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A review on learning effects in prospective technology assessment

Gwenny Thomassen[a,b,*], Steven Van Passel[a], Jo Dewulf[b]

[a] = Department of Engineering Management, University of Antwerp, Prinsstraat 13, 2000 Antwerp, Belgium
[b] = Research Group Sustainable Systems Engineering, Ghent University, Coupure Links 653, 9000 Ghent, Belgium

Abstract

Global environmental problems have urged the need for developing sustainable technologies. However, new technologies that enter the market have often higher economic costs and potentially higher environmental impacts than conventional technologies. This can be explained by learning effects: a production process that is performed for the first time runs less smooth than a production process that has been in operation for years. To obtain a fair estimation of the potential of a new technology, learning effects need to be included. A review on the current literature on learning effects was conducted in order to provide guidelines on how to include learning effects in prospective technology assessment. Based on the results of this review, five recommendations have been formulated and an integration of learning effects in the structure of prospective technology assessment has been proposed. These five recommendations include the combined use of learning effects on the component level and on the end product level; the combined use of learning effects on the technical, economic and environmental level; the combined use of extrapolated values and expert estimates; the combined use of learning-by-doing and learning-by-searching effects and; a tier-based method, including quality criteria, to calculate the learning effect. These five complementary strategies could lead to a clearer perspective on the environmental impact and cost structure of the new technology and a fairer comparison base with conventional technologies, potentially resulting in a faster adoption and a shorter time-to-market for sustainable technologies.

Highlights

- Learning effects quantify the principle “practice makes perfect” for technologies
- A review on learning effects in prospective technology assessment was performed
- Learning effects have mainly been used for investment costs of energy technologies
- Based on best practices, guidelines on the use of learning effects were formulated
- These guidelines enable including learning effects for a wide range of technologies

Keywords

Learning effects, life cycle assessment, techno-economic assessment, prospective technology assessment, learning-by-doing, learning curve, progress rate, experience curve

Word count

9996

List of abbreviations including units and nomenclature

	Abbreviations	L	Literature
NOAK	n^{th} of a kind	Es	Estimate

* = corresponding author details, gwenny.thomassen@ugent.be

FOAK	First of a kind	RoT	Rule-of-thumb
PR	Progress rate	OT	Other technologies
LR	Learning rate	u	Unspecified
TRL	Technology Readiness Level	Q	Quality class
R^2	Coefficient of determination	y	Years
PV	Photovoltaic	n/a	not applicable
BOS	Balance of system	M	Months
gen.	generation	uc	unclear
CSP	Concentrated solar power	Me	Methodology
DCP	Direct combustion power	CA	Cost analysis
CHP	Combined heat and power	Re	Regression
SOFC	Solid oxide fuel cell	com	Cost optimization model
E&P	Exploration and production	PA	policy analysis
EV	Electric vehicles	ROA	Real options analysis
Dep.	Dependent variable	PEM	Partial equilibrium model
Pc	End product cost	GEM	General equilibrium model
Cc	Component cost	IDM	Investment decision model
Pi	End product environmental impact	LCA	Life Cycle Assessment
Ci	Component environmental impact	EnA	Energy analysis
Ind.	Independent variable	CBM	Cost breakdown model
Sc	Scale	MRIO	Multi-regional input output
Pr	Exogenous price fluctuations	ABM	Agent-based modelling
Ot	Other factors	CBA	Cost-benefit analysis
Exp	Experience	I	Included
CC	Cumulative capacity	E	Excluded
CP	Cumulative production	S	Separately assessed
R&D	Research and development	Ln	Linear function
DLI	Databases, literature, industry	o	Other function
Sim	Simulations	MAV	Maximum achievable value
Fu	Functional form	LBD	Learning-by-doing
P	Power function	LBS	Learning-by-searching
O	Other functional form		**Nomenclature**
Ref.	Reference	C	cost per unit
CCS	Carbon capture and storage	P	number of units produced
CCR	Carbon capture ready	C_0	initial cost
NGCC	Natural gas carbon capture	P_0	initial production unit number
CCU	Carbon capture and usage	α	learning-by-doing coefficient
Coal-to-L	Coal-to-liquid	K_0	initial patent-based knowledge stock
UHVPT	Ultra high voltage power transmission	K	patent-based knowledge stock
HCPV	High concentrated photovoltaic	β	learning-by-searching coefficient
C	Calculated	#	number of units

1.0 Introduction

New technologies have a disadvantage compared to conventional technologies. Where conventional technologies had sufficient time for optimization, new technologies still have to go down that road. An established technology can be considered as the nth of a kind (NOAK), while a new technology will start as the first of a kind (FOAK) [1]. The optimization of a new technology by increasing its performance will induce a decrease in economic costs [2]. Besides the cost, also the environmental impact is reduced by an improved technological performance [3]. The disadvantage of a FOAK technology compared to a NOAK technology is therefore translated in higher economic costs and potentially higher environmental impacts. The decrease of costs and environmental impacts of a new technology through a better technological performance when more experience is gained, is considered as a learning effect [4]. The more a technology is used, the more efficient it will become until approaching a maximum achievable value. Learning effects will therefore decrease costs and environmental impacts of FOAK technologies on their path to NOAK technologies as illustrated in Fig. 1. This experience path from FOAK technologies to NOAK technologies is often expressed as the cumulative installed capacity, but can also be expressed as the cumulative number of products or production plants. The NOAK stage can also be indicated by the term 'materiality', where the technology covers 1% market share [5].

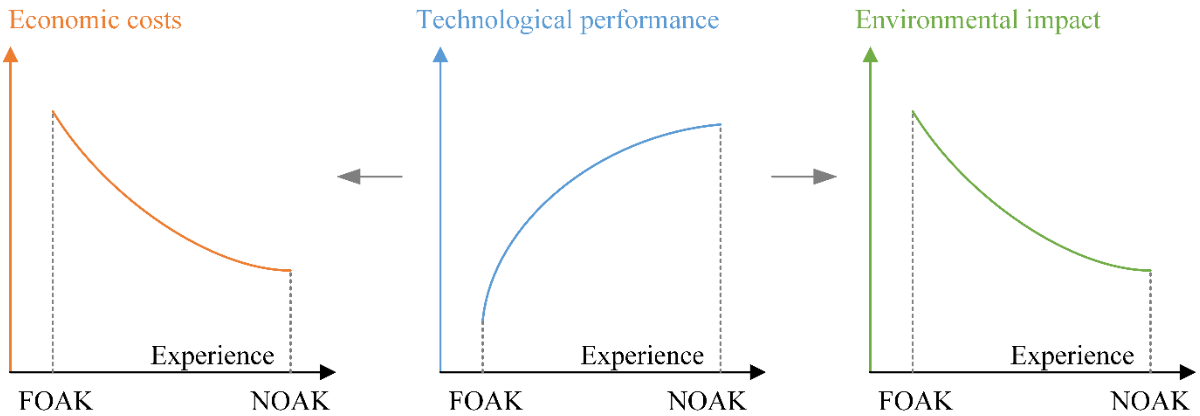

Fig. 1. Learning effects on technological, economic and environmental performance

Different types of learning effects exist. The most common learning effect is learning-by-doing, where a repeated action leads to a higher efficiency. The first example of learning-by-doing was provided in 1936 by Wright [2] who demonstrated that the labour hours decrease in airplane manufacturing when the cumulative production volume increases. This has also an impact on the production costs due to decreasing labour costs. This relation is expressed in the following equation:

$$C = C_0(P/P_0)^{-\alpha} \tag{1}$$

where C is the cost per unit, P is the number of units produced, C_0 and P_0 are the initial cost and production values and α is the learning-by-doing coefficient. Based on this equation, the progress rate (PR) and learning rate (LR) are calculated. The learning rate expresses the percentage cost reduction per doubling of experience and the progress rate expresses the relative residual cost for this increase of experience:

$$PR = 2^{-\alpha} \tag{2}$$
$$LR = 1 - PR \tag{3}$$

A similar relation based on the learning effect was postulated in 1965 by Moore, who stated that the complexity for minimum component costs on integrated circuits had doubled every two years and would continue to do so [6]. With this statement, Moore predicted the exponential decrease in costs of semiconductors of the last decades [7]. Instead of using cumulative production as a proxy for experience, Moore used time. However, according to a comparison between the predictive power of these two laws, the original learning curve as postulated by Wright is more accurate and cumulative production is a better proxy for experience than time [8].

In the semiconductor learning path as predicted by Moore, not only learning-by-doing had an effect, but also learning-by-searching (also called learning-by-researching) played a role. In this effect, R&D leads to optimization of the new technology, which increases its efficiency. While learning-by-doing investigates the effect of a similar technology with better practices, learning-by-searching covers the improvement of the technology itself [9]. The effects of learning-by-doing and learning-by-searching can be assessed using a two-factor learning curve [10]:

$$C = C_0 (P/P_0)^{-\alpha} (K/K_0)^{-\beta} \tag{4}$$

where K is the patent-based knowledge stock, K_0 is the initial patent-based knowledge stock and β is the learning-by-searching coefficient.

