Received: 19 December 2021 | Revised: 5 September 2022 | Accepted: 9 September 2022

DOI: 10.1002/wene.463

ADVANCED REVIEW

WIREs ENERGY AND ENVIRONMENT WILEY

Technological learning: Lessons learned on energy technologies

Reinhard Haas | **Marlene Sayer** | **Amela Ajanovic** | **Hans Auer**

Energy Economics Group, Vienna University Technology (TU Wien), Vienna, Austria

Correspondence
Reinhard Haas, Energy Economics Group, Vienna University Technology (TU Wien), Gußhausstraße 25-29, 1040 Vienna, Austria.
Email: haas@eeg.tuwien.ac.at

Funding information
Climate and Energy Fund; TU Wien Bibliothek

Edited by: Peter Lund and John Byrne, Co-Editors-in-Chief

Abstract

The concept of technological learning is a method to anticipate the future development of the costs of technologies. It has been discussed since the 1930s as a tool for determining manufacturing cost reductions, starting in an airplane manufacturing plant, by means of learning curves and has been widely used since the 2000s in energy models to endogenize technological change. In this paper, the theoretical concept of technological learning based on energy technologies is analyzed based on examples from the literature. The main low-carbon power generation technologies, photovoltaics, concentrated solar power, wind and nuclear energy were analyzed, showing different cost trends. Additionally, the impact of policy support on technological learning was discussed in concrete examples of bioethanol and heat pumps. We find that the homogeneity and the modularity of a technology are essential for high learning rates. A good proof is the manufacturing cost development of photovoltaics in recent decades, where a rather stable learning rate of 20% has been identified. On the contrary, nuclear power did not evolve into a homogeneous technology due to required environmental adaptations caused by accidents and the lack of standardization and application of new engineering approaches. In that case, the overall price further increased. Finally, another important condition is stable legal and regulatory conditions regarding the implementation.

This article is categorized under:

Policy and Economics > Green Economics and Financing

KEYWORDS

energy technologies, learning rates, technological learning

Abbreviations: CSP, concentrated solar power; FIT, feed-in tariffs; LCOE, levelized cost of electricity; ONC, overnight costs; PPA, power purchase agreements; PV, photovoltaics; TGC, tradable green certificates; TL, technological learning; TRL, technology readiness level.

1 | INTRODUCTION

Long-term forecasts of the future costs of energy supply and demand technologies are difficult to make due to some uncertainties and should therefore be interpreted with appropriate caution. Nevertheless, longer-term statements cannot be made without taking into account possible future cost reductions and efficiency increases in the calculation.

The idea of technological learning (TL) goes in principle along with the dynamic development of manufacturing costs of any technology, as it is well known that the cost of technology is expected to drop as installed capacities increase. That is to say, it is of interest to identify whether, with increasing capacities, a related decrease in manufacturing costs takes place and to what extent.

In recent years, there have been major literature reviews on various energy technologies. Rubin et al. (2015) analyze electricity supply technologies in view of learning rates, including coal-based, natural gas-fired, nuclear, hydro, wind, PV, biomass, and geothermal power plants. They discover a significant range of predicted learning rates among the investigated studies. Another review on energy supply technologies has been conducted by Samadi (2018). He analyzes 67 empirical studies between 1997 and 2017 and finds that renewable energy technologies show a substantial negative link between cost and installed capacity. Furthermore, he acknowledges the limitations and uncertainties of the technological learning concept, like commodity price variations, or stricter environmental and safety regulations, that may have also influenced the technology costs. Despite that, the analysis suggests that learning does occur when an energy generation technology is more widely deployed (Samadi, 2018). Thomassen et al. (2020) build upon this work and define recommendations for incorporating learning curves based on the analyzed literature. Their main suggestion is to include environmental factors besides the learning concept because as the experience of renewables grows, so will the negative effects on the environment. Another major work on experience curves is Junginger and Louwen (2020) giving a comprehensive overview, including case studies on major renewable technologies. The learning effect has been empirically observed in the past and applied to various technologies. A broad range of literature investigates the learning rates of the most common renewable technologies, such as photovoltaics (PV; e.g., Goldschmidt et al., 2021; La Tour et al., 2013; Liu et al., 2021; Mauleón, 2016; Nemet, 2006) and wind technologies (e.g., Häner, 2021; Junginger et al., 2005; Lindman & Söderholm, 2012; Odam & Vries, 2020; Tang, 2018; Yu et al., 2017). In Yao et al. (2021), the future levelized cost of electricity from wind, solar, geothermal, hydropower, and bioenergy is analyzed with the learning curve concept, concluding that wind and solar show a substantial cost decrease due to competition and upgraded technologies. In contrast, the others require more site-specific adaptations for each project, making them more expensive. Also, nuclear energy has been widely analyzed (e.g., Berthélemy & Escobar Rangel, 2015; Escobar Rangel & Leveque, 2015; Grubler, 2010; Haas et al., 2019; Lang, 2017; Lovering et al., 2016), which will be further outlined in Section 3. Additional research is conducted on storage technologies such as batteries (e.g., Beuse et al., 2020; Matteson & Williams, 2015a, 2015b; Nykvist & Nilsson, 2015) and power-to-gas (Ajanovic & Haas, 2019; Böhm et al., 2019), as well as hydrogen production (Schoots et al., 2008) and fuel cells (Wei et al., 2017). Further, bioenergy systems (Junginger et al., 2006), the development of fossil fuel systems with carbon capture (Li et al., 2012), transition scenario to renewables (Handayani et al., 2019), and low-carbon power plants (Rubin, 2019) were analyzed. Fukui et al. (2017) discuss the substantial cost reductions in the US shale gas industry based on a 13% learning rate and highlight that these learning effects cannot be fully compared to renewables as the impacts on the environment, including water consumption, might already be the lower constrained for future price development.

The core objective of this article is to analyze and document the historical developments of the concept of technological learning for energy technologies and to derive recommendations for its future use. This is of particular relevance for identifying the proper technologies regarding the efforts to combat global warming. Therefore, the focus of this article is on the documentation of existing studies and analysis of low-carbon power generation technologies, namely photovoltaics, concentrated solar power, wind, and nuclear power plants. To show the impact of different government policies on technological learning, different funding schemes for bioethanol and heat pumps were included in the analysis. In addition, the major points of criticism of technological learning in the literature are analyzed.

In this article, in principle, all peer-reviewed publications relevant for the topic of renewable energy technologies and published in major energy journals have been included. In addition, it is not a pure statistical review paper but rather a survey paper focusing on providing a comprehensive historical overview organized in a systematic way describing the evolvement of the approach as documented step by step in the literature.

The article is organized as follows: Section 2.1 identifies the main learning types, while Section 2.2 documents the historical development of technological learning. The formal framework for technological learning is outlined in Section 2.3. In Section 3, selected low-carbon power generation technologies, mentioned above, are discussed. Section 4 documents major points of criticism regarding technological learning. Finally, in Section 5, major conclusions are presented.

2 | HISTORICAL DEVELOPMENTS OF TECHNOLOGICAL LEARNING PRINCIPLES

2.1 | Learning types and basic principle of technological learning

The main learning effects identified in the literature are "learning-by-doing" and "learning-by-searching" (Pieper, 2003). Two additional types, namely the Technology Readiness Level (TRL) effect (first part of the learning-by-searching effect until the product is on the market) and the background effect, were explained by Thomassen et al. (2020). As the latter, they considered changes in the surrounding circumstances of different inputs factors, like the electricity mix or materials. All mentioned learning effects can be found at various steps of the market diffusion process, with different significances.

Learning curves and experience curves are frequently used interchangeably. In contrast to the learning curve, the experience curve should not be based on individual input costs, such as labor costs, but on total costs of a production process and thus include all cost elements that could affect each other (Henderson, 1968). Hence, the learning curve is limited to one input factor and is a subcategory of experience curves (Wei et al., 2017). According to Thomassen et al. (2020) the line between the two blurs, especially with an assembly of different components as the end product. We will therefore use both interchangeably in this work.

Two approaches are used when applying the learning curve concept to the energy sector. In some studies, cumulative electricity production by the respective technology is considered as an influencing variable on costs. It corresponds to the original concept in which cumulative goods production was used. The specific costs are thus expressed as the cost per kilowatt-hour of electricity produced, for example, EUR/kWh. The common approach is to use the cumulative installed capacity as a variable to influence costs. In that approach, the costs refer to the pure manufacturing costs of the energy conversion plant and are expressed, for example, in euros per installed capacity in the case of a wind turbine or euros per m^2 for photovoltaic modules (Pieper, 2003).

The origin of learning occurs through research and development or investment in new technologies across a multitude of companies that are part of a value chain. The resulting learning effects occur through improved know-how, improved design, and economies of scale. These learning phenomena are practically described with the help of learning curves based on a calculated learning rate. Typically, production costs decrease with increasing output (in the form of an exponential curve). The resulting exponentially decreasing function is usually represented with a logarithmic scale, resulting in a straight line, restricted by a certain floor price, which is being used in some learning rate models to keep the technology from becoming unrealistically cheap (Figure 1; Kohler et al., 2006). In a more recent work, the floor price has been introduced for calculation of cost development for electric vehicles, as some components (e.g., car frame) are already mature technologies with many years of experience (Edelenbosch et al., 2018). The basic principle of technological learning is explained in Figure 1. On the horizontal axis, the cumulative quantity installed is indicated using a logarithmic scale and on the vertical axis, the costs per unit are shown. When analyzing learning curves, it is critical that the doubling of the cumulative quantity is assessed numerically rather than through time. The time required to double the installed capacity does not influence the learning rate. As a result, applying learning curves in future years implies estimating how the cumulative quantity will develop.

As with most concepts, several strengths and weaknesses of the concept of technological learning were identified in the literature, which will be further analyzed in this work. Among the strengths, Pieper (2003) identified the good empirical confirmation of the causal relationship between costs and cumulative production or cumulative installed capacity and the ability to predict cost developments of specific technologies based on past learning curves. One shortcoming when using this concept is that dividing the cost reductions into the different areas (e.g., economies of scale, material costs, automation, etc.) often proves difficult (also pointed out by McDonald & Schrattenholzer, 2001). It is specifically problematic when two- or multi-factor approaches are used. Additionally, he highlights a need for further research on long-term extrapolation of learning curves, when the learning rate is changing or the life cycle of a technology, what might happen frequently within energy system technologies (Pieper, 2003).

