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A literature review

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Abstract
The experience curve theory assumes that technology costs decline as experience of a technology is gained through production and use. This article reviews the literature on the experience curve theory and its empirical evidence in the field of electricity generation technologies. Differences in the characteristics of experience curves found in the literature are systematically presented and the limitations of the experience curve theory, as well as its use in energy models, are discussed. The article finds that for some electricity generation technologies, especially small-scale modular technologies, there has been a remarkably strong (negative) relationship between experience and cost for several decades. Conversely, for other technologies, especially large-scale and highly complex technologies, the experience curve does not appear to be a useful tool for explaining cost changes over time. The literature review suggests that when analysing past cost developments and projecting future cost developments, researchers should be aware that factors other than experience may have significant influence. It may be worthwhile trying to incorporate some of these additional factors into energy system models, although considerable uncertainties remain in quantifying the relevance of some of these factors.

Keywords
Experience curves
Learning curves
Learning rates
Electricity generation technologies
Literature review

1. Introduction

Access to electricity is widely regarded as a prerequisite for ensuring a high standard of living, yet more than one billion people globally still lack access to electricity [1]. One of the targets of the Sustainable Development Goals (SDGs) is, therefore, to "ensure universal access to affordable, reliable and modern energy services" by 2030

[2]. At the same time, decarbonisation scenarios for many different countries agree that substituting fossil fuel use with electricity in final energy demand (e.g. switching from conventional to electric vehicles) is a key element of decarbonisation strategies [3]. Electricity demand is, consequently, expected to continue to increase globally in the decades to come, while electricity supply will simultaneously need to undergo a transformation towards low or zero-carbon technologies.

As a wide variety of electricity generation technologies exist using either fossil fuels, nuclear energy or renewable energy sources, this leads to the following question: which technologies should be used to what extent to meet future electricity demand? Ideally, electricity supply should evolve in a way which allows electricity demand to be met at the lowest cost to society. Although the societal costs of electricity supply include system and external costs in addition to the plant level costs of generating electricity, the plant level costs are an important component of the overall societal costs.

A widely-used method for anticipating future changes in the costs of electricity generation technologies (as well as other technologies) is the experience curve approach. This approach assumes that technology costs decline as experience of a technology is gained through its production and use. Empirical evidence indeed demonstrates a strong negative correlation between experience and cost for various electricity generation technologies, with costs declining at a certain rate – the so-called learning rate – for each doubling of a technology's capacity. Based on assumptions about future deployment levels, this relationship can be used to anticipate future changes in the cost of electricity generation technologies, e.g. by assuming that the learning rates observed in the past will remain stable in the future. During the past two decades the experience curve approach has been used increasingly in energy modelling to endogenise future cost developments by representing an interrelationship between a technology's cost and its deployment [4–11].

This article reviews the literature on the experience curve theory and on its empirical evidence in the field of electricity generation technologies. A number of reviews of experience curve literature have previously been published, covering both electricity generation technologies in general [4,12,13] and individual technologies, such as wind [14–16] and solar PV [17]. This article aims to complement the existing literature and specifically the recent review study by Rubin et al. [13], by:

- providing a systematic overview of the differences in the characteristics of experience curves for electricity generation technologies;
- providing a structured discussion of the limitations of the experience curve theory and the use of learning rates (including suggestions on how researchers can deal with these limitations);
- including additional and more recent empirical literature sources on experience curves for electricity generation technologies; and
- deriving plausible ranges of future learning rates for electricity generation technologies.

Section 2 introduces the experience curve theory and discusses the differences in experience curve characteristics, as well as the theory's limitations. Section 3 provides an overview and a discussion of the learning rates observed for electricity generation technologies in the past, distinguishing between onshore wind plants, offshore wind plants, photovoltaic (PV) systems, concentrating solar thermal power (CSP) plants, biomass power plants, nuclear power plants, coal power plants and natural gas power plants. Section 4 attempts to derive plausible ranges of future learning rates, drawing on the findings from Section 2 and Section 3. Finally, Section 5 draws conclusions and provides suggestions for future research in the field.

2. The experience curve theory

2.1. Deployment-induced learning and the experience curve theory

A large volume of empirical research indicates that specific costs fall as experience gained from the production and use of a particular technology increases. Initially, such learning was investigated at individual company level but, progressively, similar observations were made at industry level. These industry level observations suggest that a significant share of the knowledge gained by individual companies and their customers through experience can ultimately be appropriated by other companies and customers (i.e. the spillover effect). Alternatively, or additionally, some learning may take place at industry level; for example, through exchanges between company representatives within associations or at conferences.

The literature suggests that experience gained by deployment can lead to learning through at least three different channels:

- *Learning-by-doing:* as more and more units of a technology are produced, managers gain experience with the production process and may learn how to improve it, e.g. by increasing work specialisation or by reducing waste. Workers may become more efficient in their respective tasks as they continuously repeat their individual production steps.
- *Learning-by-using:* this can be regarded as the "demand-side counterpart" [18] of learning-by-doing. Users may gain experience by using a technology and learn how to install and operate it more efficiently. The existence of formal user groups who interact with each other can strengthen this kind of learning through networking effects [19].
- *Learning-by-interacting:* by informing them about problems related to the use of a technology, users enable manufacturers to learn from actual on-site experiences of the product. Manufacturers can use this information to improve their respective products [20,21]. Furthermore, companies, users and other stakeholders – such as research institutes and policy makers – can learn from one another through the formal and informal exchange of information [22–24].