Other learning effects, such as learning-by-using and learning-by-interaction occur as well. Learning-by-using originates from feedback from user experience whereas learning-by-interaction is caused by the diffusion of knowledge [11]. Besides learning effects, also forgetting effects occur due to interruptions in production [12].

Most applications of learning effects cover the overall cost of a technology. However, this overall cost can be subdivided in different components such as input costs or assembly costs. The main learning occurs in an improvement of the underlying components. To capture this effect, a component-based learning effect was introduced, where n components are used to calculate the overall costs due to learning-by-doing effects [13]:

$$C = C_0^1 (P^1/P_0^1)^{-\alpha^1} + C_0^2 (P^2/P_0^2)^{-\alpha^2} + \cdots + C_0^n (P^n/P_0^n)^{-\alpha^n} \tag{5}$$

The underlying effect that causes the cost reduction is a more efficient technical performance. However, some cost reductions can also be caused by indirect effects such as an improved financial operation management, which may be excluded in the component-based approach. A more efficient technical performance has an impact on the cost, but also influences the environmental impact. A more efficient production can reduce the material and energy requirements. Moreover, technology improvements can also increase the environmental performance. Therefore, not only the costs and technical performance are influenced by a more efficient production, also the environmental impacts decrease due to learning effects [3].

A related effect to learning that also decreases costs and environmental impacts is the scale effect. When a technology is used on a larger scale, less material and utilities will be required per unit scale. This scale effect can occur due to different reasons, for example, the capacity of a specific process can increase, the size of the plant itself can increase, or the number of units on one location can increase. Doubling the capacity does therefore not imply doubling of the material requirement. The scale effect is considered as an additional effect to the learning effect, as it does not follow the trajectory of FOAK to NOAK. However, many studies consider scale effects as a part of a general learning effect [14]. A second related effect is the Technology Readiness Level (TRL) effect, induced by technology development and related to learning-by-searching. The TRL scale classifies the different stages of technology development and ends with commercialization of the technology at TRL 9. A FOAK technology relates to this final stage of technology development. While the TRL effect occurs between zero and the FOAK point on the x-axis of Fig. 1, learning-by-searching occurs between the FOAK and NOAK point of this x-axis. A third related effect is the background effect, where alterations in the background conditions, such as a different electricity mix or reduced material prices, induce an alteration in the technological, economic or environmental performance. This background effect can originate for example from learning effects in other technologies, new regulations or market fluctuations.

Consequently, different sorts of learning effects and related effects exist that will alter the technological, economic and environmental performance of a new technology. An overview of these effects and how these effects influence the performance in these three dimensions is provided by Table 1.

Table 1. Different sorts of learning and related effects[11]

Learning effect	Technical performance	Economic performance	Environmental performance
Learning-by-doing	Direct effect (repeated activity)	Indirect effect	Indirect effect
Learning-by-searching	Direct effect (improved activity)	Indirect effect	Indirect effect
Learning-by-using	Direct effect (consumer feedback)	Indirect effect	Indirect effect
Learning-by-interacting	Direct effect (knowledge diffusion)	Indirect effect	Indirect effect
Related effects			
Scale effect	No effect	Direct effect (less materials and fixed costs)	Direct effect (less materials)
TRL effect	Direct effect (technology development)	Indirect effect	Indirect effect
Background effect	Direct effect (altered performance of inputs or outputs)	Direct effect (altered prices of inputs or outputs)	Direct effect (altered impact of inputs or outputs)

The calculation of learning effects can lead to forecasting the future learning curve. Experience curves and learning curves are often used as synonyms. However, according to Wei, Smith [15], learning curves are a subset of experience curves. Learning curves are more related to the underlying component improvement, such as labour hours, whereas experience curves determine the overall effect on the cost of the product. However, this distinction becomes vague when a certain product is used as a component for another product. Moreover, this definition is too narrow as it limits the learning effect to economic costs or labour hours, while in this review, also the learning effect on technological performance and environmental impact is included. Therefore, learning curves and experience curves will be considered as synonyms in this study.

The larger costs of FOAK plants to NOAK plants has also been covered by the RAND method. Based on a study of 1981, different cost factors were formulated for 21 chemical processes which represent the larger costs of FOAK plants compared to prospective estimates of NOAK plants. These larger costs are due to higher investment costs and reduced plant performance of pioneer production plants, compared to their initial estimates [16]. Although this method is still used, little recent empirical evidence is available [17].

A vast literature of prospective technology assessments exists that use learning effects to forecast the NOAK potential of an emerging technology. These learning effects are in general based on retrospective studies, which analyse the historical trend in the potential of an emerging technology using a regression analysis. A review on the calculation of learning effects for electricity generation technologies has been performed by Samadi [18]. He concluded that other factors, such as commodity price fluctuations, should be included as well when studying past or future cost reductions. As different approaches are followed in using and calculating these learning effects, no standardized strategy on how to include learning effects in a reliable way is available. Moreover, no in-depth study on the calculation and use of learning effects covering multiple sectors has been performed. Therefore, no uniform strategy in the introduction of learning effects in prospective technology assessment exist. The current paper introduces a review on how the learning effects have been obtained and how they are used in prospective technology assessments, providing an overview of the different approaches found in literature. Therefore, it builds further on the review of Samadi [18], broadening the scope to a broad range of technologies and including prospective studies as well. Based on the results of this review, guidelines are provided on how to include learning effects in prospective assessments. These learning effects are not restricted to forecasting the economic performance, as mostly found in literature, but also cover the effect on future environmental impact. The main novelty of this paper is therefore the provision of an in-depth critical study of used learning effects in prospective technology assessment, including recommendations and guidelines on how to improve this practice. The main research questions of this paper are: 1) How are learning effects specified?; 2) How are learning effects obtained?; 3) How are learning effects used?; and 4) How should learning effects be used?.

2.0 Methods

A vast literature exists on learning effects on the operational level, where learning influences the manufacturing efficiency [19]. As an addition to this literature, the current study will mainly focus on a technological level, where the learning effects are attributed to the end product instead of the firm. Behavioural and psychological effects will therefore also not be discussed. The review was performed by a Web of Science search on journal papers, reviews and conference proceedings in the period from January 2014 to March 2019 including a search term on economic or environmental technology assessment and a search term on learning effects. These searching terms resulted in over 200 articles, from which a further selection was made.

The resulting selection excluded theoretical papers that only used fictive numbers to simulate their models. Other sorts of excluded papers were: papers investigating learning effects during surgeries, as these learning effects do not fit with prospective technology assessment; technological forecasting studies focusing solemnly on technological predictions without calculating learning effects; studies only assessing scale advantages; studies assessing new technologies on an earlier stage than FOAK, as these cannot be compared with mature technologies without additional scale-up measures [20] and; studies that do not focus on a specific technology or product. Consequently, papers focussing on production and operations management of individual firms were not included. Another consequence of this last criterion is the exclusion of a specific form of learning effects, designated as ‘environmental learning curves’. Environmental learning curves relate the decrease of environmental pollution to the increase in GDP or to specific learning effects [21]. These learning effects are industry-wide and therefore not related to a specific technology or product.

After this second selection 105 papers remained. These papers included 54 prospective assessments using learning effects to forecast technology development and 25 retrospective assessment calculating learning effects to explain historical trends. The other 26 studies included both a prospective and retrospective studies. This way, 80 prospective studies and 51 retrospective studies were assessed.

In the reviewed studies, the use of specific terminology such as learning rates and learning-by-doing was assessed. The specific learning rates were further assessed in detail, both including the learning rates as calculated by the retrospective studies as well as the original learning rates as used in the prospective studies. The following aspects were defined: the original data source of the underlying dataset, the years of the original data, the original case and original x- and y-axis, the specified location and the sort of learning effect. For the retrospective and prospective studies, it was assessed whether the learning effect was only considered for the end product or also for the underlying components. In addition, the functional form of the mathematical specification and the different dependent and independent variables were identified. For the prospective studies, the source of the learning effects, the goal of the prospective study, the year of the forecasted value and the inclusion of scale effects were reviewed in addition.

The quality of the learning rates was assessed based on three categories, being the number of underlying data points, the number of doublings in the range of the underlying data points and the coefficient of determination (R^2). The number of doublings and the underlying data points were often not mentioned in the reviewed studies, however, for some studies, sufficient information on the used data set was provided to calculate these values. Based on the 444 learning rates that were calculated and used in the reviewed studies, different quality categories were identified. These quality categories are provided in Table 2. Quality class A corresponds to the criteria used by the top 25% of the reviewed learning rates. Quality class B is used for relatively reliable learning rates that do not belong to this top category. Learning rates with quality class C are rough estimates, which are preferably not used by other studies. Quality class D is assigned to learning rates for which information on one of the quality class criteria is missing. If the different criteria belong to different classes, the lowest class is assigned to the learning rate.

