160E-03		
Commercial PV	Sigmoid	-3.022E+05	3.196E+00	6.982E-02	9.646E+04	
CSP Solar	Wright	9.218E+00	-2.391E-01			
CSP Solar	S-curve	1.461E+01	-2.053E+00	2.740E+06		1.000E-04
CSP Solar	Plateau	1.000E-03	-3.275E-01	1.073E+04		
CSP Solar	Boone	1.073E+04	-3.275E-01	5.249E+09		
CSP Solar	Sigmoid	-3.853E+05	5.557E+00	1.279E-01	6.970E+04	
ALK Electrolysis	Wright	6.826E+00	-1.056E-01			
ALK Electrolysis	S-curve	-8.863E-02	-1.295E-01	7.445E+02		4.884E-01
ALK Electrolysis	Plateau	6.029E+02	-3.222E+00	3.064E-01		
ALK Electrolysis	Boone	4.820E+02	-3.719E+02	1.009E-04		
ALK Electrolysis	Sigmoid	-5.808E+04	-3.161E+05	8.093E-03	7.617E+03	
PEM Electrolysis	Wright	6.008E+00	-3.855E-01			
PEM Electrolysis	S-curve	-3.102E-03	-4.465E-01	6.482E+02		6.829E-01
PEM Electrolysis	Plateau	7.250E+02	-8.421E-01	3.457E+01		
PEM Electrolysis	Boone	1.932E+02	-5.532E-01	2.713E+06		
PEM Electrolysis	Sigmoid	-3.469E+02	1.025E-01	2.592E+02	4.510E+03	
SOEC Electrolysis	Wright	3.435E+00	-6.324E-01			

SOEC Electrolysis	S-curve	-1.000E-06	-4.860E-01	8.277E+01		1.000E-02
SOEC Electrolysis	Plateau	1.000E-06	-4.885E-01	8.060E+01		
SOEC Electrolysis	Boone	6.244E+02	-2.875E-01	1.655E-03		
SOEC Electrolysis	Sigmoid	-6.201E+01	8.141E-03	1.414E+04	2.552E+06	
GSHP	Wright	7.512E+05	-5.971E-01			
GSHP	S-curve	3.052E-01	-3.001E+00	5.097E+03		7.891E-01
GSHP	Plateau	1.000E-03	-5.015E-01	5.572E+03		
GSHP	Boone	5.572E+03	-5.015E-01	1.009E+07		
GSHP	Sigmoid	-8.114E+06	1.493E+01	8.356E+00	5.489E+05	
Geothermal	Wright	6.837E+00	5.498E-01			
Geothermal	S-curve	6.718E+01	2.718E+00	1.728E-01		8.478E-01
Geothermal	Plateau	-3.428E+04	4.099E-02	3.441E+04		
Geothermal	Boone	2.081E+06	-8.165E+01	4.093E-02		
Geothermal	Sigmoid	3.952E-02	1.000E-05	1.325E+00	-1.142E+00	
Carbon capture	Wright	4.724E+00	-1.332E-01			
Carbon capture	S-curve	6.469E+02	-7.063E-01	2.104E+06		1.000E-03
Carbon capture	Plateau	-4.490E+04	-1.894E-04	4.501E+04		
Carbon capture	Boone	2.100E+01	4.853E-01	3.124E+02		
Carbon capture	Sigmoid	2.612E+05	5.838E+03	-9.547E-03	4.038E+01	
Total hydropower	Wright	-3.476E+00	1.527E+00			
Total hydropower	S-curve	-1.166E+02	1.240E+00	2.654E-01		1.000E-03
Total hydropower	Plateau	-5.750E+03	2.862E-01	9.587E+02		
Total hydropower	Boone	7.423E+03	-8.709E+02	3.053E-01		
Total hydropower	Sigmoid	-6.320E+05	2.362E+02	-6.395E-03	1.844E+03	

Table 15: Learning curves parameters