The following aspect of the cost assumptions of calculated learning curves is essential. Because market prices are more accessible than production costs, market prices are often used for the calculation. Those prices could induce

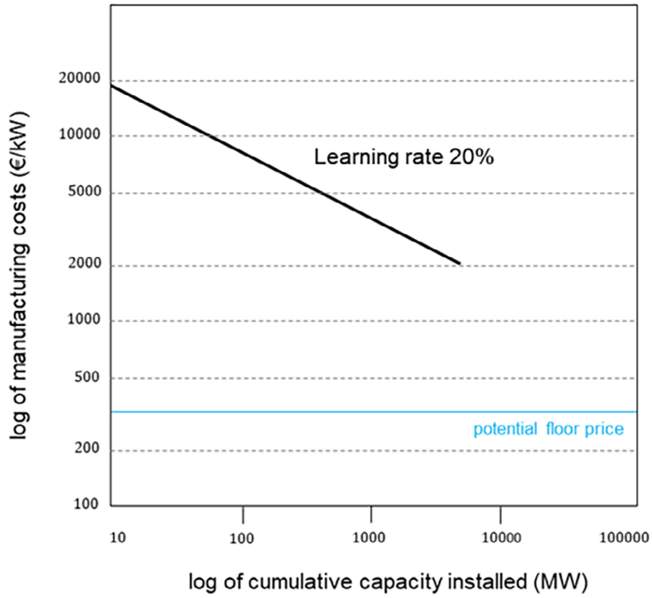

FIGURE 1 The basic principle of technological learning curves

uncertainty in technological learning as they might obscure the cost structure of the related company, especially in the case when the company has a particular price-setting agenda. Nevertheless, prices are frequently utilized in learning calculations when cost data is not available (Wei et al., 2017).

Learning rates are often used to develop government policies and subsidy schemes. It allows the identification of the driving force for past technology cost reduction and help to forecast future developments. Overall, the concept is used to incorporate technological change of renewable energy technologies in energy and climate change analyses, to evaluate the energy technology policies of governments to estimate future costs on a company level, and to create global energy technology development scenarios (Junginger et al., 2005; Nemet, 2006).

2.2 | Historical developments

The concept of learning curves was first published by Wright (1936) as a tool for determining costs for mass-produced products in an airplane manufacturing plant. The idea is that if a particular technology is used more and more due to ever-increasing technological maturity, an increasingly improved product will result, usually characterized by higher operational reliability, lower costs, and improved efficiencies. Other studies on cost decrease in the manufacturing sector were published by Alchian (1963) for aircraft and Rapping (1965) for shipbuilding. More recently, Nolan (2012) showed in the Boeing case study that the approach of learning curves is still used in the aviation industry. Dutton and Thomas (1984) later expanded the first learning curve approach by clustering and analyzing specific sectors. A good overview of the initial learning curve process in production economics is given by Grosse et al. (2015) through a detailed meta-analysis.

Yet, regarding learning, one has to be careful. The original definition of Arrow (1962) was very narrow and encompassed better performance using the same capital stock. In short, the workers improved the efficiency of using the equipment. This may be too narrow, but it is probably useful to distinguish between design changes that arose because technical change/progress allowed new options to be pursued and design changes that resulted from experience with existing designs. Later this definition was generalized by Conley (1970) to include all production cost reductions, not only the learning of workers.

Another approach was published by Moore (1965), using time instead of the cumulative installed capacity. He showed with the example of integrated circuits that technology advances exponentially throughout time. However, Nagy et al. (2013), find that Moore's concept might only provide good results for brief periods of time. Compared to the learning concept initiated by Wright, it shows less accurate predictions over longer timeframes, which has also been highlighted by McDonald and Schrattenholzer (2001), saying that not exactly the time has a substantial effect but the experience gained over that period. They mention the example of leaving a technology on the shelf and not using it, leading to "forgetting by not doing" and rising costs.

While the first research on learning curves was production-oriented and focused on the manufacturing process and learning by doing on one plant or product, in 1968, the Boston consulting group introduced with Henderson (1968) a more inclusive approach, which also focused on business and management and the aggregation of entire industries. They introduced the term "experience curve" and highlighted its importance in predicting potential competing companies' production cost decreases. Additionally, there is a strict separation of experience curves and learning curves (only including labor and production inputs) in the publications of Henderson, which we use, as indicated earlier, interchangeably in this work.

Among the first ones to criticize the learning concept of manufacturing processes were Hall and Howell (1985) with their analysis "The Experience Curve from the Economist's Perspective." They highlighted that the advantages of learning-by-doing for one single site are quickly saturated. Furthermore, they found that the association of cumulative production and the average cost is misleading and concluded that experience curves are rather distorted and have limited practical utility for strategic planning. After this work, more authors criticized the learning approach. Those will be further analyzed in Section 4.

On a more general level, it has to be pointed out that prior to the work of Romer (1986) technological change was exogenous to the models (e.g., Solow, 1956), which earlier were classified as "external learning" or even disregarded in the models (Azar & Dowlatabadi, 1999). Beginning with Romer (1986) also energy supply models introduced the learning curve concept, thus endogenizing technological change, which has then evolved into a robust and frequently used model for forecasting technological learning (Nemet, 2006). Some important references, in this context, are Neij (1999b), Grübler et al. (1999), Wene (2000), McDonald and Schrattenholzer (2001), and Kobos et al. (2006).

Wene (2000) can be seen as a major work dealing with technological learning. Besides analyzing the experience curves, it also discusses certain uncertainties of the concept that decision-makers should consider when evaluating the respective policy. Experience curves are essential for predicting technological progress and evaluating energy policy decisions. For instance, it may be used to assess government measures supporting innovative technologies (Duke & Kammen, 1999). Especially for energy, studying wind power and wind turbines, the European Commission implemented the project "EXTOOL" to further develop and evaluate the concept (Neij et al., 2003). They concluded that experience curves could be used to evaluate the cost-cutting effects of policy measures, however, not to assess the cost-effectiveness of the respective measures. Van der Zwaan & Rabl (2004) applied the policy research on PV, calculating that with certain policy measures, PV will hold a significant share of energy production worldwide in 2020. With the work of Wiesenthal et al. (2012), the European Commission published additional research on the concept in view of policy support.

Most studies that evaluate policy acknowledge certain uncertainties when using the learning curve concept. An approach to how those might be taken care of has been applied by Neij (2008). By combining the economically oriented "top-down" experience curve concepts with the engineering-oriented "bottom-up" approach and a "judgmental expert assessment," she shows that in most situations, outcomes of all three methodologies match. By including additional concepts in her analysis, specific technologies with uncertainties have been revealed through the additional methods and were pointed out (Neij, 2008). Yeh and Rubin (2012) suggest that for the development and validation of more robust models of technological change, ways to significantly improve the characterization and reporting of learning model uncertainties and their impacts on the results of energy-economic models have to be identified to help reduce the potential for drawing inappropriate or erroneous policy conclusions.

The main historical developments discussed in this section are documented in Figure 2.

2.3 | The formal framework for technological learning

The main approach used in the literature is the one-factor approach, where the cumulative output at a time t can be seen as a first-instance approximation of the learning process. Mathematically, the effect of "technological learning" can be described by the cost function

$$IC(x_t) = IC(x_{t_0}) \cdot \left(\frac{x_t}{x_{t_0}}\right)^{-b} \tag{1}$$

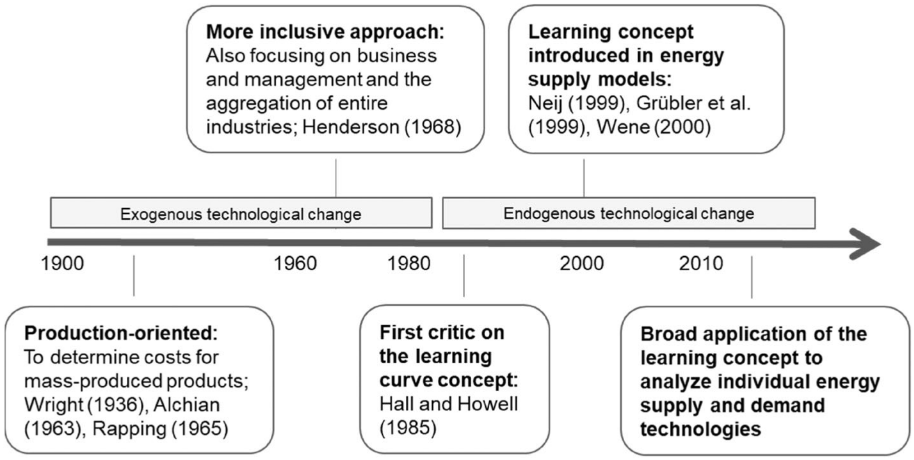

FIGURE 2 A timeline of major milestones in the development of technological learning

with $IC(x_t)$ is the investment cost of one unit at time t, $IC(x_{t_0})$ is the investment cost of one unit at time t_0, x_t is the cumulative output (e.g., installed capacity) at time t, x_{t_0} is the cumulative output (e.g., installed capacity) at time t_0, and b is the parameter used to measure the extent of learning.

In this model, investment costs $IC(x_t)$ decrease as output x_t increases. The cumulative output can be understood as the installed capacity of technology at time t, which can be described by a diffusion curve. In this formulation, the exponent $-b$ describes the "learning effect" and can be used to calculate the learning rate. The learning rate corresponds to a constant percentage in the reduction of the investment costs, which is accompanied by a doubling of the cumulative output.

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

For more accurate calculations, we can divide the investment costs of the technology into conventional and into new components with the formula

$$IC(x_t) = IC_{\text{Con}}(x_t) + IC_{\text{New}}(x_t) \tag{3}$$

with $IC_{\text{Con}}(x_t)$ is the specific investment cost of conventional "mature" technology components and $IC_{\text{New}}(x_t)$ is the specific investment cost of new innovative technology components.