Table 2. Quality classes for the reviewed learning rates

Class	A	B	C	D
R^2	>=0.91	0.5-0.91	<0.50	Not available
Data points	>=23	3-23	<3	Not available
Doublings	>=7.7	3-7.7	<3	Not available

3.0 Results

3.1 The definition of learning effects

Fig. 2 provides an overview of the terminology in the reviewed studies. Almost half of the reviewed studies only mentioned a general learning effect. Of the other half, all studies mentioned a learning-by-doing effect, except for one that only mentioned learning-by-searching. Some studies, such as Kavlak, McNerney [22] looked at the impact of R&D, but did not specifically mention the term learning-by-(re)search(ing). Most reviewed studies mentioned the learning rate and learning curve. The terms progress rate and experience curve were mentioned by respectively 40% and 44% of the studies.

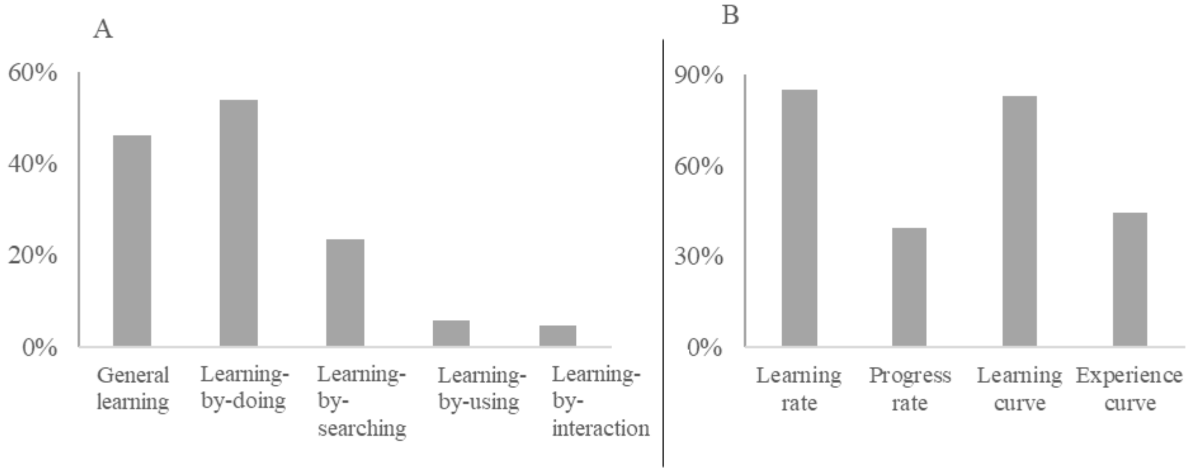

Fig. 2. Nomenclature learning parameter; (A) Percentage of reviewed studies mentioning the different learning effects; (B) Percentage of reviewed studies mentioning learning rate, progress rate, learning curve and experience curve

3.2 The calculation of learning rates

Table 3 provides an overview of the reviewed retrospective studies. The 51 studies that included a retrospective study mostly used a regression analysis with one independent and one dependent variable. The dependent variable was usually the investment cost, for example the module cost of a photovoltaic (PV) cell [22]. This is considered as a component cost as it partially defines the costs of the end product, which is electricity in this example. A focus on the end product was used by 21 studies, while 28 studies only assessed the cost of the components. The other studies focussed on improvements on a technological or environmental level.

The independent variable was for 28 studies the cumulative capacity and for 21 studies the cumulative production. The difference between the use of cumulative capacity and cumulative production is that cumulative production also includes the operational phase, while cumulative capacity does not [18]. For some energy technologies, the use of cumulative capacity can be useful to study the learning effects during for example the manufacturing of a wind turbine or a solar panel. Fifteen studies also included other independent variables to investigate their effect on the cost variation. A lot of different independent variables can be included, as this depends on the specific objective of the retrospective study. For example, besides the cumulative production of solar cells, Gan and Li [23] included three other independent variables, being silicon prices, a variable on the imbalance between supply and demand and a variable on the influence of China in the global solar panel market. Only for the prices of silicon, empirical evidence was found to prove the relation of this variable with the cost decline. Kavlak, McNerney [22] aimed to assess a broad range of underlying factors instead of only a general learning effect. They distinguished between low-level and high-level mechanisms of cost reduction. Low-level mechanisms are defined as individual variations in the parameters of the cost model, such as a yield improvement of a production process. These low-level mechanisms can be attributed to high-level mechanisms, such as learning-by-doing, learning-by-searching and scale economy effects, where the costs decrease with an increasing output. Similar work has been performed by Pillai, concluding that the cost reduction of PV is more related to input price decrease, increased efficiency, transfer of the production to China and industry investment than to the cumulative capacity [24]. Williams, Hittinger [25] included wind quality and the cumulative fluctuation of material prices (e.g. steel prices) and currency movements as independent variables. They also advocated the use of energy cost and cumulative production instead of capital cost and cumulative capacity as a better correlation for these variables was obtained.

Almost all studies used literature, database or industrial data to calculate the learning effect. These three data sources were aggregated in one data source category as it was not possible for all reviewed studies to separate them. A study that uses a different data source is the study of Esmaieli and Ahmadian [26] who used simulated results to define the cost reduction due to accumulation of the R&D budget (learning-by-searching). The learning rate quality was classified based on the previously determined quality classes (Table 2). Due to lack of information on the R^2, number of data points or number of doublings in the data set, a quality class D was assigned to learning rates in 35 studies. For 13 studies, a quality class B was assigned. Only three studies had a quality class A for their learning rates. Most studies used the power functional form, however, two studies used a different functional formulation.

Table 3. Review of the retrospective studies: how are learning effects calculated?

Technology[a]	**Dep.**[b]	**Ind.**[c]					**Data**[d]	**Quality**[e]	**Fu**[f]	**Ref**[g]
		LBD	LBS	Sc	Pr	Ot				
Solar energy										
PV module	Cc	Exp	x	x	x	x	DLI	D	O	[22]
PV module	Cc	CP		x	x		DLI	B	P	[27]
PV module	Cc	CC					DLI	D	P	[28]
PV module	Cc	CC					DLI	D	P	[29]
PV module	Cc	CP		x	x	x	DLI	D	P	[24]
PV module	Cc	CP			x	x	DLI	D	P	[23]
PV module	Ci	CC					DLI	D	P	[30]
PV module/energy	Cc/Pi	CC					DLI	D	P	[31]
PV module/system	Cc	CP					DLI	D	P	[32]
PV system	Cc	CC					DLI	B	P	[33]
PV module + BOS	Cc	CC					DLI	D	P	[34]
PV soft deployment	Cc	CC/#					DLI	D	P	[35]
PV installation	Cc	CC					DLI	D	P	[36]
PV system	Pi	CC					DLI	D	P	[4]
PV power	Pc	CC					DLI	D	P	[37]
PV power	Pc	CP	x				DLI	A	P	[38]
CSP	Pc	CC					DLI	D	P	[39]
PV module/BOS+CSP	Cc	CC					DLI	D	P	[40]
Wind energy										
Wind power onshore	Cc	R&D					Sim	D	P	[26]
Wind power	Cc	CC	x	x		x	DLI	D	P	[41]
Wind power	Pc	CP			x	x	DLI	A	P	[25]
Wind power	Cc	CC	x				DLI	D	P	[42]
Wind energy	Cc	CC	x		x	x	DLI	C	P	[43]
Biomass energy and fuel										
Biomass DCP	Pc	CC				x	DLI	B-C	P	[44]
Biomass DCP	Cc/Pc	CC		x	x	x	DLI	D	P	[45]
Biomass power	Cc	CC					DLI	D	P	[46]
Biodiesel	Pc	CP					DLI	D	P	[47]
Sugarcane ethanol	Pc	CP		x	x	x	DLI	B	P	[48]
Hydro										