A relationship between specific costs and experience has been empirically observed for numerous technologies in various fields [25–27]. As early as the 1930s, a negative correlation between specific costs and production volume was documented for airplanes by Wright [28]. He observed a steady decrease in the specific amount of labour and material input required as the cumulative construction of airplanes increased [28]. This relationship is nowadays referred to as a learning curve. Subsequently, the concept has typically been applied to the total costs of a product, including the combined effect of learning, scale and potentially other factors. The concept is now also commonly applied to entire industries, not only to single companies. The curves derived from this broader understanding of the concept can be referred to as *experience curves* [29].[1] Such experience curves can capture the three different channels of deployment-induced learning, as described above.

[1] However, as Junginger et al. [26] note, many authors today use the term "learning curve" as a synonym for "experience curve".

However, they are not able to separate the individual effects of each channel of learning.

An experience curve typically describes the relationship between a technology's specific costs (expressed in real terms) as the dependent variable and the technology's experience as the independent variable. [2] The experience of a technology is depicted on the horizontal axis of a two-dimensional coordinate system, while the associated costs are depicted on the vertical axis. Typically, in the early stages of deployment, technology costs decrease more steeply for a set increase in production than in the later stages of deployment. Therefore, when costs are depicted on a double-logarithmic scale, experience curves tend to take a more or less linear form.

An experience curve can be described by either the learning rate or the progress ratio it depicts. The learning rate (LR) is the rate at which a technology's costs are found to decrease for each doubling of experience. The progress ratio (PR) is an alternative way of describing this relationship and can be defined as:

PR = 1 – LR

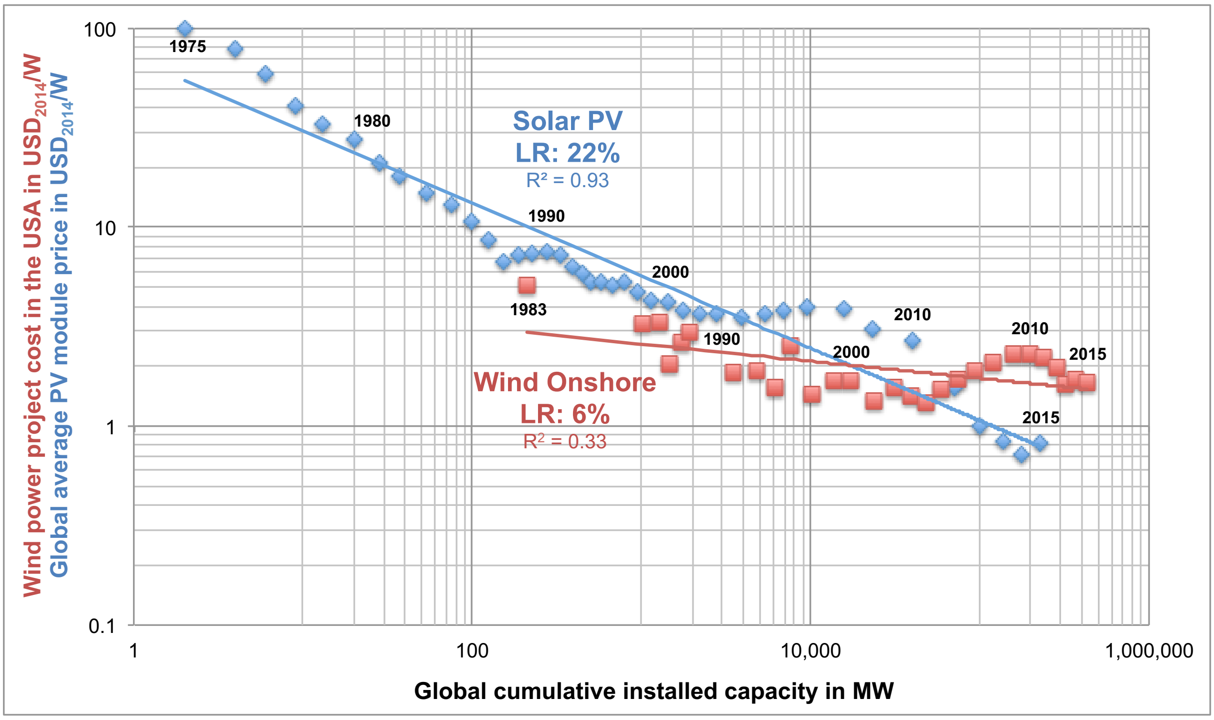
It informs about the relative technology costs remaining after a doubling of experience.

Figure 1 depicts two experience curves as examples. One of the curves shows the development of the average global PV module price from 1975 to 2015 and describes a learning rate of 22%. The curve's R^2 value is 0.93.[3] The other curve shows the development of wind power project costs in the USA between 1983 and 2015 and describes a learning rate of 6%. Its R^2 value is 0.33, considerably lower than that of the PV module price curve.