$IC_{\text{Con}}(x_t)$ shows lower learning rates due to its larger "knowledge stock" and thus learning related to the "novel" technology is not observed. For $IC_{\text{New}}(x_t)$, one might consider two effects: one national and one international:

$$IC_{\text{New}}(x_t) = IC_{\text{New}}(x_{\text{Nat}_t}) + IC_{\text{New}}(x_{\text{Int}_t}) \tag{4}$$

with $IC_{\text{New}}(x_{\text{Nat}_t})$ is the specific national share of $IC_{\text{New}}(x_t)$ in new technology components and $IC_{\text{New}}(x_{\text{Int}_t})$ is the specific international share of $IC_{\text{New}}(x_t)$ in new technology components.

The one-factor approach, which is most commonly used because of its simplicity, considers future cost reduction as a function of cumulative production in the energy sector expressed by cumulative installed capacity and a constant learning rate over certain market phases. Two-factor models consider not only cumulative production but also research and development expenditures, which, in addition to optimizing production, also lead to cost degression. This second parameter takes into account that cost degressions are often caused by research and development activities.

The two-factor approach results from:

$$IC(x_t) = \left(IC(x_{t_0}) - IC_{\text{Floor}}(x)\right) \cdot \left(\frac{x_t}{x_{t_0}}\right)^{-b} \cdot \left(\frac{IC_{RDt}}{IC_{RDt_0}}\right)^{-k} + IC_{\text{Floor}}(x) \tag{5}$$

with $IC(x_t)$ is the investment cost of one unit at time t, $IC(x_{t_0})$ is the investment cost of one unit at time t_0, IC_{Floor} is the minimum costs (e.g., material costs), x_t is the cumulative output (e.g., installed capacity) at time t, x_{t_0} is the cumulative output (e.g., installed capacity) at time t_0, IC_{RD_t} is the cumulative investment in research and development at time t, IC_{RDt_0} is the cumulative investment in research and development at time t_0, b is the parameter used to measure the extent of learning for the product, and k is the parameter used to measure the extent of learning for research and development.

$$LR_X = 1 - 2^{-b} \tag{6}$$

$$LR_{RD} = 1 - 2^{-k} \tag{7}$$

with LR_X is the learning rate of cumulative production and LR_{RD} is the learning rate of research and development.

Kouvaritakis et al. (2000) were, to the best of our knowledge, the first authors to incorporate learning by searching as "cumulative production" and "cumulative R&D expenditures" in the learning models. This has been further developed by Miketa and Schrattenholzer (2004), for analysis of the right amount of R&D subsidies on energy technologies, using the model ERIS (Energy Research and Investment Strategies; Barreto & Kypreos, 2004). Jamasb (2006) investigated the factors influencing technological learning of power generation technologies in the context of an analysis of historical cost developments. By ignoring the influence of research and development, single-factor approaches overestimate the influence of production (Figure 3). This effect is especially true for technologies in the early market phases. According to Jamasb (2006), there is a relatively low elasticity concerning learning effects from research expenditures and capacity expansion, which leads to the conclusion that research expenditures cannot be substituted by production and vice versa.

However, one problem arising when considering research and development effects is the availability of data. Klaassen et al. (2005) use the annual public research and development expenditures of the analyzed country for their analysis of PV development. The same approach has been taken by Söderholm and Sundqvist (2007). Grafström and Lindman (2017) introduce further data in the model, such as the number of patents and the number of researchers working in the area. A more recent study by Odam and Vries (2020) uses patents directly related to the technology being researched. This data can be gathered from the European Patent Office. Public research and development spending, as well as the number of researchers, are classified as "input-based" measures, while patent data is regarded as "output-based" as it indicates the product of the whole research process (Odam & Vries, 2020).

Another approach used in the literature is the component-based approach. It is based on the one-factor approach and used for cost predictions of newer technology components, without historical learning rates, as for example in Rubin et al. (2007) for power plants with carbon capture and storage (Rubin et al., 2015). When possible, the technology is divided into different components or sub-sections and the learning effects are then calculated using the component's experience or another component that is related. In the end, the learning curve is a result of the sum of all analyzed components (Rubin et al., 2015). This approach has been applied in recent publications on power-to-gas

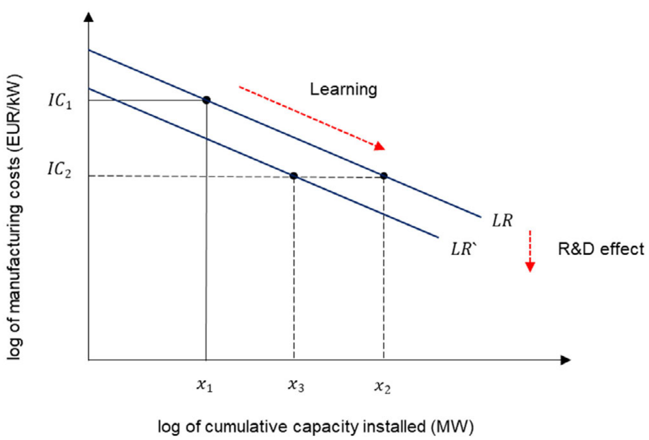

FIGURE 3 Two-cost reduction effects due to technological learning and R&D (Jamasb, 2006)

(Böhm et al., 2019, 2020). The authors highlight the necessity of a component-based approach application for new technologies with a low technology readiness level due to the lack of historical data on the new technology. In a comparison of the results of the component-based approach to the one-factor learning rate approach, they find that both approaches are appropriate (Böhm et al., 2019).

3 | COMPARISON OF LEARNING RATES FOR SELECTED ENERGY TECHNOLOGIES

Next, the specific learning rates of different technologies are discussed. So-called low-carbon electricity generation technologies were selected, as they will form the future of our energy system, including photovoltaics (PV), concentrated solar thermal, wind energy, and nuclear energy. The respective learning rates are analyzed and the possible reasons for the different development of the learning rates are discussed. In order to show the influence of support regimes for renewable technologies on learning rate development, in addition to the electricity generation technologies, the specific effects of bioethanol in Brazil and of heat pumps in Switzerland and Sweden are presented in further subsections.

3.1 | Photovoltaics

The first price indication of historic PV modules dates back to 1956, when the specific cost for PV was 256 $/W (Perlin, 1999). It would be around $2500 today when adjusted for inflation. At that time, PV was mostly used in aerospace, which changed in the following years and the further use in other applications allowed lower levels of quality and dependability (Kavlak et al., 2018). Since then, the cost of PV have dropped rapidly and sparked interest in research on learning effects (Figure 4). However, a variety of factors attributed to the cost reductions of PV, not only technological learning (Nemet, 2006). Among the mentioned reasons for the cost reductions are improved module efficiency and research and development investments (private and government) from 1980 to 2012 (Kavlak et al., 2018). Economies of scale were a significant factor after 2001 and government policies were also of high importance (Kavlak et al., 2018). The observed learning rate between 1979 and 2012 for solar PV modules was 22%, as calculated by IRENA (2021).

However, obtaining true cost data for the analysis from the PV manufacturing sector might be difficult. For this reason, analysts often refer to market price data. The use of market price data explains, to a certain extent, the fluctuation in the learning curve figures, as market prices may not necessarily reflect manufacturing costs. They might be different due to manufacturing capacity constraints, which leads to a price increase, while costs may stay the same or decrease. The struggle of the PV sector to keep up with the fast-increasing German market expansion after 2002 is an example (Yu et al., 2011). Other possibilities for price increases are raw material shortages, like in 2006, the polysilicon shortage (IRENA, 2021). This factor increased the price and also the production costs. However, learning still occurred in that period.

Further, it is important to include the balance of system costs in the cost analysis, as they accounted for approximately 64% of total installed costs in 2019 (excluding the module and inverter; Grafström & Poudineh, 2021;

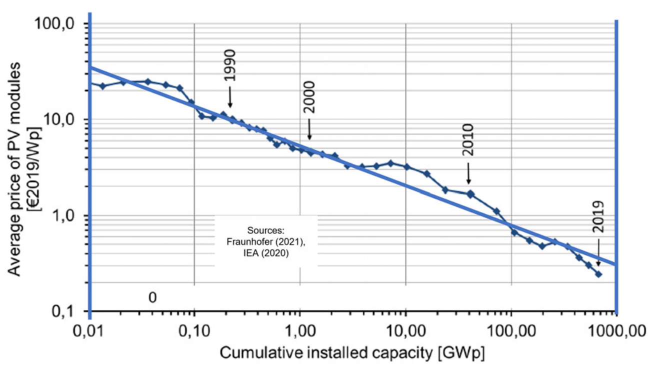

FIGURE 4 Price development of PV modules (Fraunhofer, 2021, IEA, 2020)

IRENA, 2020). Under "balance of system", everything that is required to make the modules operational, such as cables, mounts, and construction, is being accounted (Elshurafa et al., 2018). Fu et al. (2017) analyze different parts of overall project costs (module, inverter, balance of system, and soft costs) of a PV plant and find a substantial difference in the cost development of those individual parts. The overall balance of system cost decreased substantially over the last years as smaller PV areas were needed for the same wattage due to efficiency increase on the module part (from 14.7% in 2010 to 19.2% in 2019), hence directly reducing the overall balance of system costs (IRENA, 2020). When analyzing the learning curves of PV projects, the pricing of the different parts is to be emphasized. PV modules are subject to great international competition, while the pricing of parts of the balance of system costs (e.g., soft cost in relation to labor, legal-administrative processes) is done nationally in each country (Elshurafa et al., 2018). This explains one of the reasons for lower learning rates of the balance of system costs. Elshurafa et al. (2018) calculate the learning rates of residential-scale PV modules and balance of system separately for 27 countries. When merging the acquired country-specific data, they obtain global learning rates of an average of 10% for system costs and 20% for modules (time of analysis 1992–2015; Elshurafa et al., 2018). The learning rate of the overall PV project installed cost (utility-scale) in the period between 2010 and 2019 has been 33%, according to our calculations based on data from (IRENA, 2020).

3.2 | Concentrated solar power

While for a technology such as PV, which competes globally and is largely a homogeneous technology in terms of modules, substantial and practically continuous learning effects could be realized, the picture looks different for concentrating solar power.