Small hydropower	Cc	CC				DLI	B	P	[49]
Energy: general									
Energy technologies	Pc	CC				DLI	D	P	[50]
Renewable energy	Pc	CC				DLI	D	P	[51]
Renewable energy	Cc	CC				DLI	D	P	[52]
Low-carbon energy	Ci	CC				DLI	D	P	[53]
Power sector	Cc	CC				DLI	D	P	[54]
Electricity and storage	Pc	CC				DLI	D	P	[55]
Energy-related	Pc/Cc	CP				DLI	D	P	[15]
Fuel cell+battery									
CHP and SOFC	Cc	CP				DLI	B-C	P	[56]
Lead-acid batteries	Cc	CP				DLI	B-C	P	[57]
Li-ion batteries EV	Pc	CC				DLI	B	P	[58]
Li-ion batteries	Pc	CP				DLI	B	P	[59]
Other									
Petroleum E&P	Pc	CP			x	DLI	B	P	[60]
Desalination	Cc	CC				DLI	B	P	[61]
Shale gas and oil	Pc	CP				DLI	C	P	[62]
Aircrafts (3 fighters)	Pc	CP	x	x		DLI	A-B	P	[63]
Lamps, water heater	Pc	CP				DLI	D	P	[64]
Torpedo	Pc	CP				DLI	D	P	[65]
Software	Cc	CP				DLI	D	P	[66]
Automobile	Pc	CP			x	DLI	D	O	[67]
Hydrogen vehicle	Cc	CP				DLI	D	P	[68]
Construction bridges	Pc	CP				DLI	D	P	[69]
Pipeline compressor	Cc	CC				DLI	B, D	P	[70]

Legend:
[a] **Technology**. BOS : balance of system; gen.: generation; CSP: concentrated solar power; Biomass DCP: biomass direct combustion power generation; CHP and SOFC: Combined heat and power and solid oxide fuel cell; Petroleum E&P: petroleum exploration and production; EV: electric vehicles.
[b] **Dep**.: Dependent variable: variable on the y-axis of the learning curve. Pc: end product cost; Cc: component cost; Pi: end product environmental impact; Ci: component environmental impact.
[c] **Ind**.: Independent variable. CC: cumulative capacity; CP: cumulative production; LBD: learning-by-doing; LBS: learning-by-searching; Sc : scale; Pr: exogenous price fluctuations; Ot: other factors, including time, geographical considerations, market characteristics, supply and demand considerations, firm characteristics, environmental factors, policy incentives, output factors, other production cost and substitution ratios; Exp: experience; R&D: research and development; #: units of production.
[d] **Data**. DLI: databases, literature, industry, Sim: simulations;
[e] **Quality**: Quality criteria class as specified in Table 2.
[f] **Fu**: Functional form. P: power function; O: other functional form.
[g] **Ref**.: Reference.

An overview of the 444 learning rates, both including the learning rates as used in the prospective studies as well as the learning rates obtained by the retrospective studies, is provided in Table A.1 in the Appendix. To enable comparison between the learning rates, only the learning rates that follow the equations (1) to (5) have been included.

Fig. 3 gives an overview of the 444 learning rates with their minimum and maximum value. The lowest learning rate, equalling -11%, was found for wind power in Taiwan by Trappey, Trappey [71] and included in the review of Rubin, Azevedo [72]. This negative learning rate was explained by the wind power market in Taiwan, which is still in development. In addition, the power generation market is an oligopoly, where learning effects cannot be measured in a correct way [71]. As the geographical circumstances are responsible for the negative learning rate, this may be an inappropriate learning rate to use in other countries or on a global level. The same learning rate was found for capital costs for NGCC, based on data from 1981-1991 and was also included in the review of Rubin, Azevedo [72]. Also this learning rate was explained by oligopolistic reasons. Other technologies that included negative learning rates were for example pumped hydropower and lead-acid modules. However, these were statistically not significantly different from zero [55]. A negative learning rate was also found by Bergesen and Suh [73] for the energy conversion efficiency of CdTe PV modules. However, for this technical efficiency, a higher efficiency is better than a lower efficiency. A negative learning rate, signifying that the parameter increases over time, therefore indicates a positive effect for this parameter. The highest learning rate, 78%, was found for compact fluorescent lighting, for the period 1999-2005 for North America. However, no explanation was provided for this high value.

An R^2 for their learning rate was provided by 23% of the total learning rates. The median value for this R^2 was 0.73. Of these studies that provided a R^2, 25% had an R^2 of 0.91 and higher and the highest 10% had an R^2 of above 0.97. For 46% of the learning rates, the number of points under the regression curve was given. Sometimes these points averaged multiple values. The median number of points was 9. Of the studies for which the number of points was provided, 25% used at least 23 points, and 10% used more than 95 points. Only for 41% of the learning rates, the number of doublings in the underlying dataset could be identified. The median value for these learning rates was 6 doublings, where the top 25% had more than 7.7 doublings and the top 10% of the learning rates had more than 11.3 doublings.

Of all the learning rates, 61% were calculated for energy-producing technologies such as photovoltaics. Also, for energy storage multiple learning rates have been obtained. A third major category was carbon capture technology.

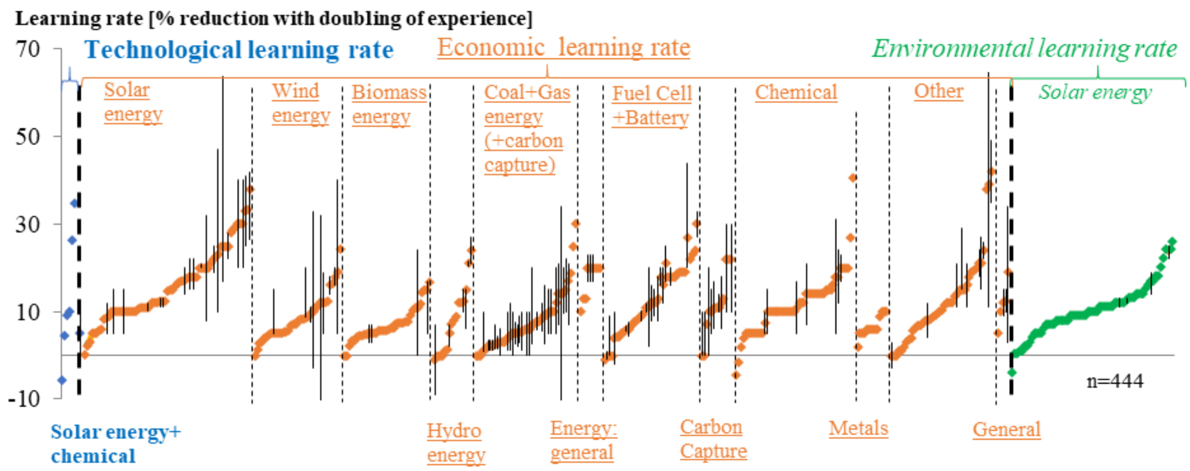

Fig. 3. Overview of the 444 learning rates in the reviewed papers, categorized according to sort of technology and technological (f.e. material requirement), economic (f.e. production cost) or environmental improvement (f.e. Global Warming Potential)

A study by Williams, Hittinger [25] found that differences in model specifications (different axes) and the temporal and geographical scope of the underlying datasets explained a large part of the variation in learning rates. Of all the learning rates, 45% was defined on a country level, 17% was defined on a global level and 35% did not specify the geographical scope. Also regional or city-based specifications were found. For 60% of the learning rates, the temporal scope was provided. A cost reduction was assumed by 84% of the learning rates, 15% analysed the impact on an environmental indicator and 1% looked at the technological performance.

3.3 The use of learning effects

Table 4 gives an overview of how the learning rates are used by the 80 prospective studies. The main included technologies were different sorts of renewable energy production. The learning effects on carbon capture technologies, focussing in general on the entire energy production plant, have also been investigated by multiple studies. Of all the prospective studies, 27 calculated their learning rates themselves. Thirty-four studies used a literature value, the other studies used either an estimate, a rule-of-thumb, a learning rate from a different technology or an unspecified source. There was no prospective study that used a learning rate with quality class A. Learning rates with quality class B were used by 19 studies. Quality class C was used by 6 studies. However, 70 of the 80 prospective studies used learning rates with quality class D, which means information on the R^2, number of data points or number of doublings in the dataset was missing.

Most studies used a one-factor learning curve. The inclusion of scale effects varies largely, sometimes it is part of the learning rate and sometimes it is a separate effect. The predictions cover time periods between 2016 and 2100. Fifty-nine studies used the learning to predict the expected cost of a component of the total product price. Two studies used the learning rate to predict a change in the environmental impact. Cumulative capacity was used by 46 studies where cumulative production was used by 22 studies. Most studies did not incorporate other cost reduction factors. An exception was the study by Gan and Li [23], who assumed silicon prices to be constant and used projected oil prices till 2035 for their predictions.

The reviewed studies aimed for a forecast of the future cost of the technology for different methodologies. The main applications of the use of learning effects are the provision of future cost estimates and broader studies investigating trends in for example the energy market. Three studies performed an environmental impact analysis, being life cycle analysis (LCA) or an input-output analysis. One study assessed the future trend in energy consumption. A national learning rate was used by 38 studies and 23 studies used a global learning rate. The power-law equations of (1)-(5) were used by 68 studies to specify the learning effect. A linear relation was used by 6 studies.