[2] While experience curves are typically used to investigate the relationship between costs and experience, other characteristics of technologies can also be related to experience. In the case of electricity supply technologies, for example, experience curves have also been constructed for the thermal efficiency of coal power plants [30], for the capacity factor of nuclear power plants [31] and for the energy required to manufacture PV modules and systems [32].

[3] R^2 is the coefficient of determination, a measure of the curve's goodness of fit. It takes on values between 0 and 1, with an R^2 of 1 indicating that the regression line perfectly fits the data.

Figure 1: Experience curves for global solar PV module manufacturing (1975-2015) and for wind power projects in the USA (1983-2015)



Data sources: [33–39]

2.2. Different characteristics

Experience curves in the literature for electricity generation technologies differ in relation to various characteristics, as documented in Table 1.

Table 1: Differences in the characteristics of experience curves for electricity generation technologies [a, b]

Methodology	
Factors considered	• *Only experience* • Experience and one or more additional factors
Use of costs or of prices	• Market costs • *Market prices (as a proxy for market costs)*
Experience curve continuity	• *Continuous curve and stable learning rate* • Discontinuous curve and varying learning rate
Learning system boundary	
Level of perspective	• Production perspective (company level) • *Market perspective (industry level)*
Object of investigation	• Specific part of a power plant technology • *Power plant technology* • Power plant project (e.g. including construction)
Definition of specific costs (dependent variable)	
Product definition	• *Technology costs* • Investment costs • Costs per unit of electricity generated
Geographical scope [c]	• Costs from an individual country • Costs from a group of countries • Costs from all relevant countries
Definition of experience (independent variable)	
Product definition	• *Cumulative capacity* • Cumulative number of plants or parts of plants • Cumulative electricity generation
Geographical scope [c]	• Experience within an individual country • Experience within a group of countries • Global experience

[a] *It should be noted that not all combinations of these characteristics lead to meaningful experience curves. For example, if the object of investigation is a specific part of a power plant technology, it would not be consistent to choose the costs per unit of electricity generated as the dependent variable, as these costs are also influenced by the costs of all other parts of the plant. Instead, one would choose the technology costs of that specific part.*

[b] *The most common form of each characteristic found in the experience curve literature is indicated by italic font.*

[c] *For geographical scope, it is not obvious which form is the most commonly used in the experience curve literature. However, for some technologies the preferred choice is clear: for PV technology, costs from all relevant countries and global experience are typically chosen, while for wind turbines both costs and experience usually relate to an individual country or to a small group of countries.*

Methodological issues

The traditional one-factor experience curve uses only experience as the independent variable to explain cost changes over time. However, this approach potentially suffers from the problem of omitted variable bias (as explained in Section 2.3 below) and, as a result, some authors have suggested the construction of multi-factor experience curves and associated learning rates. These curves aim to properly consider and isolate the combined effect of other relevant factors in order to derive a "true" learning rate [24]. While theoretically appealing, multi-factor experience curves are difficult to construct due to data limitations. For example, learning through research and development or spillover effects from other industries are difficult to reliably quantify. Furthermore, experience and other factors explaining cost changes often show high levels of multicollinearity, making it difficult to distinguish between the effects of experience and the other factors [40–43].

Most of the available empirical studies that construct experience curves for electricity generation technologies do not use technology costs as the dependent variable – as would be theoretically preferable – but instead use a technology's market price. Market prices are frequently used as a proxy for market costs, as the former are more readily available [22]. See Section 2.3 for a discussion of the problems associated with using price data instead of cost data.

It is typically assumed in experience curve theory and application that individual technologies exhibit stable learning rates, i.e. continuous experience curves that take the form of single linear curves when depicted on log-log scales. However, some empirical studies find that two or more periods with separate learning rates better describe the historical cost (or price) development of a certain electricity generation technology [for example 44–46]. In such cases, a technology's experience curve shows discontinuities.

Learning system boundaries

Most experience curves for electricity generation technologies are constructed based on an industry level (or market) perspective. In such a perspective, the combined learning effects of all companies offering a certain type of power plant technology are analysed. The independent variable is defined as the cumulative experience of all companies, while the dependent variable is defined as the average cost or average market price. This perspective implicitly assumes that inter-company learning spillovers are significant, or that learning predominantly takes place at industry level. However, a limited number of literature sources also develop experience curves for individual companies or a confined group of companies [for example 47–52]. This company level (or production) perspective attempts to identify the learning that takes place within individual companies, although this learning can be supported by industry level spillovers.

When power plant technologies consist of different parts that are assumed to exhibit distinct learning rates or different deployment curves, it is more consistent to construct separate learning rates for these individual parts instead of a single learning rate for the entire technology [53]. For example, it has been suggested that separate experience curves should be constructed for the main elements of concentrating solar thermal power plants [54]. For these plants, three main components can be differentiated: the collector field, the thermal storage system and the power block. All three elements of the power plant are distinct technologies and none of them share the same development of experience.