For concentrated solar power (CSP), Junginger and Louwen (2020) compiled a comprehensive analysis. The first CSP plant was built in the 1980s in California, with a total capacity of 344 MW, mainly due to the search for alternatives as a cause of the oil price increase. Since the oil price recovered, there has not been much further development. Only, in 2007, has CSP been put back on the agenda, mainly through very ambitious renewable targets and subsidies of Spain. However, they were canceled in 2013 due to the financial crisis, and once again, not all of the planned capacities were installed, thus, the expected price reduction could not be achieved. The installed capacity per power plant is typically around 30–200 MW (Junginger & Louwen, 2020).

There are still a few studies predicting substantial learning rates (e.g., 10%–16% Pietzcker et al., 2014, Platzer & Dinter, 2016, Garzón Sampedro & Sanchez Gonzalez, 2016), which have to be considered carefully, as not many plants were constructed and the investment cost data is not publicly displayed for many plants (Samadi, 2018). Furthermore, it is not only one technology but also four different ones, adding different storage options, making it hard to compare projects (Samadi, 2018). Considering project cost data (average of all CSP technologies) and installed capacity with data from IRENA (2020), we calculated a learning rate of 17% in the period between 2010 and 2019.

Junginger and Louwen (2020) conclude that the low learning of CSP in the past is a result of a variety of factors, among them, the substantial cost decrease of the competing PV technology, high investment costs, and the cut of subsidies in Spain. One reason for more moderate learning might also be the low-tech level of CSP, as this cannot be optimized easily compared to PV. Despite that, they are still optimistic that learning rates of up to 10% could be achieved and highlight that CSP will also be essential for the energy transition.

3.3 | Wind technologies

Wind energy technologies consist of onshore and offshore wind farms. While onshore electricity generation showed learning rates of 15% between 2010 and 2019, offshore only had a 6% learning rate on total installed cost in the same period, according to our calculations based on IRENA (2020) data (Figure 6).

Neij (1999a) conducted the first analysis on investment cost reductions of onshore wind turbines. Especially in Denmark, wind turbines were upgraded every few years (Neij, 1999a). Junginger et al. (2005) find that after 1995 the cost reductions slowed down, although the turbine capacity still increased. This finding is also supported by Samadi (2018). He reviews several studies and concludes that the learning rates are much lower in more recent studies (2%–8%) than in older ones with a learning rate between 10% and 19%. Among the reasons for the limited investment cost decrease were increasing prices of commodities (highest 2005–2008), supply restrictions as a result of rapid expansion, maturing of technology, and therefore more installed capacity needed for cost reductions (Samadi, 2018). Furthermore, investment cost reductions tend to be lower than the costs per kWh when analyzing wind power, see for example (IRENA, 2017). This results from the fact that changes in turbine design (e.g., higher towers, longer rotor blades, or improved control electronics) might have higher investment costs but can also utilize weak and erratic wind resources, generating more electricity. Overall, wind turbines were optimized over those years (Samadi, 2018).

Only very few studies also include offshore wind parks in their learning analysis and in general, studies on wind energy strongly focus on Scandinavian countries. Samadi (2018) analyzed them and found learning rates up to 3%. Mentioned reasons for the much lower rates are commodity price increases, a tight market for turbines and components, insufficient competition, and supply problems (Samadi, 2018). Offshore wind energy, in comparison to onshore, is very new, only having the first turbine installed in 1990 in Sweden. In general, each wind park had only a few turbines with up to 2 MW capacity in total. However, offshore wind farms grew from 2 MW per turbine in 2000 up to 5 MW in 2007, mainly in Denmark, UK, and Sweden (Lako et al., 2010).

3.4 | Nuclear power

Regarding technological learning of nuclear power plants, Grubler (2010) is one of the most famous and widely recognized works, which provides a seminal contribution and a very comprehensive analysis of the nuclear power cost developments in France and the US. He was the first to compare the specific investment costs of nuclear power plants in France and the US in the period 1970–2000. The cost of nuclear reactors was for a long time significantly below the US costs, but eventually, the costs practically exploded there as well.

Grubler's major criticism is that the lack of standardization and new engineering approaches have avoided the learning and standardization effect. He points out that France is widely but wrongly seen [e.g., by Escobar Rangel and Leveque (2015)] as having a fully standardized program. Actually, its 58 reactors are spread over at least three main designs (900, 1300, and 1450 MW) and seven variants. Hence, many of the plants used a new, untested design. The scope for learning was restricted because the new reactors were ordered before there was any operating experience with their predecessors. There was no conscious decision by France not to standardize. Design changes were required because of experience elsewhere, for example, the need to learn lessons from the Three Mile Island disaster and the need to improve the economics, for example, by scaling up.

Nuclear technology shows the opposite trend toward cost reductions (Figure 5). In our opinion, four factors would lead to lower costs in a typically successful technology: Economies of scale, economies of scope, learning-by-doing, and technical progress. We are convinced that learning has occurred, but either it has not lowered costs, or other factors have overridden the lowering of learning costs. For example, the experience at Three Mile Island was certainly learning, but it increased costs. We think it is important to really distinguish and accurately delineate these effects, which are quite different. Of course, that is not easy. A key phrase may be "a successful technology." It could be that technologies with no scope for these effects fail for that reason. The problem with nuclear power is that it was not allowed to fail. Also, as Escobar Rangel and Leveque noted, all else being equal, the larger the reactor, the fewer identical units were built.

The studies of Lovering et al. (2016) and Lang (2017) provide the overnight costs (ONC) of acclaimed 58% of the world's nuclear reactors. The findings have been extensively criticized by Koomey et al. (2017), alleging they were cherry-picking data and incorporating deceptive statistics about early reactors, which cannot be verified as the data set is not accessible to readers. The ONC of nuclear power plants is used to separate the interest cost during construction periods. However, this is a major flaw, as they are large-scale, complex, and not standardized with extremely long development times (years or even a decade), as we pointed out earlier. For those reasons, they are very high-risk investments (Koomey et al., 2017).

In terms of technological learning for NPPs, the critical point is this: even during the boom in plant construction in the 1970s and 1980s, nuclear power was one of the few exceptions in the sense that additional capacity built did not lead to a resulting reduction in costs. The reason is that no real costs were revealed for the early plants. Costs were distorted by public subsidies, industry subsidies (from plant builders to get to market), and financing subsidies due to very favorable interest rates. Over time, these subsidies were gradually removed and costs increased instead of following the classical learning theory. In addition, it is worth mentioning that learning could increase costs, for example, if a cheap material is not good enough or existing designs are not safe enough (Haas et al., 2019). In the last few years, no substantial new capacities have been constructed (IAEA, 2022). The overall number of nuclear reactors is also relatively low, contrasting with PV or wind technologies.

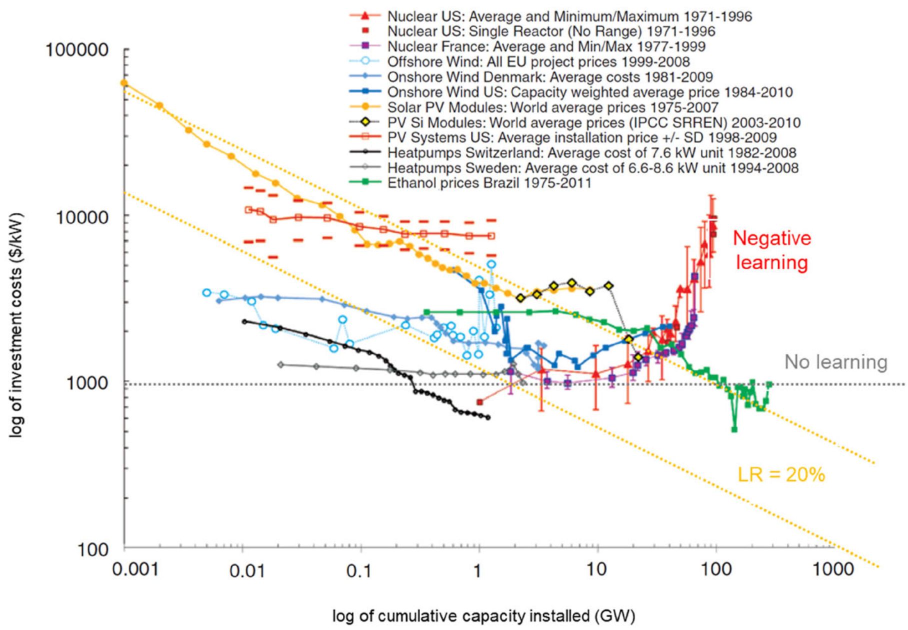

FIGURE 5 A comparison of the development of the specific investment costs of nuclear power plants, wind, and PV in different countries over the period 1971–2010 (Grübler & Wilson, 2014)

3.5 | Bioethanol in Brazil

A political strategy can be a "buy-down" of the costs of a technology. The best-known example of this is Brazil's government subsidies for bioethanol. The program "ProAlcool" was established in 1975 as a reaction to the oil price crisis, as the country could only supply 20% of its petroleum consumption locally. Furthermore, Brazil has a vast sugar industry, which was threatened by the introduction of corn syrup as a near alternative and Europe's trading preferences. This technology was subsidized gradually to extend ethanol production until bioethanol was at the market price level of gasoline (Grübler & Wilson, 2014).

Besides that, they persuaded car owners to switch to ethanol-specific engines capable of handling fuel blends containing 5%–10% ethanol. When fuel prices declined again, people had to pay higher costs for ethanol, leading to another government decision to make the existing industry more efficient and competitive with market fuel prices through research and innovation. All mentioned in combination led to annual production volumes of 12.6 million m^3 in 2002 (initial 0.6 m^3) and a sharp price decrease, for times also below Rotterdam gasoline prices. Overall, a learning rate of 30% was reached between 1989 and 2002 (Goldemberg et al., 2004). No further subsidies are needed and as of 2014, 90% of all newly sold cars are flex-fuel, enabling buyers to choose the fuel type depending on actual pricing. Brazil was an example of subsidizing production and increasing demand, even through difficult times, resulting in vast learning effects on a technology (Grübler & Wilson, 2014).