Table 4. Use of learning effects in technology assessments

Technology[a]	**LR**[b]	**Q.**[c]	**Yr**[d]	**Dep.**[e]	**Ind.**[f]	**Me**[g]	**Sc**[h]	**Fu**[i]	**Ref**[j]
Solar energy									
PV system	C	D	2025	Pi	CC	LCA	S	P	[4]
PV module	C	B	2020	Cc	CP	CA, Re	S	P	[27]
PV module+ BOS	C	D	2020	Cc	CC	CA, Re	S	P	[34]
CSP plant	L	D	2050	Cc	CC	CA	u	P	[74]
PV module	C	D	2030	Cc	CC	CA	u	P	[28]
CSP	C	D	2050	Pc	CC	CA	S	P	[39]
PV power generation	C	D	2050	Pc	CC	COM	I	P	[37]
CSP	L	D	u	Pc	CC	CA	S	P	[75]
PV system	C	B	2016	Cc	CC	SDM	u	P	[33]
CdTe PV module	L/Es	D	2030	Cp/c	CP	LCA, CA	I	P	[73]
PV module	C	D	2020	Ci	CC	EnA	u	P	[30]
PV/BOS/CSP	C	B,D	2030	Cc	CC	CA	u	P	[40]
PV module	C	D	2030	Cc	CC	CA	u	P	[29]
PV power generation	RoT	D	u	Pc	CC	CA	I	P	[76]
PV power installation	L	D	2026	Cc	CC	ABM	u	P	[77]
CSP and PV installation	L	D	2050	Cc	CC	CA	I	P	[78]
PV module	C	B	2035	Cc	CP	CA	S	P	[23]
PV module/system	C	D	2030	Cc	CP	CA	I	P	[32]

Wind energy									
Offshore wind	L	D	2040	Pc	CC	GEM	u	u	[79]
Wind energy	C	D	2050	Pc	CC	Survey	u	P	[80]
Wind farm	L	D	u	Cc	#	COM	S	P	[81]
Hydro energy									
Wave energy	L	D	2030	Cc	CC	CA	I	P	[82]
Marine energy	RoT	D	2025	Pc	u	CA	I	u	[83]
Marine energy	E	D	2050	Cc	CC	CA	I	P	[84]
Energy: general									
Renewable energy	L	B	2050	Cc	CP	GEM	u	P	[85]
Energy generation technologies	u	D	2050	u	u	PEM	u	P	[86]
Power sector	C	D	2050	Cc	CC	PEM	I	P	[54]
Wind + solar energy	L	D	u	Cc	CC	ROA	u	o	[87]
Renewable energy and batteries	u	D	2050	Cc/Pc	CP	CA	u	P	[88]
Electricity and storage	C	D	2040	Pc	CC	CA	I	P	[55]
Energy production	L	B-D	2050	Cc	CC	COM	u	P	[89]
Energy technologies	C	D	2050	Cc	CC	Re	I	P	[42]
Renewable energy	L	D	2021	Cc	CC	CA	u	P	[90]
Power systems	L	D	20 y	Cc	CC	COM	u	P	[91]
Energy technologies	C	D	2040	Pc	CC	COM	I	P	[50]
Renewable energy	L	D	2100	Pc	CP	COM	I	P	[92]
Renewable energy	C	D	2020	Pc	CC	PA	S	P	[51]
Renewable energy	L	D	2030	Pc	CP	CBA	u	P	[93]
Renewable fuels	L	B	2050	Cc	CC	CA	S	P	[94]
Low-carbon energy technology	L	D	2050	Cc	CC	PEM	u	P	[95]
Low-carbon energy technology	C	D	2040	Ci	CC	MRIO	u	P	[53]
Renewable energy	C	D	2020	Cc	CC	COM	u	P	[52]
Bioenergy and biofuel									
Biofuel conversion	L	D	u	Pc	CP	PEM	S	P	[17]
Biofuels	RoT	D	2050	Cc	CC	CA	E	P	[96]
Cellulosic ethanol	RoT	D	2020	Pc	CP	COM	u	P	[97]
Biogas+ biofuel	OT	B	2042	Cc	CP	CA	S	P	[98]
Biomass power	C	D	2020	Cc	CC	Re	u	P	[46]
Biomass jetfuel	RoT	D	40 y	Cc	CP	CA	S	P	[99]
Biorefineries	RoT	D	2022	Cc	CC	CA	S	P	[100]
Biofuels	u	D	2020	Cc	Y	CA	S	Ln	[101]
Biofuels	E	D	2020	Cc	Y	CA	S	Ln	[102]
Chemical									
H_2 production	L	B-D	2060	Cc	CC	CA	u	P	[103]
Power-to-gas	L	D	2050	Cc	CC	CA	S	P	[104]
Hydrogen for energy	u	D	2050	Cc	CC	CA	S	P	[105]
Biohydrogen	OT	B	2042	Cc	CP	CA	S	P	[106]
Carbon Capture									
CCS	L	D	40 y	Cc	u	IDM	I	u	[107]
CCR plants	L	D	u	Cc	Y	IDM	u	Ln	[108]
CCS	L	B,D	2050	Cc	CC	CA	u	P	[109]
CCS	u	D	2100	Cc	CC	PA	u	P	[110]
NGCC	L	D	u	Cc	#	CA	S	P	[111]
CCS	L	B-D	u	Cc	CC	CA	u	P	[112]
Coal with CCU	L	B-D	n/a	Cc	CP	CA	S	P	[113]
Coal-to-Liquid/CCS	L	B-D	u	Cc	CP	CA	S	P	[114]
Fuel cell+battery									
H_2 fuel cell vehicles	L	B,D	2050	Cc	CP	LCC	S	P	[115]
Batteries for EV	L	D	2030	Cc	C	CA	I	o	[116]
Lead-acid batteries	C	B-C	u	Cc	CP	CA	u	P	[57]

Li-ion batteries	C	B	20 y	Pc	CC	PA	I	P	[59]
Other									
H_2 vehicle	C	D	2050	Cc	CP	PEM	u	P	[68]
Biobased plastic	E	D	2030	Cc	M	SDM	I	Ln	[117]
UHVPT	L	D	2020	Cc	#	COM	u	P	[118]
Desalination	C	B	2050	Cc	CC	Re	I	P	[61]
Toilet paper to energy	L	B,D	u	Cc	CC	CA	S	P	[119]
Iron, steel sector	L	D	2050	Cc	CP	COM	u	P	[120]
Urban low-carbon measures	u	D	2050	u	Y	CA	u	Ln	[121]
Biobased propylene	L	D	u	Cc	CC	CA	u	P	[122]
Lamps, solar water heater	C	D	40 y	Pc	CP	PA	u	Ln	[64]
Software	C	D	u	Cc	CP	CA	u	P	[66]
Electric vehicles	u	D	2050	Cc	CC	CA	u	u	[123]
HCPV	L	D	2020	Cc	CC	CA	u	P	[124]
Aircraft	E	D	n/a	Cc	CP	CA	u	P	[125]

Legend

[a] **Technology**. BOS: balance of system; CSP: concentrated solar power; CCS: carbon capture and storage; CCR: carbon capture ready; NGCC: natural gas carbon capture; Coal with CCU; coal with carbon capture and usage; Coal-to-L with/o CCS: coal to liquid with or without carbon capture and storage; EV: electric vehicles; UHVPT: Ultra high voltage power transmission; HCPV: high concentrated photovoltaic power plant.

[b] **LR**: Learning rate. C: calculated; L: literature; Es: estimate; RoT: rule-of-thumb; OT: other technologies; u: unspecified.

[c] **Q.**: Quality class, see Table 2.

[d] **Year** = Year of the forecasted value. u: unspecified; y: years; n/a: not applicable.

[e] **Dep.**: Dependent variable: variable on the y-axis of the learning curve. Pc: end product cost; Cc: component cost; Cp: component performance; Pi: end product environmental impact; Ci: component environmental impact.

[f] **Ind.**: Independent variable: variable on the x-axis of the learning curve. C: capacity; #: units of production; Y: years; M: months; u: unspecified; uc: unclear; n/a: not applicable.

[g] **Me**: Methodology. CA: cost analysis; Re: regression; com: cost optimization model; PA: policy analysis; ROA: real options analysis; PEM: partial equilibrium model; GEM: general equilibrium model; IDM: investment decision model; Survey: expert elicitation survey; LCA: life cycle analysis; EnA: energy analysis; CBM: cost breakdown model; MRIO: multi-regional input output model; ABM: agent-based modelling; CBA: cost-benefit analysis.

[h] **Sc** = Scale. I: included in the learning effect; E: specifically excluded from the learning effect; S: separately assessed; u: unspecified.

[i] **Fu** = Functional form of the learning curve. P: power function; Ln: linear function; o: other function.

[j] **Ref** = Reference.