Experience curve analysis can relate not only to the power plant technology (e.g. wind turbines) or parts of that technology (e.g. rotor blades); it can also refer to an entire power plant project (e.g. wind farms). In that case, costs related inter alia to on-site construction, grid connection and/or the costs of obtaining approval to build the plant are included. All these additional costs, as well as any learning realised by these additional elements of the power plant project, are included in the experience curve and the resultant learning rate as the system boundary is expanded [14].

Definition of specific costs

Experience curves for electricity generation technologies either use a technology's specific capacity costs, a power plant's specific investment costs or its specific electricity generation costs as the dependent variable. The choice of the type of cost is closely related to the learning system boundary (see above). When only the technology itself, or a certain part of the technology, is investigated, technology capacity costs should be chosen as the cost dimension. When, on the other hand, entire power plant projects are investigated, either investment costs or electricity generation costs should be analysed, as these include all other cost elements of a project. These additional cost elements include on-site construction or installation costs and grid-connection costs and – in the case of electricity generation costs – also include operating and maintenance costs, fuel costs, decommissioning costs and the cost of capital [14].[4]

Most studies, especially those looking at wind and solar PV technologies, focus on the technology itself and use specific capacity costs. They may do this in order to focus on the learning-by-experience reflected in plant manufacture.[5] After all, it could be argued that other elements of electricity generation costs, such as construction or installation costs, operating and maintenance costs and fuel costs do not benefit from experience or might be subject to learning rates that are very different from those observed in the manufacturing process. However, there are also arguments in favour of using specific electricity generation costs. For investors, as well as for society as a whole, the generation costs are more relevant than the capacity costs when assessing and comparing different power plant technologies. Some technological improvements do not manifest themselves in lower specific capacity costs but still lead to lower specific electricity generation costs. For example, technological improvements in wind turbine design may enable higher full load hours at any specific site. Furthermore, improvements in operation and maintenance (corresponding to the above-mentioned learning-by-using) are only captured when specific electricity generation costs are used as the dependent variable.

It should, therefore, be kept in mind that learning rates based on technology costs or investment costs do not necessarily closely correlate with these technologies' generation-based learning rates. Differences can be especially marked for technologies for which other cost elements, such as fuel costs, play a large role (e.g. fossil fuel power plants) or for technologies for which design improvements can lead to higher achievable full load hours (e.g. wind power).

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[4] It is noteworthy that demand-side learning ("learning-by-using", see Section 2.1 above) can only fully be taken into account by experience curves that use electricity generation costs as their measure for specific costs, as these costs include working stages where demand-side learning can take place, such as installation or operating and maintenance.

[5] Another reason why much of the empirical experience curve literature focuses on capacity costs may be because these figures are more readily available than investment costs or generation costs. This holds true when prices are used as a proxy for costs, which is a typical approach.

Costs can be based on data from a single country, from a group of countries or from all countries in which a technology is manufactured (production perspective) or used (market perspective). If learning is assumed to be mostly industry-wide and global in nature, as in the case of PV module manufacture [55,56] and wind turbine manufacture [14,57], global data, or at least data from as many countries as possible, should preferably be considered. This reduces the risk of unwittingly capturing unique country-specific cost or price swings during the time period considered. If, on the other hand, learning is assumed to be mostly national, as in the case of PV plants' balance of system costs [19], national cost data should be used to capture the effects of national learning.

Definition of experience

Experience as the independent variable of an experience curve can be defined either as a technology's cumulative capacity built, its cumulative number of plants (or parts of plants) built or its cumulative electricity generation [46,58]. Choosing an appropriate definition of experience is case-sensitive and is again closely related to how the learning system boundary is defined (see above). That is, it requires consideration about where exactly experience is expected to occur [22,59]. If, for example, experience is largely expected to occur in the manufacturing process, cumulative capacity should be chosen. If, however, learning can be expected to occur to a large extent during the on-site installation or construction of single power plants, irrespective of their size (as may be the case for nuclear power plants which are large and complex in nature), cumulative number of plants should be chosen. Finally, if significant learning is expected to occur not only during manufacture and installation but also during the operation of power plants (or if learning during manufacture or installation has an effect on full load hours or efficiency), cumulative electricity generation might be an appropriate definition of experience – if the aim is to capture the combined learning [60].

As in the case of the geographical scope of specific costs, the geographical scope of experience should consider the level at which learning is expected to occur. Consequently, the geographical scope of specific costs and experience should ideally be identical [14,61].

2.3. Limitations of the experience curve concept

The literature on experience curves widely acknowledges and discusses the limitations of the concept. While many authors nonetheless believe experience curve analysis to be useful in describing and understanding past technology cost developments and learning about possible future developments, some authors [e.g. 62–64] are highly critical of the traditional one-factor experience curve concept in general and of the use and interpretation of experience curve results in particular. This section discusses the key limitations of the traditional one-factor experience curve concept and includes suggestions on how researchers can deal with these. The limitations can be classified in three categories, as shown in Table 2.