3.6 | Heat pumps

Heat pumps were largely endorsed by many countries in the 1970s as means to save energy. For example, Switzerland and Sweden implemented numerous policies for market uptake and cost decrease of heat pumps. The development of heat pumps focusing on those two countries was analyzed in detail by Grübler and Wilson (2014). They find that the price development of heat pumps in those markets differs significantly. Switzerland started with a higher consumer price level in 1982, however, the cost decrease over time has been more significant than in Sweden. Switzerland's approach was based on a law that defined a certain percentage of nonrenewable heat sources allowed, accompanied by a voluntary standard. In comparison, Sweden used higher subsidies, which explains the price increase in 2006. An additional subsidy was announced at that time, but the market was already saturated. Another possible reason might be little competition among heat pump suppliers in Sweden and unpredictable subsidy schemes, however, this has not been validated in the mentioned analysis. They also highlight that in Sweden, all heat pumps are locally produced, whereas Switzerland imports most of the components, which might lead to significant cost savings (Grübler & Wilson, 2014).

The actual learning rate percentage has been analyzed by Louwen et al. (2018), estimating a 10% global learning rate for heat pumps. They additionally highlight that the heat pump price in Switzerland is below the one in the Netherlands. In Junginger and Louwen (2020) also, the learning rates for the heat pump modules are comparably higher, with 22% in Switzerland and 18% in the Netherland. In another recent study, (Renaldi et al., 2020) find much lower learning rates of between 5.5% to −2.3% for air-source heat pumps and 3.3% to −0.8% for ground-source heat pumps (total project cost) in Great Britain. Comparing those estimates, it becomes clear that, heat pumps are not a globally traded global commodity with universal prices and that each country has its specific subsidy schemes leading to different market prices and the number of installed heat pumps. This has also been emphasized by Junginger and Louwen (2020) saying that with the great variety of prices and cumulative capacities among countries, learning rates from one country or region cannot be applied to the global heat pump development.

4 | COMMON FEATURES AND REQUIREMENTS FOR TECHNOLOGICAL LEARNING

As highlighted in the previous sections and can be seen clearly in Figure 6, the learning rates among energy technologies differ remarkably. From this, a key insight is that learning rates practically cannot be generalized. Therefore, in this section, based on the analyzed technologies, we discuss which features lead to high learning rates and which ones rather hinder the development.

Analyzing all technologies, we find that modularity (size of the plant), granularity and homogeneity of the technology, as well as continuous development are essential for high learning rates.

Modularity and granularity have been discussed by Wilson et al. (2020), with granular technologies providing more room for repetition and reproducing specific processes for faster cost reductions. Moreover, it is easier to improve the performance of modular technologies and test them in actual demonstration facilities with smaller capacities. Another aspect of smaller, modular technologies is that they can easily be assembled in a factory and then shipped to the site where they are used, whereas nonmodular, larger capacities mostly have to be assembled and constructed to a certain extent on the construction site of the power plant (e.g., nuclear reactors). One good technology example that shows homogeneity, modularity, and granularity is photovoltaics. In the case of PV, the panels showed tremendous cost

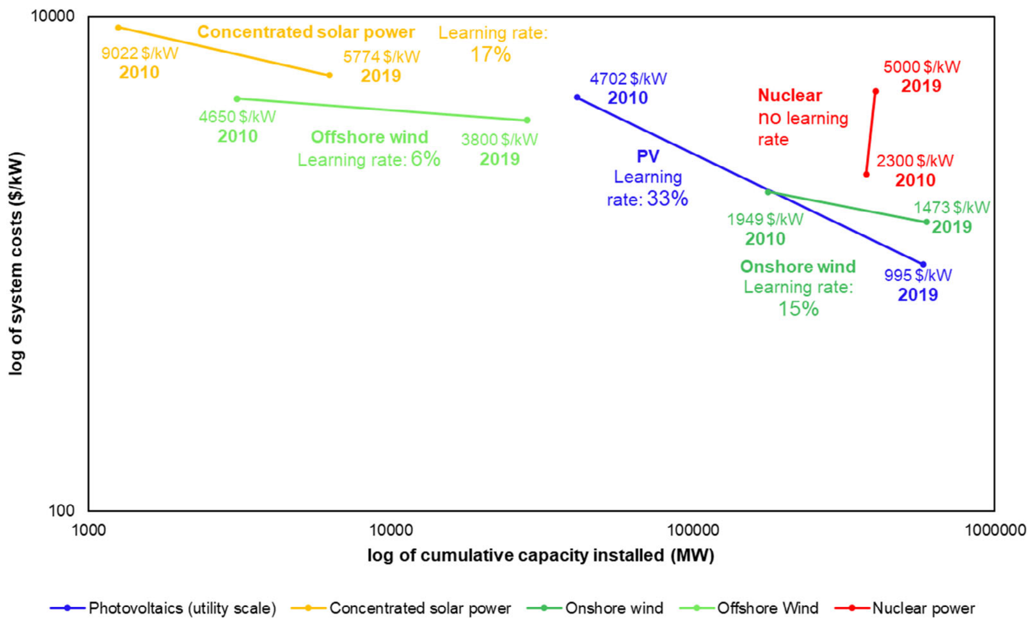

FIGURE 6 Comparison of technologies analyzed in this paper (own elaboration based on data from IAEA (2022), IEA (2020) and IRENA (2020)), remark: We use total installed costs for analysis (e.g., including balance of system costs for PV) for better comparison among the technologies

reductions and were traded globally and shifted production to countries where they could be produced with the lowest costs. Generally, the learning rate is higher when technologies are globally traded since international learning rates tend to be higher than national ones due to stronger competition. Modular technologies tend to have a higher international share as they are mostly traded worldwide without being country-specific. Those higher global learning rates have also been found by Schaeffer et al. (2004) as they conclude that PV had an average global learning rate of 23%, whereas the national module prices in, for example, Germany, have been stable or elevated (Schaeffer et al., 2004). Regarding the overall PV system costs, this has also been visible in comparing PV modules to balance of system costs. Modules being highly granular result in much higher learning rates than the balance of system costs, which include various required parts and have substantial price differences among countries. Junginger et al. (2008) also find that especially large-scale technologies lack an EU-wide action to boost investment and prevent uncertainties for the investors. They also highlight that interchange of information often works well nationally but not internationally (Junginger et al., 2008).

Another aspect that has been prevalent and has been pointed out by Samadi (2018) is the size respective the modularity. The larger the capacities of the individual power plants (e.g., nuclear reactors, offshore wind), the lower the learning effects were. A reason for that is that the small-scale technologies can be easier standardized, whereas, in large-scale applications, the construction must be done at the respective construction place (Samadi, 2018). In addition, larger plants such as nuclear power plants consist of more different components compared to a PV module. In addition, there are different reactor types, which makes standardization difficult, similar to the discussion on concentrated solar thermal power. There are also four different technologies, each of which differs in the storage tank size, which leads to fewer learning opportunities. This issue has already been discussed very early on by Neij (1997), who clustered the technologies into modules (e.g., PV panel), large and small plants (whole power plants), and continuous processes (e.g., mass production of chemicals). Neij identified learning rates from 30% to 5% (average 20%) for modules, up to 18% (average 10%) for power plants and 36%–10% (average 22%) for processes (Neij, 1997).

Another similarity between CSP and nuclear power is the number of power plants. Although a relatively large amount of nuclear power capacity is installed, it consists of only 448 power plants due to the size of a power plant (IAEA, 2022). Furthermore, there has been no remarkable capacity expansion of nuclear power in recent years (+27 GW in the last 9 years; IAEA, 2022), as can also be seen in Figure 6. This also leads to lower learning opportunities. CSP, in comparison, has a small number of power plants and capacities but has increased fivefold in the last 9 years.

When reviewing the learning rates of PV compared to nuclear reactors, we found that having stable conditions in terms of environmental regulations for implementing the technologies is essential. PV has become a high-demand technology with minor environmental implications attached, whereas nuclear power manufacturers often had to adapt to tighter safety standards due to nuclear disasters, which was partly a reason for the cost increase. On a more general note, we can also apply that to fossil power plants as generally, the focus of energy technology evolved into supplying electricity generated through environmentally friendly and cheap means from originally only cheap ones.

5 | MAJOR POINTS OF CRITICISM REGARDING TECHNOLOGICAL LEARNING

Based on the preceding analyses, in this section, the criticisms of technological learning by various authors are documented.

The first major concern is that often price data instead of costs are used, simply, because most of the time, the cost data is not available. As a result, new uncertainties are introduced and have to be considered. The concept, in general, builds upon showing the true production cost of a technology, as the market price of a technology might also depend on the price-setting of the manufacturers (in each step of the product life cycle), the demand, the competition, availability of the technology and subsidies (Figure 7; Junginger et al., 2008). Nemet (2006) proves this argumentation through an empirical study of different periods of the price development of photovoltaics. He finds that the industry structure, meaning the level of competitiveness, influences the learning rate (Nemet, 2006). Nevertheless, he recommends using cost data, where available, which might be hard to obtain due to the fear and hesitation of companies to disclose real costs. For the analysis of technologies that are in strong competition with each other, it might give more insight to use prices for the calculations as this is the basis for the customer's decision to purchase the technology (Nemet, 2006).

The above argument leads to the result that at some point in the lifetime of a technology, no substantial further learning effect takes place and market aspects take over because full competition is reached. For example, for a major

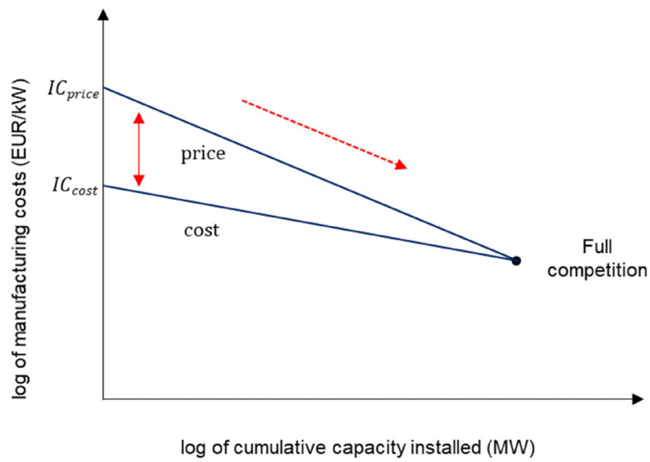

FIGURE 7 Development of price versus cost data

conventional car, the costs increase because of improvements in the quality of services (e.g., air conditioning, additional electronic devices…) cause additional costs, which have virtually offset most of the cost savings that have occurred in the "naked" car due to learning.