4.0 Discussion

Based on the reviewed studies, guidelines and recommendations are formulated on what kind of learning effects to include, how to calculate these learning effects and how to use them in prospective technology assessments. An example of a prospective technology assessment to calculate the future cost of solar panel recycling is used to illustrate the recommendations.

4.1 Recommendation 1: Combine component and end product level

Learning rates can be used both on the overall end product level as well as on the level of underlying components. A disadvantage of learning effects on the end product level, is that the use of price data has more severe effects than on a component level. When using the component level, prices are only used for the underlying components and not for the overall technology. In the reviewed studies, price data are often used instead of cost data, as price data are more readily available. However, price data may not follow the same 'path' as cost data. Initially, the price of a new product might remain constant. Only after a shake-out phase, where the price reduces drastically, the price will follow the same trend as the costs [11]. The component-based approach also has a disadvantage compared to the end product approach. Nemet [126] found that when only the improvements in the underlying components were included, a large fraction of the overall end product learning effect remained unexplained. Besides the learning effect, other factors such as scale and input price variations influence the prospective performance of a new technology. If a component-based approach is followed, the forecasted value of these related effects needs to be included separately from the learning effects. However, when the learning effects are included following an end product approach, these related effects will all be included in the forecasted economic cost or environmental impact. As both approaches have their advantages, a combined approach, including both the end product and component-based learning effects, is proposed.

In the example of solar panel recycling, following the end level approach, historical data on the total recycling costs are used to estimate the historical cost reduction and to extrapolate this to a future value. Following the component level approach, the recycling process is divided into different subprocesses, such as the collection and the separation of the modules. Historical data on these different processes is used to calculate the total cost reduction of these different process components and to extrapolate this into the future. The sum of the extrapolated process components costs gives then the prospective cost of solar panel recycling and can be compared with the estimated cost from the first approach.

4.2 Recommendation 2: Combine technical and economic/environmental dimension

In the first recommendation, the combined use of an end product level and a component level learning rate was recommended. On a component level, also two approaches are available. In a first approach, the learning rate is calculated from an economic/environmental perspective, where the historical economic cost or environmental impact for the different cost or impact components is assessed. Following a second approach, the learning effect on the underlying technical performance is calculated, using bottom-up modelling. This approach allows one to use similar system boundaries and assumptions to forecast both the economic as well as the environmental potential of the emerging technology. This second approach has also been advocated by Nadeau, Kar [127], referring to it as dynamic process-based cost modelling, and arguing that this approach enabled the identification of the main cost learning drivers that could differ from one technology to the next. The learning effect can therefore be included on the level of technical performance, economic costs or environmental impacts, where the learning effects on the technical performance will influence the performance in all three dimensions. This concept is illustrated in Fig. 4.

Besides the component level and the end product level which occur in the foreground, learning effects can also occur further along the value chain, in upstream or downstream processes in the background [73]. For example, a learning effect in a waste treatment process can lower the downstream environmental impact of this waste product. Modelling all the learning effects in these background processes on the level of their technical performances would imply an unrealistic modelling effort. Therefore, the learning effects on these background processes are recommended to be included on the level of the economic or environmental performance, for example as a learning rate in the cost of the input. The bold parameters in Fig. 4 illustrate where the main learning effects are modelled for the component-based approach; being on the technical process level and in the inputs and outputs for technical, economic or environmental performance.

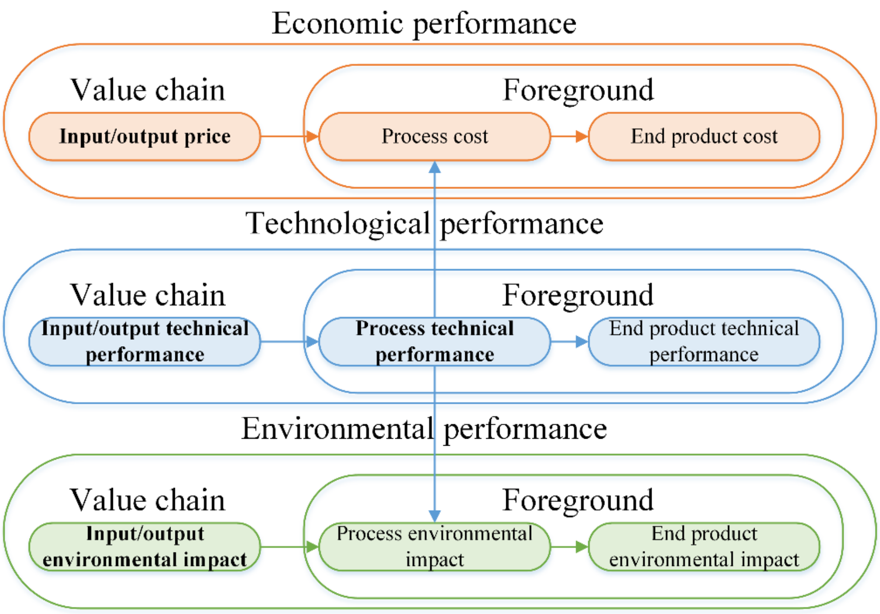

Fig. 4. Learning rates at different levels and dimensions (partially based on Bergesen and Suh [73])

Using the example of solar panel recycling, the component costs are assessed in further detail. Instead of using the total component costs, the evolution in the different underlying parameters is assessed. For example, more efficient logistics may reduce the transport costs or a higher metal recovery efficiency may increase the profits; both lead to a smaller net recycling cost. If these parameter alterations are extrapolated, a future total net recycling cost can be calculated and compared with the value from the end product costs, where only the alteration in the total cost was assessed and extrapolated.

4.3 Recommendation 3: Combine extrapolated and projected values

Economic studies often extrapolate learning rates to incorporate technological evolution. Environmental studies, in general, make use of projected or historic values without specifying a learning rate. For example, Pehnt [128] provided future environmental impact estimates on renewable energy technologies by means of projected efficiency improvements. Pawelzik and Zhang [129] introduced a Life Cycle Assessment (LCA) with technological advances over time, which uses industry estimates for multiple technological parameters for different years. In the technology-evolution LCA of Mendivil, Fischer [130], the environmental impact for ammonia production from 1950 to 2000 was estimated, based on technological improvements and environmental regulations. A learning rate could have been calculated from these results, however, this was not included.

The use of projected values can also be found in economic studies. A floor cost, as for example used by Ruffini and Wei [115], is a minimum achievable cost, specified by the point on the learning curve where the costs cease to decrease with experience, which is the NOAK point. The use of a floor cost prevents that the learning effect pushes the costs to an unrealistic low level. Also technological forecasts or roadmaps on future technological performance can be used to provide projected values for future costs [131]. In these studies, the forecasted values are usually based on expert estimates. These expert estimates can be obtained by expert elicitation studies, as performed by Wiser, Jenni [80] and Few, Schmidt [132]. Expert estimates can be useful to estimate a maximum achievable value (MAV), similar to the concept of floor cost, and other projected values.

The recommended learning effect is illustrated in Fig. 5 and combines both strategies to define the learning effects: 1) extrapolation of the learning curve; 2) estimation of future values, by using the MAV or other projected values.

In the example of solar panel recycling, the extrapolated values from both the component-based approach and end product approach are supplemented with a projected value. For the end product approach, this means that an estimate on a potential cost estimate in the future is made, for example based on expert opinions. In the component-based approach, estimates for all parameters are made. For example, instead of extrapolating the historical recovery efficiency evolution, an estimate on what this recovery efficiency could be in the future is included. Based on all these estimated future values, a total projected recycling cost for the component-based method can be obtained as well.