Table 2: Key limitations of the traditional one-factor experience curve theory

Criticism of the theoretical concept
• Concept implies that experience is the only driver of technology cost changes
• Effect of experience tends to be overestimated (*omitted variable bias*)
• Concept cannot prove that experience is indeed the *cause* of observed cost changes
• High level of aggregation does not allow for a deeper understanding of cost drivers
• Aspects of technological change that have no impact on market costs are neglected
Criticism of the empirical data
• Frequently used prices are often an inadequate proxy for costs
• Uncertainty in historic cost data can lead to substantive learning rate uncertainty
Criticism of the use of learning rates
• Learning rates are often uncritically assumed to remain constant in the future
• Uncertainties are frequently neglected when using learning rates in energy models

Criticism of the theoretical concept

A key criticism of the traditional one-factor experience curve concept is its implication that experience is the only driver of technology cost changes. Many academics point out that a number of other factors have been found to play significant roles in influencing technology cost developments, but these are not explicitly taken into account in experience curve analysis [for example 10]. These other factors notably include [43]:

- Learning through RD&D
- Knowledge spillovers from other technologies
- Economies of unit scale (upsizing)
- Economies of scale (mass production)
- Cost changes of input materials and labour
- Changes in regulations

One-factor experience curves not only fail to appreciate these factors' respective roles in technology cost developments, but can also lead to *omitted variable bias*, i.e. the overestimation of the relevance of experience in reducing technology costs (as well as by the learning rates derived from these curves).[6]

Omitted variable bias occurs when neglected additional independent variables are correlated not only with technology costs but also with experience [65]. Experience, for example, usually has a strong correlation with time, as may be the case for other relevant variables such as knowledge stock (gained through R&D), economies of scale or the suspected influence of inter-industry spillovers [57,62,63]. As a result, the high correlation between experience and technology costs, as suggested by many experience curves derived from historic data, may actually be (to some extent) a misrepresentation caused by the correlation between experience and other key

[6] In principle, omitted variable bias may lead to either over *or* under-estimation of the effect of a chosen variable (in this case experience). However, as the omitted variables typically deemed to be of significance tend to *reduce* technology costs, their omission usually results in the cost reduction effect of experience to be *over*-estimated.

cost-influencing factors omitted from the analysis. Based on a literature review of studies deriving learning rates for PV technology, de la Tour et al. [41] find that PV learning rates based on multi-factor experience curves are considerably lower than PV learning rates based on models with experience only. They conclude: “This suggests that the experience parameter is seriously biased when it is the only explanatory variable as it captures the influence of other drivers.” [41]

Some critics maintain that even if there is acceptance of a strong correlation between technology costs and experience, this does not necessarily mean that experience drives down costs. Instead, the causal relationship may work the other way around: cost decreases (brought about by various factors other than experience) may lead to more rapid technology deployment as the technology becomes economically more attractive [9,10].

The experience curve concept is also criticised for its high level of aggregation, as the concept does not attempt to explain exactly *how* experience leads to cost reductions [62,66]. For example, the significance of learning-by-doing compared to learning-by-using or learning-by-interacting cannot be revealed by simple experience curve analysis. Similarly, Nemet [29] points out that unlike the original company level learning curve concept, in which learning is assumed to stem from employee productivity within individual plants, the industry level experience curve concept is based on the strong assumption that each company benefits from the collective experience of all companies. In other words, the concept “assumes homogenous knowledge spillovers among firms” [29].

It should also be noted that the experience curve does not necessarily capture all types of improvements in electricity supply technologies. This is because such improvements do not necessarily manifest themselves in plant level cost reductions. Beyond this single dimension, technological improvements may lead to reductions in external costs, such as air pollution mitigation or improvements in the quality of electricity generation, e.g. with regard to generation reliability or a technology’s contribution to grid stability [29].

This criticism of the theoretical concept of the experience curve can be addressed by researchers by:

- discussing the possible influences (and interdependencies) of factors other than experience on cost changes and deriving learning rates that take relevant cost-influencing factors other than experience into account [17,24,57,67–69];
- preparing in-depth case studies of individual technologies’ learning systems [29,70];
- and reflecting whether past learning may also have reduced non-plant level costs (such as external costs).

Criticism of the empirical data used

For reasons of data availability, market prices as a proxy for market costs are frequently used as the dependent variable in the construction of experience curves. It is often argued that in competitive markets a very close correlation between costs and prices can be assumed (as companies that charge prices considerably higher than their costs will not remain competitive). However, critics point out that this is not necessarily the case in real world markets. Instead, individual technology suppliers may exert market power over prolonged periods of time, allowing them to charge considerable mark-ups. If the mark-up between costs and market price is assumed to be constant but, in fact, varies considerably over time, wrong conclusions about the actual experience curve and its associated learning rate are likely to be drawn [22,58].

Furthermore, reliable historic cost and even price data is often difficult to source. Especially for the early years of a technology's deployment, data is often scarce and uncertain, as early markets are small and the prices charged in niche markets by only a few market actors are not always publicised. This uncertainty about early costs or prices can be a problem for experience curves as the early data in particular can have a significant influence on the slope of the experience curve and, consequently, its learning rate [29].

This criticism of the empirical data used can be addressed by researchers by:

- discussing to what extent prices and costs might deviate during the observed time period and – if possible – making efforts to correct observed prices for market power [29];
- and stepping up efforts to obtain reliable historic cost or price data (e.g. by carefully analysing existing datasets) and refraining from using data that appears to be unreliable [71].