Another reason may be, as already mentioned, that the technology has changed (and realistically every technology changes over time, efficiency is increased and service features are extended). This also applies, for example, to PV modules and wind turbines, which are not the same as a few years ago due to further developments and innovations of components to increase the functions and costs.

Some adjustments are also required by regulation, for example, wind turbines also have to provide an operating reserve within the ENTSO-E grid-connection codes or PV inverters with storage functions. In addition, nontechnology-specific costs, such as labor or land, increase total costs or limit further learning. Especially the latter tend to increase as soon as the most favorable locations are built. Moreover, labor or land costs also inflict variability or biases as they are influenced by labor and property markets (McDonald & Schrattenholzer, 2001).

One great uncertainty problem in the concept of technological learning is that small parameter changes might substantially affect the slope of the learning curve. For example, Junginger et al. (2008) point out that variations concerning initial capacity deployed, initial costs, methodology of data collection, inflation, and different system boundaries of energy technologies might have great effects on cost development. This has also been confirmed by Neij (1999a) and Van der Zwaan and Seebregts (2004). Further, uncertainties in the progress ratios hence the learning rates, are often discussed in the literature, as the forecasts of the development of energy technologies are very sensitive. It is suggested to implement the progress ratio error to account for errors (Junginger et al., 2008). van Sark and Alsema (2010) analyze including an error in the progress ratio's value in the best possible way and also provide the instructions of use. Lafond et al. (2018) provide a model to take precautions for forecast uncertainties. Another important aspect is to consider an appropriate software for calculating and displaying learning rates, as van Sark and Alsema (2010) found different results depending on the software used (Excel, Origin).

Nordhaus (2014) argues that using technological learning in modeling raises three potential problems. First, he shows that there is a fundamental statistical identification problem in trying to separate learning from exogenous technological change and that the estimated learning coefficient will generally be biased upwards. Second, two empirical tests illustrate the potential bias in practice and show that learning parameters are not robust to alternative specifications. Finally, he shows that an overestimate of the learning coefficient will provide incorrect estimates of the total marginal cost of output and will therefore bias optimization models to tilt toward technologies that are incorrectly specified as having high learning coefficients.

Since an important aspect of technological learning is assessing policies and guiding policy making to further decide on renewable promotion instruments, some uncertainties in this respect have to be highlighted. Wene (2000) pointed out that they must be accounted for when deciding on subsidy programs and suggests including the most current cost data. Either R&D or subsidies can be chosen for dissemination (Figure 3).

Promotion programs might influence the price of technologies. For example, the German wind power plant prices were relatively stable over the period 1995–2001. According to Junginger et al. (2008) this resulted from the feed-in tariff and the resulting high request for turbines which lead to market prices higher than the costs. They assure that, in general, market simulation has no negative effect on learning rates, although it might have an impact on the pricing. They recommend addressing the market development (demand and supply) in every analysis over the period studied to account for discontinuities. According to Haas (2008) investment subsidies, feed-in tariffs (FIT), tax incentives, portfolio standards, quota-based tradable green certificates (TGC), and tendering systems are major renewable promotion instruments. There is no clear consent regarding which scheme will help achieve climate targets with minimal costs. Through an analysis of different countries, they found that the fixed feed-in tariff in Germany, Denmark, and Spain showed promising results, while the competitive tendering in UK and France did not (Haas 2008). As a further outlook, power purchase agreements (PPA) may play a more important role than subsidies.

6 | CONCLUSIONS AND OUTLOOK

The transition toward a largely sustainable energy system will depend on the timely market deployment of low-carbon energy technologies, storage, and other flexibility measures as quickly and as far as possible. The speed of this deployment will depend on the economics of these low-carbon technologies so that they become more cost-effective than fossil fuels, which are highly dependent on a reduction of manufacturing costs.

The major conclusions are:

For an appraisal of the development of the future manufacturing cost of low-carbon power generation technologies in this article, the concept of technological learning has been discussed and analyzed, with a focus on low-carbon. It turned out to be a promising tool for estimating the future manufacturing costs of energy supply technologies, if some specific characteristics of different technologies are considered when applying the concept. We found that the following three major conditions have to apply to make high learning rates visible:

- technologies have to be homogenous over time from the setup of the technology and
- technologies with have to be modular respectively granular, that is to say, also rather small capacities have to be possible up to virtually no upper size limits.
- In addition, the legal and regulatory conditions (e.g., safety) must remain stable.

From the analyses of lessons learned in the past, there are two extreme examples:

On the one hand, a technology example that shows homogeneity and modularity and high learning rates over the past years is photovoltaics, especially the modules themselves, without the balance of system costs.

On the other hand, nuclear reactors did not evolve into a homogeneous technology. There are different reasons for this: different reactor types evolved in different countries and regions, over time reactors required environmental adaptations caused by accidents, which might also be the reason for the low number of worldwide installed plants and the lack of standardization and application of new engineering approaches. In addition, for nuclear never true costs have been applied due to hidden subsidies by industry, governments, and banks, which has avoided the learning and standardization effect to a certain extent. Since nuclear power plants represent an agglomeration of multiple processes and components, analyzing the reactor types separated from peripheral processes, such as the nuclear core, could be interesting for further research. This would allow to directly compare the cost of the development of PV modules to the nuclear reactor itself.

Another important aspect of cost reductions of technologies is the suitable funding schemes from governments. The policies may either accelerate TL by promoting the dissemination of technologies—the quantities—or by R&D—the qualities (Figure 3).

However, the concept of learning curves and its application to a single technology also has its limitations and some specific conditions for its application to a single technology are essential as there are:

- For no technologies, a pure straight line for the learning rate can be derived.
- Usually, not the costs but only the market price is available for the estimates and the market price might temporarily increase or at least be volatile due to short-term scarcities.
- In principle, virtually no technology exists that is fully homogenous over time.

Eventually, an important open question is whether and when technological learning stops. At some point-of-time, every technology becomes "mature," which means that no significant further cost reductions with respect to the pure technology are expected and the pure learning effects are outweighed by other effects such as additional service features, technical change of the technology which are accompanied by having reached fully competitive markets. In detail, these effects are:

1. It is evident from the general technological learning concept that with increasing capacities, cost reductions are more difficult to obtain, as with a high base of cumulative production relative increases in production volumes, and thus the driver for technological learning is usually decreasing. In addition, it is more difficult and it takes longer to double the stock the higher the quantities already deployed are.
2. With higher quantities, market forces will take over as competitive markets are reached. Such "mature" technologies are produced with maybe different specific features (e.g., trademarks, specific service functions, i.e., inverters of PV systems). However, it might also be overtaken by a market effect with constant or increasing costs (because, e.g., the most favorable building sites have already been allocated). Of course, it is not clear how these effects will work out in the long run. Will the material costs rise due to short-term scarcity and shortages of raw materials or slightly decrease due to cheaper mining and transport options or substitution by other materials? This problem has so far not been discussed widely in the literature.

The major final conclusion is: More and more new service features are added to technologies—for example, various additional electronic devices—which will virtually outweigh the possible cost reductions due to learning of the "pure old" technology. At the same time—slowly but continuous—the technology changes more and more away from being homogenous anymore. Hence, three effects—pure TL effects, additional services, and changes in the technology itself—are blurred over time and with larger quantities produced—and finally, the technology ends up in competitive markets where other features than TL are more important.

AUTHOR CONTRIBUTIONS

Reinhard Haas: Conceptualization (equal); data curation (equal); funding acquisition (equal); methodology (equal); writing – original draft (equal); writing – review and editing (equal). **Marlene Sayer:** Conceptualization (equal); data curation (equal); methodology (equal); writing – original draft (equal); writing – review and editing (equal). **Amela Ajanovic:** Conceptualization (equal); data curation (equal); funding acquisition (equal); methodology (equal); writing – review and editing (equal). **Hans Auer:** Conceptualization (equal); methodology (equal); writing – review and editing (equal).

ACKNOWLEDGMENT

The authors acknowledge TU Wien Bibliothek for financial support through its Open Access Funding Programme.

FUNDING INFORMATION

The research leading to this work has received funding from the Climate and Energy Fund under the project "Technologiebewertung Historische und Szenarien 2030/2050," which is part of the focus area "Energy Transition 2050."

CONFLICT OF INTEREST

The authors have no competing interest to declare.

DATA AVAILABILITY STATEMENT

All data are available in article.

ORCID

Reinhard Haas https://orcid.org/0000-0001-9361-3452
Marlene Sayer https://orcid.org/0000-0003-1593-7106
Amela Ajanovic https://orcid.org/0000-0001-6840-806X
Hans Auer https://orcid.org/0000-0002-9111-9941

RELATED WIREs ARTICLE

On the long-term prospects of power-to-gas technologies

REFERENCES

Ajanovic, A., & Haas, R. (2019). On the long-term prospects of power-to-gas technologies. *WIREs Energy and Environment*, *8*, e318. https://doi.org/10.1002/wene.318

Alchian, A. (1963). Reliability of Progress curves in airframe production. *Econometrica*, *31*(4), 679–693.

Arrow, K. J. (1962). The economic implications of learning by doing. *The Review of Economic Studies*, *29*(3), 155–173.

Azar, C., & Dowlatabadi, H. (1999). A review of technical change in assessment of climate policy. *Annual Review of Energy and the Environment*, *24*, 513–544.