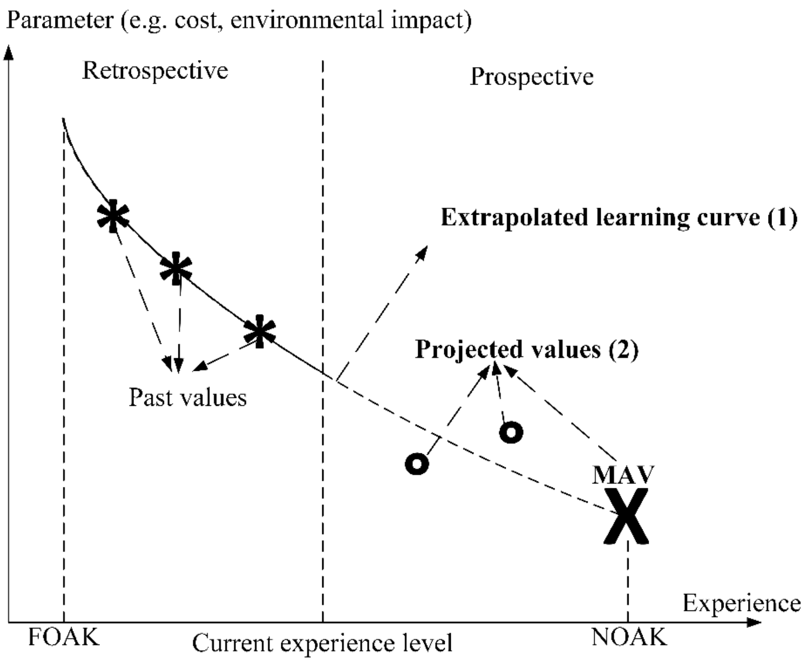

Fig. 5. Two different ways to define learning effects, (1) through extrapolation of the learning curve; (2) through projected values

4.4 Recommendation 4: Combine learning-by-doing and learning-by-searching

In the reviewed studies, learning effects were in general defined as a general learning rate or as a learning-by-doing effect. Although multiple studies mentioned the impact of R&D through learning-by-searching, it was only included in five studies. Lin and He [45] investigated the correlation between learning-by-doing and learning-by-searching. The conclusion was made that learning-by-doing and learning-by-searching could not really be separated. Finding historic data to calculate learning-by-searching rates is a challenge [72]. However, finding future values to extrapolate this learning effect is even more challenging – if not possible at all - as illustrated by the fact that none of the reviewed prospective studies uses independent variables to include learning-by-searching effects. Unless reliable data is available to calculate historic learning-by-searching rates and to extrapolate them for future values, it is therefore recommended to use a learning-by-doing rate in this case.

However, when following the second approach from recommendation 3, namely the use of projected values, learning-by-searching can have a large added value. Patent data and published experimental data may provide insights on what the projected value of a NOAK technology can be. Therefore, it is recommended to use learning-by-doing rates when the learning curve is extrapolated and to combine both learning-by-doing and learning-by-searching considerations when estimating projected values. As both approaches can have a different level of uncertainty, it is important to take both into account when calculating the uncertainty range on the results.

In the example of solar panel recycling, the extrapolated values will follow a learning-by-doing approach as no reliable data is available on independent variables that could capture the learning-by-searching effect. For the projected values, the improvement in different parameters is not only based on learning-by-doing but also on learning-by-searching. Patents and scientific literature can be consulted to obtain an overview of the research and development for recycling processes and estimated values for their expected costs. Based on this information, more accurate projected values can be used, both on a component level as well as on an end product level.

4.5 Recommendation 5: Tier-based method with quality criteria

To calculate the learning effect, a tier-based approach is proposed, containing different procedures to calculate the learning curve (Fig. 6). The appropriate procedure depends on the available data, where the procedure from a higher tier is always preferred. In the first tier, the learning curve is estimated using specific data for the assessed technology for a specific location for different cumulative production levels, leading to a regression with a good R^2, number of data points and spread of data points. The quality classes as defined in Table 2 can be used for this purpose.

In the next tier, no learning rate is calculated but a literature value of the learning rate of the technology is used. This literature learning rate should originate from the same technology with a similar geographical and temporal scope. The same quality and transparency classes are used to select an appropriate learning rate. If no appropriate learning rate is found, a learning rate for a similar technology can be used, again based on the classes. If in one of these first tiers a learning rate is obtained, the projected values are calculated and discussed with experts. This approach follows recommendation 3 to use both extrapolated learning rates and projected values. If also no learning rate for a similar technology is available, the projected values are directly used to calculate the learning rate. Preferably, this is also based on historical information on the evolution of the parameters. The obtained learning rate can be checked with the range of reviewed learning rates as provided in Table A.1. in the Appendix.

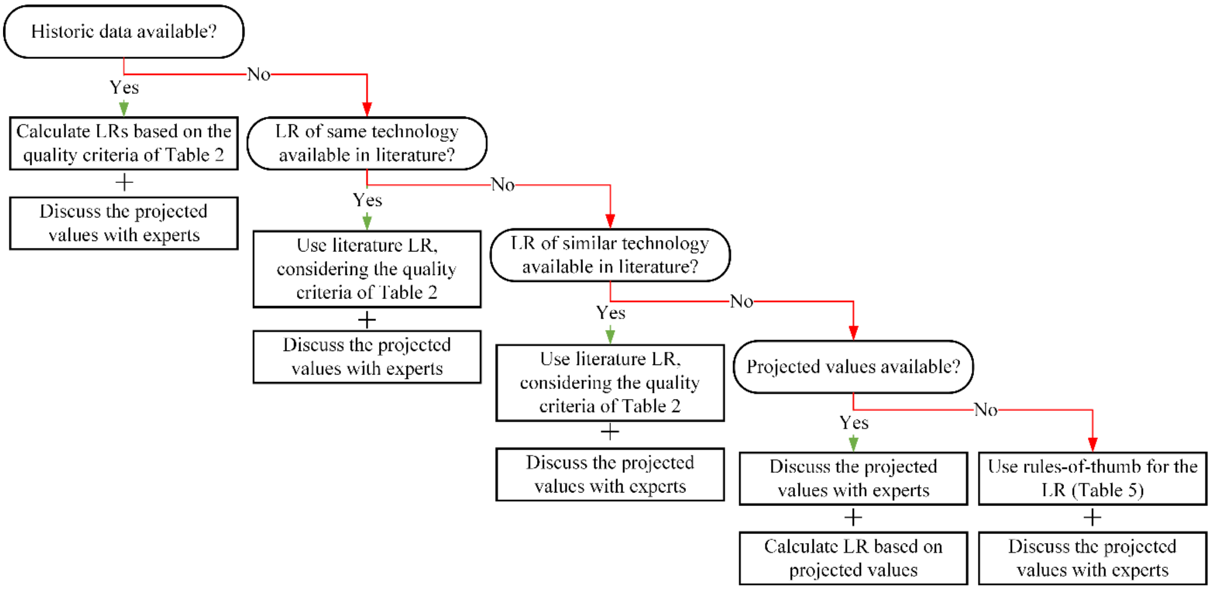

Fig. 6. Tier-based approach to calculate learning effects

If no projected values are available, rules-of-thumb can be used as for example discussed by Jones [133], [134] and by Hong et al [38], based on the technological maturity categories of Jamasb [10]. In these categories, emerging technologies are at the earliest stage of maturity. In this stage, a technology can in general not compete yet with conventional technologies and still endures many market constraints. Therefore, the learning potential remains low. However, when this emerging technology becomes more mature, it will become an evolving technology where much higher learning effects are observed [10]. An overview of these rules-of-thumb is provided in Table 5. These rules-of-thumb cover the reduction in labour hours or costs per production unit. No rules-of-thumb were found for learning effects on the environmental impact. When using rules-of-thumb, it is crucial to include uncertainty considerations and to consider the underlying learning drivers, which may vary widely between different industrial sectors [133]. Typical learning drivers to reduce labour hours on an operational level were identified by Delionback [134], including improved methods or method innovations; process improvement or time reduction; improvements in design for increased manufacturability; debugging of engineering data; rate of production and; introduction of a machine to replace hand operations. In general, learning effects are often associated with small, mass-produced systems, which can be found in a broad range of sectors [100]. This can be explained by the potential level of standardisation that can be achieved. Large-scale technologies have a lower potential for standardisation and their installation and construction depends in general on site-specific characteristics [18]. For more insights on these general learning drivers, the literature on learning effects on the operational level can be consulted [19, 135]. Rules-of-thumb for technologies within a specific sector can also be used. For example, Karali, Park [120, 136] provide general learning rates for energy-efficient technologies in the US iron and steel sector based on the level of market penetration of the specific technology.

Table 5. Rules-of-thumb for learning rates, the dependent variable is hours per unit on the operational and industry level and cost per unit on the technology level [10, 38, 133, 134]

Operational level	Proportion manual/machine-based operations [%/%]	Learning rate [%]
Simple task	100/0	15

	75/25	12.5	
	50/50	5	
	25/75	2.5	
	0/100	0	
Complex task	100/0	25	
	75/25	20	
	50/50	15	
	25/75	10	
	0/100	5	
Technology level		Learning-by-doing rate [%]	Learning-by-searching rate [%]
Mature technology (e.g. pulverized fuel)		Medium 1.96-12.39	Low 1.25-6.03
Reviving technology (e.g. combined heat and power)		Very low 0.23-0.65	Medium 8.9-20.6
Evolving technology (e.g. waste to electricity)		High 13.1-41.5	High 36.7-43.7
Emerging technology (e.g. offshore wind energy)		Low 1.0-2.2	Low 4.9-5.3
Industry level		Learning rate [%]	
Aerospace		15	
Shipbuilding		15-2	
Complex machine tools for new models		15-25	
Repetitive electronics manufacturing		5-10	
Repetitive machining punch-press operation		5-10	
Repetitive clerical operation		15-25	
Repetitive welding operations		10	
Construction operations		10-30	
Raw materials		4-7	
Purchased parts		12-15	

To calculate the learning rate as is required in the first tier, the underlying data needs to be harmonized. For example, cost data needs to be corrected for inflation and economies-of-scale. For inflation correction, cost indices such as the Chemical Engineering Plant Cost Index can be used. To correct for economies-of-scale, the data needs to be defined on the same production scale, for example by use of the six-tenth rule. This rule is a rule-of-thumb to calculate the change in costs when the equipment capacity changes. In addition, volatile input prices can play a role. Although upstream learning effects can induce this, many other market mechanisms can have a large influence on the input price. For example, in the study of Schoots, Kramer [137], the cost data was corrected for inflation rates, exchange rates and economies-of-scale effects and the price curve of platinum was included in the model. The obtained learning curves vary in reliability, based on the adopted tier. Accordingly, a scoring matrix could be developed, similar to the Pedigree matrix in LCA [138], to assign a quality score or an uncertainty range to the learning effects.