Criticism of the use of learning rates

A key objective of deriving historic experience curves for individual technologies is to gain information about their possible future experience/cost relationship. In this regard, it is often assumed that learning rates observed in the past will remain constant in the future. Critics of this approach emphasise that it should not be taken for granted that past experience curves can simply be extrapolated [53,65,72]. Since simple experience curve analysis does not provide details about the deeper cost drivers (see above), it is considered problematic to assume that the relationship between experience and cost will remain constant in the future. For example, assuming constant learning rates does not take into account possible future constraints to learning; for example, in the form of physical limits to conversion efficiency improvements or to material reductions. Equally, it does not allow for the consideration of possible future technological breakthroughs, which would manifest themselves in experience curve discontinuities [22,29,73].

More specifically, learning rates are often used in energy models to describe the future relationship between deployment and costs. Critics argue that these models should not use single values for each technology's learning rate, as is often the case, but should instead use a range of values. Using only single values, the critics argue, leads to a false sense of certainty regarding the potential future cost reductions of individual technologies.[7]

This criticism of the use of learning rates can be addressed by researchers by:

- critically reflecting whether observed learning rates in the past can reasonably be expected to remain stable in the future, especially in the medium to long term [4,54,74,75];

[7] Such a false sense of certainty is especially problematic because even relatively small variations in a technology's assumed future learning rate can have considerable implications for its long-term role in a cost-optimal energy system. For example, back in the year 2000, an IEA report [59] estimated that a future PV learning rate of 22% would mean that the technology would become cost-competitive once it reached a cumulative capacity of 150 GW, requiring learning investments (i.e. additional costs compared with the costs of a technology that is initially cost-efficient) of 40 billion USD. At a slightly lower learning rate of 18%, cost-competitiveness would only be reached at 600 GW, and would require considerably higher learning investments (120 billion USD).

- and performing several model runs when modelling the future costs of individual electricity generation technologies, using ranges of plausible future learning rate values in order to reflect the associated uncertainties [17,76].

3. Observed experience curves for electricity generation technologies

3.1. General observations

As part of this review, 67 studies with empirical observations of experience curves and associated learning rates for eight different types of electricity generation technologies have been identified. Tables A-1 to A-8 in the Appendix list the observed learning rates and associated relevant information from these studies. The following table provides an overview of the reviewed studies included in Tables A-1 to A-8.

Table 3: Overview of the reviewed experience curve studies and their associated learning rates as listed in Tables A-1 to A-8 in the Appendix

Type of power plant	Number of studies	Number of learning rates	Geographical domain of experience chosen for the learning rates [a]				Period(s) covered (all studies combined)
			Global	European countries	Asian countries	USA	
Wind onshore	30	73 [a]	17	45	10	3	1971-2012
Wind offshore	2	6	3	3	0	0	1991-2008
PV	28	63 [a]	44	10	5	6	1975-2014
CSP	5	6	2	1	0	3	1984-2013
Biomass	3	7	0	2	5	0	1980-2002; 2005-2012
Nuclear	3	3	0	1	0	2	1960-2002
Coal	3	6	2	0	0	4	1902-2006
Natural gas	2	5	4	0	0	1	1949-1968; 1981-1997

[a] *In the case of wind onshore and PV, the sum of the learning rates listed in the four 'Geographical domain' columns is higher by two than the figure stated in the 'Number of learning rates' column. This is because for both technologies two learning rates include both European countries and the USA in their geographical domains.*

For some technologies, especially for nuclear power plants and natural gas power plants, experience curve studies covering more recent time periods are rare or were unavailable in the literature. For emerging technologies with very little current market relevance (e.g. marine technologies), or for technologies which are characterised by high heterogeneity (e.g. geothermal electricity generation), no experience curve studies are available.

Regarding methodological choices, the tables in the Appendix show that almost all the studies use price as a proxy for costs. (While many studies use investment *costs*, these costs include the *prices* that were paid for the technology, not the cost of manufacturing the technology). The tables also show that over the years an increasing number of experience curve studies have attempted to consider additional independent variables (such as R&D or resource prices) to explain a technology's cost or price developments. Furthermore, by far the majority of experience curves constructed for electricity generation technologies refer to the cost developments of power plants or parts of power plants, with only a few studies aiming to investigate the broader learning system by analysing a technology's electricity generation costs.

A comparison of the reported learning rates for all technologies shows that these are generally considerably higher for small-scale generation technologies (especially for solar PV and onshore wind) than for larger-scale technologies (such as nuclear power and offshore wind). It is widely believed that the main reason for these differences is the level of standardisation that can be achieved. Small-scale technologies, which are manufactured in identical or very similar form in high volumes, offer considerable room for standardisation in both their manufacture and installation. Conversely, for large-scale power plants much of the construction has to take place on-site, as opposed to in factories, limiting the potential for standardisation [68]. Trancik [77] argues that the much smaller scale of PV technology compared to nuclear power plants also makes it much easier and less costly to conduct innovative research and to build demonstration plants.