Barreto, L., & Kypreos, S. (2004). Endogenizing R&D and market experience in the "bottom-up" energy-systems ERIS model. *Technovation*, *24*, 615–629. https://doi.org/10.1016/S0166-4972(02)00124-4

Berthélemy, M., & Escobar Rangel, L. (2015). Nuclear reactors' construction costs: The role of lead-time, standardization and technological progress. *Energy Policy*, *82*, 118–130. https://doi.org/10.1016/j.enpol.2015.03.015

Beuse, M., Steffen, B., & Schmidt, T. S. (2020). Projecting the competition between energy-storage technologies in the electricity sector. *Joule*, *4*, 2162–2184. https://doi.org/10.1016/j.joule.2020.07.017

Böhm, H., Goers, S., & Zauner, A. (2019). Estimating future costs of power-to-gas—A component-based approach for technological learning. *International Journal of Hydrogen Energy*, *44*, 30789–30805. https://doi.org/10.1016/j.ijhydene.2019.09.230

Böhm, H., Zauner, A., Rosenfeld, D. C., & Tichler, R. (2020). Projecting cost development for future large-scale power-to-gas implementations by scaling effects. *Applied Energy*, *264*, 114780. https://doi.org/10.1016/j.apenergy.2020.114780

Conley, P. (1970). Experience curves as a planning tool. *IEEE Spectrum*, *7*, 63–68. https://doi.org/10.1109/MSPEC.1970.5213421

Duke, R., & Kammen, D. M. (1999). The economics of energy market transformation programs. *The Energy Journal*, *20*, 15–64. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol20-No4-2

Dutton, J. M., & Thomas, A. (1984). Treating Progress functions as a managerial opportunity. *The Academy of Management Review*, *9*, 235. https://doi.org/10.2307/258437

Edelenbosch, O. Y., McCollum, D. L., Pettifor, H., Wilson, C., & van Vuuren, D. P. (2018). Interactions between social learning and technological learning in electric vehicle futures. *Environmental Research Letters*, *13*, 124004. https://doi.org/10.1088/1748-9326/aae948

Elshurafa, A. M., Albardi, S. R., Bigerna, S., & Bollino, C. A. (2018). Estimating the learning curve of solar PV balance-of-system for over 20 countries: Implications and policy recommendations. *Journal of Cleaner Production*, *196*, 122–134. https://doi.org/10.1016/j.jclepro.2018.06.016

Escobar Rangel, L., & Leveque, F. (2015). Revisiting the cost escalation curse of nuclear power: New lessons from the French experience. *Economics of Energy & Environmental Policy*, *4*, 103–125. https://doi.org/10.5547/2160-5890.4.2.lran

Fraunhofer, I. S. E. (2021). *Recent facts about photovoltaics in Germany*. Fraunhofer Institute for Solar Energy Systems.

Fu, R., Feldman, D., Margolis, R., Woodhouse, M., & Ardani, K. (2017). *U.S. solar photovoltaic system cost benchmark: Q1 2017*. National Renewable Energy Laboratory.

Fukui, R., Greenfield, C., Pogue, K., & Van der Zwaan, B. (2017). Experience curve for natural gas production by hydraulic fracturing. *Energy Policy*, *105*, 263–268. https://doi.org/10.1016/j.enpol.2017.02.027

Garzón Sampedro, M. R., & Sanchez Gonzalez, C. (2016). Spanish photovoltaic learning curve. *International Journal of Low Carbon Technologies*, *11*, 177–183. https://doi.org/10.1093/ijlct/ctu026

Goldemberg, J., Coelho, S. T., Nastari, P. M., & Lucon, O. (2004). Ethanol learning curve—The Brazilian experience. *Biomass and Bioenergy*, *26*, 301–304. https://doi.org/10.1016/S0961-9534(03)00125-9

Goldschmidt, J. C., Wagner, L., Pietzcker, R., & Friedrich, L. (2021). Technological learning for resource efficient terawatt scale photovoltaics. *Energy & Environmental Science*, *14*, 5147–5160. https://doi.org/10.1039/D1EE02497C

Grafström, J., & Lindman, Å. (2017). Invention, innovation and diffusion in the European wind power sector. *Technological Forecasting and Social Change*, *114*, 179–191. https://doi.org/10.1016/j.techfore.2016.08.008

Grafström, J., & Poudineh, R. (2021). *A critical assessment of learning curves for solar and wind power technologies*. Oxford Institute for Energy Studies.

Grosse, E. H., Glock, C. H., & Müller, S. (2015). Production economics and the learning curve: A meta-analysis. *International Journal of Production Economics*, *170*, 401–412. https://doi.org/10.1016/j.ijpe.2015.06.021

Grubler, A. (2010). The costs of the French nuclear scale-up: A case of negative learning by doing. *Energy Policy*, *38*, 5174–5188. https://doi.org/10.1016/j.enpol.2010.05.003

Grübler, A., Nakićenović, N., & Victor, D. G. (1999). Dynamics of energy technologies and global change. *Energy Policy*, *27*, 247–280.

Grübler, A., & Wilson, C. (Eds.). (2014). *Energy technology innovation*. Cambridge University Press.

Haas, R. (2008). Promoting electricity from renewable energy sources—Lessons learned from the EU, U.S. and Japan. *Lawrence Berkeley National Laboratory*. Retrieved from https://escholarship.org/uc/item/17k9d82p

Haas, R., Mez, L., & Ajanovic, A. (2019). *The technological and economic future of nuclear power* (p. 382). Springer Fachmedien Wiesbaden.

Hall, G., & Howell, S. (1985). The experience curve from the Economist's perspective. *Strategic Management Journal*, *6*(3), 197–212.

Handayani, K., Krozer, Y., & Filatova, T. (2019). From fossil fuels to renewables: An analysis of long-term scenarios considering technological learning. *Energy Policy*, *127*, 134–146. https://doi.org/10.1016/j.enpol.2018.11.045

Häner, J. (2021). Technologisches Lernen im Bereich Windenergie an Land. *Journal of Renewable Energy Short Reviews*, *7*, 35–41.

Henderson, B. (1968). *The experience curve*. BCG.

IAEA. (2022). PRIS—Trend reports—Nuclear Power Capacity. Retrieved from https://pris.iaea.org/PRIS/WorldStatistics/WorldTrendNuclearPowerCapacity.aspx.

IEA. (2020). *Projected Costs of Generating Electricity: 2020 Edition*. IEA.

IRENA. (2017). Onshore Wind Industry Learning Fast. Retrieved from https://www.irena.org/newsroom/articles/2017/Mar/Onshore-Wind-Industry-Learning-Fast.

IRENA. (2020). *Renewable power generation costs in 2019*. IRENA.

IRENA. (2021). Solar PV module cost learning curve for crystalline silicon and thin-film. Retrieved from https://www.irena.org/costs/Charts/Solar-photovoltaic.

Jamasb, T. (2006). *Comparative energy technology learning and policy analysis: Faculty of Economics*. University of Cambridge.

Junginger, M., Faaij, A., & Turkenburg, W. (2005). Global experience curves for wind farms. *Energy Policy*, *33*, 133–150. https://doi.org/10.1016/S0301-4215(03)00205-2

Junginger, M., Lako, P., Lensink, S., van Sark, W., & Weiss, M. (2008). Technological learning in the energy sector: WAB report No. 500102017.

Junginger, M., & Louwen, A. (2020). *Technological learning in the transition to a low-carbon energy system: Conceptual issues, empirical findings, and use, in energy modeling*. Elsevier.

Junginger, M., Visser, E. d., Hjort-Gregersen, K., Koornneef, J., Raven, R., Faaij, A., & Turkenburg, W. (2006). Technological learning in bioenergy systems. *Energy Policy*, *34*, 4024–4041. https://doi.org/10.1016/j.enpol.2005.09.012

Kavlak, G., McNerney, J., & Trancik, J. E. (2018). Evaluating the causes of cost reduction in photovoltaic modules. *Energy Policy*, *123*, 700–710. https://doi.org/10.1016/j.enpol.2018.08.015

Klaassen, G., Miketa, A., Larsen, K., & Sundqvist, T. (2005). The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom. *Ecological Economics*, *54*, 227–240. https://doi.org/10.1016/j.ecolecon.2005.01.008

Kobos, P. H., Erickson, J. D., & Drennen, T. E. (2006). Technological learning and renewable energy costs: Implications for US renewable energy policy. *Energy Policy*, *34*, 1645–1658. https://doi.org/10.1016/j.enpol.2004.12.008

Kohler, J., Grubb, M., Popp, D., & Edenhofer, O. (2006). The transition to endogenous technical change in climate-economy models: A technical overview to the innovation modeling comparison project. *The Energy Journal*, *SI2006*(1), 17–56. https://doi.org/10.5547/ISSN0195-6574-EJ-VolSI2006-NoSI1-2

Koomey, J., Hultman, N. E., & Grubler, A. (2017). A reply to "historical construction costs of global nuclear power reactors". *Energy Policy*, *102*, 640–643. https://doi.org/10.1016/j.enpol.2016.03.052

Kouvaritakis, N., Soria, A., & Isoard, S. (2000). Modelling energy technology dynamics: Methodology for adaptive expectations models with learning by doing and learning by searching. *International Journal of Global Energy Issues*, *14*(1–4), 104.

La Tour, A. d., Glachant, M., & Ménière, Y. (2013). Predicting the costs of photovoltaic solar modules in 2020 using experience curve models. *Energy*, *62*, 341–348. https://doi.org/10.1016/j.energy.2013.09.037

Lafond, F., Bailey, A. G., Bakker, J. D., Rebois, D., Zadourian, R., McSharry, P., & Farmer, J. D. (2018). How well do experience curves predict technological progress? A method for making distributional forecasts. *Technological Forecasting and Social Change*, *128*, 104–117. https://doi.org/10.1016/j.techfore.2017.11.001

Lako, P., Junginger, H., Neij, L., Engels, W., & Lensink, S. (2010). Off shore wind energy.

Lang, P. (2017). Nuclear power learning and deployment rates; Disruption and global benefits forgone. *Energies*, *10*, 2169. https://doi.org/10.3390/en10122169

Li, S., Zhang, X., Gao, L., & Jin, H. (2012). Learning rates and future cost curves for fossil fuel energy systems with CO2 capture: Methodology and case studies. *Applied Energy*, *93*, 348–356. https://doi.org/10.1016/j.apenergy.2011.12.046

Lindman, Å., & Söderholm, P. (2012). Wind power learning rates: A conceptual review and meta-analysis. *Energy Economics*, *34*, 754–761. https://doi.org/10.1016/j.eneco.2011.05.007

Liu, J., Grubler, A., Ma, T., & Kogler, D. F. (2021). Identifying the technological knowledge depreciation rate using patent citation data: A case study of the solar photovoltaic industry. *Scientometrics*, *126*, 93–115. https://doi.org/10.1007/s11192-020-03740-x

Louwen, A., Junginger, M., & Krishnan, A. (2018). *Technological learning in energy modelling: Experience curves: Policy brief*. Utrecht University.