The five recommendations are summarized in Table 6. These recommendations can be considered as ideal and may not always be feasible to perform due to time, data or other limitations. However, care should be taken when trying to forecast the future as the level of uncertainty might be high. It is possible that combining the different approaches yields disparate results. In this case it is recommended to analyze the discrepancy in further detail. It may be explained by underestimating or overestimating the learning potential on the component level. However, it is also possible that a critical learning step on the component level is expected that would alter the historical trend observed on the end product level. In addition, also the quality of data used for both approaches can provide an explanation for differing results. If this analysis cannot provide an explanation for these differing learning rates, it is advised to use the results for both approaches to make different scenarios. This way, an uncertainty range on the results can be obtained.

Table 6. Summary of the recommendations

Recommendation	Approach 1	Approach 2	Approach 3	Approach 4
1. Assessment level	End product	End product	Component	Component
2. Learning dimension	Economic/ environmental	Economic/ environmental	Technical + background	Technical + background
3. Future values	Extrapolation	Expert estimate	Extrapolation	Expert estimate
4. Learning effect	LBD	LBD+LBS	LBD	LBD+LBS
5. Data requirement	Tier-based method	Expert opinion, research data	Tier-based method	Expert opinion, research data

Abbreviations = LBD = learning-by-doing; LBS: Learning-by-searching

4.6 Integration of learning effects in prospective technology assessment

The use of learning rates in prospective technology assessments is embedded in the overall structure of the assessment as illustrated in Fig. 7. The methodologies to assess the impact of a technology, such as LCA, techno-economic assessment or an integrated environmental techno-economic assessment, usually consist of the same general steps [139]. The first step defines the goal and scope and includes a market study, covering the definition of the production scale or functional unit, the identification of potential end product applications and the definition of the system boundaries. To enable the inclusion of learning effects, the specific learning effects under assessment need to be specified. Using the compound annual growth rate, the future cumulative production can be forecasted [94]. This step also includes a search for historical cost and environmental impact values, following the tier-based method of recommendation 5. This way, the learning rates on the end product level, following the first approach of recommendation 1 can be calculated.

The second step of prospective technology assessment includes the characterization of the technology by means of mass and energy balances, which can lead to a life cycle inventory. A detailed analysis of the technological specifications and the different component characteristics is performed, including the learning effects, based on extrapolated learning rates and projected values.

The third step of the prospective technology assessment is the impact assessment step, including an economic or environmental analysis or both. This step is based on the previous mass and energy balance and incorporates the learning effects of the technological components. For prospective technology assessments, it is important to ensure that there is no temporal mismatch between the foreground and the background processes [140]. A temporal mismatch occurs when for example the electricity price of 2010 is used to calculate a production cost in 2015. Besides market fluctuations, also changes in background systems such as the electricity mix need to be incorporated. Based on the mass and energy balance, the economic and environmental potential can be defined, both for historical values as well as for future estimates, incorporating the learning rates on all parameters and alterations in external factors.

In the last step of the prospective technology assessment, additional analyses such as a sensitivity analysis or an uncertainty analysis are added to interpret the results. The introduction of learning effects in prospective technology assessment introduces additional uncertainty, as the aim of the learning effect is to forecast a future trend. Most-likely, best-case and worst-case values of the learning effects can be used to illustrate the effect on the output indicators. Data quality considerations, as introduced in the determination of the learning rates, can also be used in the uncertainty analysis. The method of Lafond, Bailey [141] can be used to provide a distributional forecast of the error rate of the estimated output indicators. However, this can only be used in learning rates from the first tiers, as the underlying data for the calculation of the learning rate is required.

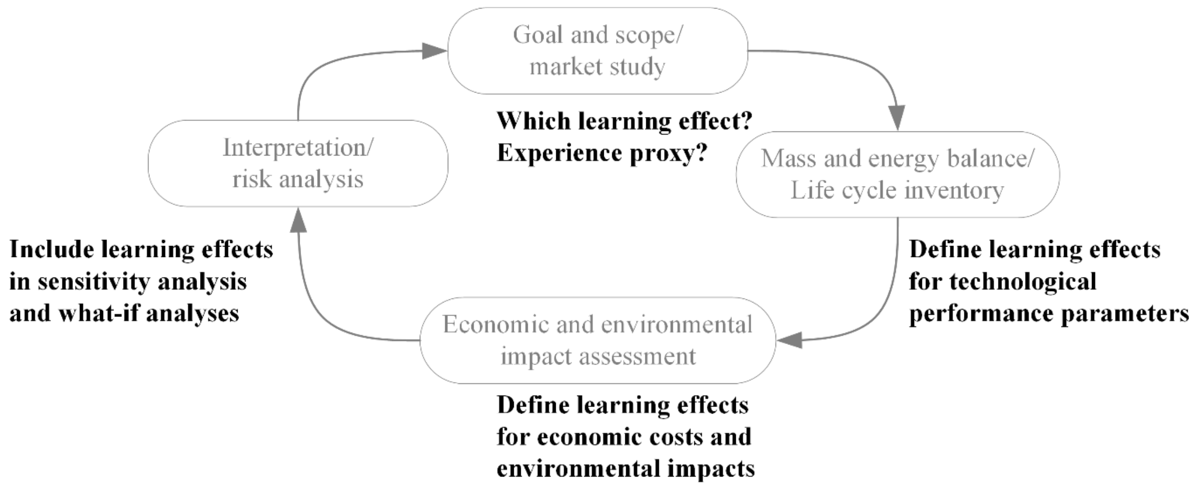

Fig. 7. Inclusion of learning rates in the four general steps of prospective technology assessment

Care should be taken that learning effects are not used to double-count expected performance improvements. For example, if the labour requirement has been estimated for a mature technology, an additional decrease due to learning effects might be unrealistic.

4.7 Potential applications

Learning effects have been mainly used in energy-related technologies. However, also in other sectors emerging technologies exist that still need to follow their learning path. A particular field of interest are new technologies enhancing a circular economy. New recycling technologies or new concepts such as design-for-disassembly or product-service systems will still experience learning effects. An example of such a potential application is the solar panel recycling technology as used to illustrate the recommendations. However, although the concept of technological learning curves as explored in this study can be applied to specific technologies, other innovative measures such as new business models may require a different interpretation of the learning effect concept.

In general, learning effects have been used to quantify the reduction in labour hours and costs of a new technology. This is also illustrated by the rules-of-thumb as provided by Table 5. The learning effects on the environmental impact of a technology have been included by a few studies, however, no rules-of-thumb have been identified yet. An interesting path for further research would be a harmonized economic and environmental assessment, both including learning effects, to assess to what extent learning in the economic and environmental dimension are related and if the underlying learning drivers correspond. This way, also rules-of-thumb for the environmental impact may be deduced.

There are multiple sectors where applications of learning effects in prospective technology assessment are relevant. A first major application can be found in research and development to forecast future technical, economic and environmental performance of a new technology. By investigating the underlying drivers of the learning rates, the parameters with the largest learning potential can be identified and further optimized. A second application of learning effects is on an investment level. Learning effects can provide additional information on the future potential of a technology at the moment of the investment decision. In addition, information on the expected learning effects of competing technologies can be interesting for investors. A third application is the use of learning effects by policy makers. By incorporating learning effects, future technology trends can be analysed and the impact of new policies can be modelled.

5.0 Conclusion

Learning effects have been used extensively in prospective technology assessments. However, their use is mostly limited to a few sectors such as energy production and storage technologies. Most of the learning curves focus on the investment costs to predict the learning path of an emerging technology. However, also the environmental impacts will reduce when the experience increases. The underlying factors that cause these learning effects are often not investigated. Based on an extensive literature review, guidelines are proposed. With these guidelines, learning effects can be estimated in a broader range of technology sectors. Moreover, the disadvantage of emerging technologies compared to conventional technologies, regarding to their higher economic costs and potentially higher environmental impacts, can be countered by providing reliable forecasts on their future potential.

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