For some technologies, namely onshore wind turbines, nuclear power plants and coal power plants, observed learning rates tend to be lower for less recent time periods. The reasons for these changes in observed learning are technology-specific and are discussed in detail in the respective sections below. Finally, it is noticeable that the learning rates for conventional power plants, especially for nuclear and natural gas power plants, vary considerably from one study and/or time period to another. This significant variation indicates that the experience curve concept may not be suitable for explaining these technologies' past and possible future cost developments [78,79].

3.2. Renewable energy power plants

Onshore wind power plants

Many studies have investigated the learning rate of onshore wind power plants. Most of these studies use regional or national deployment and price data. Assuming here that the learning system for wind turbines is mainly global in nature [14,57,67], it is particularly relevant to examine those studies that use global deployment as an indicator for experience. The less recent of these global studies [14,42,57,72,80,81] typically find learning rates for specific wind turbine prices or project-specific investment costs to be in the range of 10% to 19%. However, three studies [11,38,67] using more recent data on specific investment costs arrive at lower learning rates of only 2% to 8%.

There are several possible reasons why the learning rates from these three sources, which include data up to 2008, 2012 and 2014 respectively, are lower than the learning rates identified by older studies:

- Rising commodity prices

Prices for commodities (including steel and copper, which are both relevant cost factors in wind turbines) increased considerably during the first decade of the century and were especially high between 2005 and 2008 [22,82,83].

- Supply constraints due to strong market growth
  Throughout the first decade of the century, global demand for wind turbines grew strongly as global annual installed wind capacity grew more than tenfold between 2000 and 2009, from 3,760 MW to 38,478 MW [84]. This led to supply constraints, allowing turbine manufacturers and component suppliers to charge higher prices and increase their profits [22,38].
- Limits to learning
  Some authors expect a technology's learning rate to decline as the technology becomes more mature. For example, [85] argue that mature technologies typically require more time until they reach doublings in cumulative capacity, leading to a higher risk of knowledge depreciation. Another explanation [44] is that as technologies become more mature, their inherent cost reduction potentials are increasingly exploited. To the extent that the previously discussed factors cannot fully explain recent reductions in the learning rate, this may be an indication that such a "flattening" of the experience curve for wind power plants is indeed taking place.

It is important to keep in mind that for wind power there is not necessarily a linear relationship between rated capacity and electricity generation. Instead, changes in turbine design, such as higher towers, longer rotor blades and improved control electronics, tend to lead to higher capacity factors by allowing relatively weak and erratic wind resources to be captured. Such design changes were observed over the years for new wind power plants as these plants were increasingly optimised for use at sites with non-optimal wind conditions. However, when deriving experience curves based on turbine prices or investment costs, as most studies do, only the *costs* associated with these design changes are taken into account, while the *benefits* in the form of additional electricity generation are not captured [86,87].[8]

As a consequence, and as Neij [60] points out, wind power learning rates expressed in terms of the levelized production cost of electricity are generally higher than learning rates expressed in terms of turbine prices or investment costs. This is illustrated by the results of a limited number of studies in Table A-1 [87–89], which derive experience curves for both turbine prices or investment costs, as well as for electricity generation costs, using the same region and the same or very similar time period.

Offshore wind power plants
Only a few literature sources derive experience curves for offshore wind technology. The two studies identified for this article [45,90] find similar learning rates (between 0% and 3%) for offshore wind power investment costs, lower than the vast majority of values for onshore wind power plants. The values for the coefficient of determination (the R^2 values) are also lower than typical R^2 values of wind onshore experience curves. This indicates that the explanatory power of the experience curve approach is limited for offshore wind power.

[8] The work of Coulomb and Neuhoff [80] is an exception in this regard as the authors adjust turbine costs in an attempt to take into account the fact that bigger turbines tend to be exposed to higher wind speeds and, therefore, produce more energy per installed capacity. Without this adjustment, their learning rate for onshore wind power plants built in Germany between 1991 and 2003 would be 11% instead of 13%.

As for onshore wind power plants, increases in commodity prices during the first decade of the century are thought to have played a role in (temporarily) reversing the trend of declining costs. Van der Zwaan et al. [90] find that correcting for copper and steel price increases leads to an increase in the wind offshore learning rate of 3% (from 0% to 3%). Likewise, the tight market for wind turbines and components (see discussion above in relation to onshore wind) during much of the first decade of the century is also likely to have led to higher prices for offshore wind power plants.

While Voormolen et al. [91] do not derive a learning rate for offshore wind power, they analyse the development of offshore wind farm investment costs in Europe between the year 2000 and January 2015 and find that investment costs, as well as the levelized cost of electricity, increased during this period. Correcting for commodity price changes and locational characteristics (distance to shore and ocean depth) shows a slowly decreasing trend for the period from 2000 to 2008. This is largely in line with the findings from van der Zwaan et al. [90], who use investment cost data up to 2008. However, Voormolen et al. [91] identify cost increases between 2008 and 2015 even after correcting for commodity price changes and locational characteristics. The authors infer that there must have been additional factors leading to cost increases and they suggest that limited competition and bottlenecks in the supply chain for offshore wind power plants are likely to have driven up prices.

Solar PV power plants

The PV learning rates listed in Table A-3 are either for all types of PV systems on the market (a market which has always been dominated by PV systems using silicon modules), or specifically for PV systems using silicon modules. Only a few studies have looked at learning rates for non-silicon PV technology, such as cadmium-telluride thin film modules [92], or for concentrating PV systems [93].