Lovering, J. R., Yip, A., & Nordhaus, T. (2016). Historical construction costs of global nuclear power reactors. *Energy Policy*, *91*, 371–382. https://doi.org/10.1016/j.enpol.2016.01.011

Matteson, S., & Williams, E. (2015a). Learning dependent subsidies for lithium-ion electric vehicle batteries. *Technological Forecasting and Social Change*, *92*, 322–331. https://doi.org/10.1016/j.techfore.2014.12.007

Matteson, S., & Williams, E. (2015b). Residual learning rates in lead-acid batteries: Effects on emerging technologies. *Energy Policy*, *85*, 71–79. https://doi.org/10.1016/j.enpol.2015.05.014

Mauleón, I. (2016). Photovoltaic learning rate estimation: Issues and implications. *Renewable and Sustainable Energy Reviews*, *65*, 507–524. https://doi.org/10.1016/j.rser.2016.06.070

McDonald, A., & Schrattenholzer, L. (2001). Learning rates for energy technologies. *Energy Policy*, *29*, 255–261. https://doi.org/10.1016/S0301-4215(00)00122-1

Miketa, A., & Schrattenholzer, L. (2004). Experiments with a methodology to model the role of R&D expenditures in energy technology learning processes; first results. *Energy Policy*, *32*, 1679–1692. https://doi.org/10.1016/S0301-4215(03)00159-9

Moore, G. (1965). Cramming more components onto integrated circuits. *Electronics*, *38*, 114–117.

Nagy, B., Farmer, D., Bui, Q., & Trancik, J. (2013). Statistical basis for predicting technological Progress. *PLoS One*, *8*(2), e52669. https://doi.org/10.1371/journal.pone.0052669

Neij, L. (1997). Use of experience curves to analyse the prospects for diffusion and adoption of renewable energy technology. *Energy Policy*, *25*, 1099–1107. https://doi.org/10.1016/S0301-4215(97)00135-3

Neij, L. (1999a). Cost dynamics of wind power. *Energy*, *24*, 375–389. https://doi.org/10.1016/S0360-5442(99)00010-9

Neij, L. (1999b). *Dynamics of energy systems: Methods of analysing technology change (Lund University, PhD Thesis)* (p. 59). Lund University.

Neij, L. (2008). Cost development of future technologies for power generation—A study based on experience curves and complementary bottom-up assessments. *Energy Policy*, *36*, 2200–2211. https://doi.org/10.1016/j.enpol.2008.02.029

Neij, L., Andersen, P.D., & Durstewitz, M. (2003). The use of experience curves for assessing energy policy programs. In *Proceedings of the EU/IEa Workshop on Experience Curves*: *A Tool for Energy Policy Analysis and Design*.

Nemet, G. F. (2006). Beyond the learning curve: Factors influencing cost reductions in photovoltaics. *Energy Policy*, *34*, 3218–3232. https://doi.org/10.1016/j.enpol.2005.06.020

Nolan, R. L. (2012). Ubiquitous IT: The case of the Boeing 787 and implications for strategic IT research. *The Journal of Strategic Information Systems*, *21*, 91–102. https://doi.org/10.1016/j.jsis.2011.12.003

Nordhaus, W. (2014). The perils of the learning model for modeling endogenous technological change. *The Energy Journal*, *35*(1), 1–13.

Nykvist, B., & Nilsson, M. (2015). Rapidly falling costs of battery packs for electric vehicles. *Nature Climate Change*, *5*, 329–332. https://doi.org/10.1038/nclimate2564

Odam, N., & Vries, F. P. d. (2020). Innovation modelling and multi-factor learning in wind energy technology. *Energy Economics*, *85*, 104594. https://doi.org/10.1016/j.eneco.2019.104594

Perlin, J. (1999). *From space to earth: The story of solar electricity*. Aatech Publications.

Pieper, F. (2003). *Das Konzept von Lernkurven im Energiesektor—Beschreibung, Modellierung und Aggregation*. Diplomarbeit.

Pietzcker, R. C., Stetter, D., Manger, S., & Luderer, G. (2014). Using the sun to decarbonize the power sector: The economic potential of photovoltaics and concentrating solar power. *Applied Energy*, *135*, 704–720. https://doi.org/10.1016/j.apenergy.2014.08.011

Platzer, W. J., & Dinter, F. (2016). A learning curve for solar thermal power. In *Proceedings of the SOLARPACES 2015*: *International Conference on Concentrating Solar Power and Chemical Energy Systems*, Cape Town, South Africa, 13–16 October 2015. p. 160013.

Rapping, L. (1965). Learning and world war II production functions. *The Review of Economics and Statistics*, *47*, 81. https://doi.org/10.2307/1924126

Renaldi, R., Hall, R., Jamasb, T., & Roskilly, A. (2020). Experience rates of low-carbon domestic heating technologies in the United Kingdom. Copenhagen Business School [wp]. Working Paper/Department of Economics. Copenhagen Business School No. 16-2020 CSEI Working Paper No. 14-2020.

Romer, P. M. (1986). Increasing returns and long-run growth. *The Journal of Political Economy*, *94*, 1002–1037.

Rubin, E. S. (2019). Improving cost estimates for advanced low-carbon power plants. *International Journal of Greenhouse Gas Control*, *88*, 1–9. https://doi.org/10.1016/j.ijggc.2019.05.019

Rubin, E. S., Azevedo, I. M., Jaramillo, P., & Yeh, S. (2015). A review of learning rates for electricity supply technologies. *Energy Policy*, *86*, 198–218. https://doi.org/10.1016/j.enpol.2015.06.011

Rubin, E. S., Yeh, S., Antes, M., Berkenpas, M., & Davison, J. (2007). Use of experience curves to estimate the future cost of power plants with CO2 capture. *International Journal of Greenhouse Gas Control*, *1*, 188–197. https://doi.org/10.1016/S1750-5836(07)00016-3

Samadi, S. (2018). The experience curve theory and its application in the field of electricity generation technologies—A literature review. *Renewable and Sustainable Energy Reviews*, *82*, 2346–2364. https://doi.org/10.1016/j.rser.2017.08.077

Schaeffer, G.J., Alsema, E., Seebregts, A., Beurskens, L., De Moor, H., van Sark, W., Durstewitz, M., Perrin, M., Boulanger, P., Laukamp, H., & Zuccaro, C. (2004). Learning from the Sun: Analysis of the use of experience curves for energy policy purposes: The case of photovoltaic power. Final report of the Photex project.

Schoots, K., Ferioli, F., Kramer, G., & Van der Zwaan, B. (2008). Learning curves for hydrogen production technology: An assessment of observed cost reductions. *International Journal of Hydrogen Energy*, *33*, 2630–2645. https://doi.org/10.1016/j.ijhydene.2008.03.011

Söderholm, P., & Sundqvist, T. (2007). Empirical challenges in the use of learning curves for assessing the economic prospects of renewable energy technologies. *Renewable Energy*, *32*, 2559–2578. https://doi.org/10.1016/j.renene.2006.12.007

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, *70*, 65. https://doi.org/10.2307/1884513

Tang, T. (2018). Explaining technological change in the US wind industry: Energy policies, technological learning, and collaboration. *Energy Policy*, *120*, 197–212. https://doi.org/10.1016/j.enpol.2018.05.016

Thomassen, G., van Passel, S., & Dewulf, J. (2020). A review on learning effects in prospective technology assessment. *Renewable and Sustainable Energy Reviews*, *130*, 109937. https://doi.org/10.1016/j.rser.2020.109937

Van der Zwaan, B., & Rabl, A. (2004). The learning potential of photovoltaics: Implications for energy policy. *Energy Policy*, *32*, 1545–1554. https://doi.org/10.1016/S0301-4215(03)00126-5

Van der Zwaan, B., & Seebregts, A. (2004). Endogenous learning in climate-energy-economic models? An inventory of key uncertainties. *IJETP*, *2*(4591), 130. https://doi.org/10.1504/IJETP.2004.004591

van Sark, W., & Alsema, E. A. (2010). Potential errors when fitting experience curves by means of spreadsheet software. *Energy Policy*, *38*, 7508–7511. https://doi.org/10.1016/j.enpol.2010.06.053

Wei, M., Smith, S. J., & Sohn, M. D. (2017). Experience curve development and cost reduction disaggregation for fuel cell markets in Japan and the US. *Applied Energy*, *191*, 346–357. https://doi.org/10.1016/j.apenergy.2017.01.056

Wene, C.-O. (2000). *Experience curves for energy technology policy* (p. 132). OECD.

Wiesenthal, T., Dowling, P., Morbee, J., Thiel, C., Schade, B., Russ, P., Simoes, S., Peteves, S., Schoots, K., & Londo, M. (2012). Technology Learning Curves for Energy Policy Support. JRC Scientific and Policy Reports.

Wilson, C., Grubler, A., Bento, N., Healey, S., de Stercke, S., & Zimm, C. (2020). Granular technologies to accelerate decarbonization. *Science*, *368*, 36–39. https://doi.org/10.1126/science.aaz8060

Wright, T. P. (1936). Factors affecting the cost of airplanes. *Journal of the Aeronautical Sciences*, *3*, 122–128. https://doi.org/10.2514/8.155

Yao, Y., Xu, J.-H., & Sun, D.-Q. (2021). Untangling global levelised cost of electricity based on multi-factor learning curve for renewable energy: Wind, solar, geothermal, hydropower and bioenergy. *Journal of Cleaner Production*, *285*, 124827. https://doi.org/10.1016/j.jclepro.2020.124827

Yeh, S., & Rubin, E. S. (2012). A review of uncertainties in technology experience curves. *Energy Economics*, *34*, 762–771. https://doi.org/10.1016/j.eneco.2011.11.006

Yu, C. F., van Sark, W., & Alsema, E. A. (2011). Unraveling the photovoltaic technology learning curve by incorporation of input price changes and scale effects. *Renewable and Sustainable Energy Reviews*, *15*, 324–337. https://doi.org/10.1016/j.rser.2010.09.001

Yu, Y., Li, H., Che, Y., & Zheng, Q. (2017). The price evolution of wind turbines in China: A study based on the modified multi-factor learning curve. *Renewable Energy*, *103*, 522–536. https://doi.org/10.1016/j.renene.2016.11.056

How to cite this article: Haas, R., Sayer, M., Ajanovic, A., & Auer, H. (2022). Technological learning: Lessons learned on energy technologies. *WIREs Energy and Environment*, e463. https://doi.org/10.1002/wene.463