Most of the identified learning rate studies for PV technology construct global one-factor experience curves using specific module prices. The learning rates of these experience curves are typically between 15% and 25%. No flattening of the PV experience curve is observed over time when module price data for more recent years is included. While most solar PV learning rate studies focus on module costs, there are indications that balance of system costs have decreased in the past to at least a similar extent to PV module costs [19,94,95].

Solar thermal power plants

Two recent studies [74,96] deriving global experience curves for solar thermal power plants include not only solar thermal power plants built during the 1980s in the USA but also plants built more recently (mostly in Spain and the USA). They find similar learning rates of 10% and 11% respectively. The most recent study identified [97] finds a learning rate of 16% for parabolic trough plants built in Spain between 2006 and 2011.

However, literature results for learning rates of solar thermal power plants need to be treated with special care, as so far relatively few such plants have been built, investment cost data is not fully transparent for all power plant projects and comparisons of costs or prices are complicated by major differences in power plant characteristics – some solar thermal power plants are equipped with expensive thermal storage devices enabling them to generate electricity even during times when there is no or insufficient sunshine, while others are not. Furthermore, there are different types of solar thermal power plant technologies, most notably the parabolic trough and the power tower design. These different types of technologies may also exhibit different learning rates [98].

Looking only at CSP projects from a certain developer within one country and using identical technology, Feldman et al. [99] find learning rates of between 5% and 12% for plants built in Spain and the USA, with an average rate of 8.5%.

Biomass power plants
Experience curves for biomass power plants are difficult to construct as there are variations in the characteristics of such plants, concerning the type of technology used, plant size and the type of biomass feedstock used. Perhaps as a consequence, only a few literature sources derive experience curves for biomass power plants. The three studies identified [23,59,69] provide learning rates for the specific generation costs in the European Union, Sweden and China, respectively. They find learning rates of between 2% and 15%. For biomass feedstock (not shown in Table A-5), learning rates of about 10% to 45% have been found in the literature [23,100,101].

3.3. Nuclear power plants

Only a few literature sources derive industry level experience curves for nuclear power plants. Two of the three sources identified refer to nuclear power plants built in the USA during the 1960s and 1970s. One study [46] uses specific investment cost data from plants built between 1960 and 1973 and finds a learning rate of 22%, while the other study [102] uses specific investment cost data from plants completed between 1971 and 1978 and derives a learning rate of -49%, suggesting cost increases or “negative learning”. While these learning rates appear to be irreconcilable, they can be explained in the main by the different time periods analysed. Cost increases for nuclear power plants built in the US appear to have set in by the early 1970s. Komanoff [102] interprets the negative learning rate as an indication that growth in nuclear power capacity leads to stricter safety regulations which, in turn, increase specific power plant costs. A more recent study [68] also found a negative industry level learning rate (-17%) for nuclear power plants built in France between 1978 and 2002.

Factors that have exerted upward pressure on the costs of nuclear power plants are thought to include [103]:

- Increased technological complexity in part due to ever larger plants
- Deterioration of the quality of sites available for new plants
- Increase in prices for commodities and skilled labour
- Continuous changes and tightening of regulations

A number of additional studies [for example 78,79,103–105] have analysed the cost developments of nuclear power plants built in several countries: mostly in France, Japan and the USA. For most countries they find significant investment cost increases for newly built plants since the 1970s, but do not attempt to derive country level or even global experience curves and learning rates.

Some studies [for example 47,48,50,52,106] have looked at learning rates for construction companies or utility companies building nuclear power plants in the USA and have found evidence of *company level* learning. Rangel and Lévêque [68] also report a type of learning in nuclear power plant construction. Their linear regression analysis of the costs of nuclear power plants in France finds evidence for learning effects when confining the analysis to *individual groups or types* of reactors. However, the learning rate they derive is relatively small (about 3%). Berthélemy and Rangel [47], in their analysis of nuclear cost data from both France and the USA, find significant learning with a rate of about 10% to 12% for individual types of reactors when these are also built by the same architect-engineering (A-E) company.

3.4. Fossil fuel power plants

Coal power plants

A limited number of studies construct experience curves for coal power plants. The three studies identified [30,46,107] find learning rates of 6% to 12% for the specific investment costs of coal power plants or the specific costs of subcritical pulverised coal boilers. All price data is from the USA, while the experience variable is either based on global deployment levels (in one of the studies) or on US deployment levels (in two studies).

Despite the positive learning rates derived over the observed periods as a whole, the three studies show cost *increases* since about the early 1970s. According to the literature, the main reasons for the increases in specific investment costs observed over recent decades are:

- stricter environmental regulations forcing coal power plant owners to invest more in air pollution control technologies;
- increased prices for commodities and skilled labour;
- and the use of more complex technologies and higher quality materials in order to increase the plants' thermal efficiency.

Natural gas power plants

Only a few literature sources derive experience curves for natural gas power plants. Two such studies have been identified for this article. A study by Ostwald and Reisdorf [46] finds a learning rate of 15% for specific investment costs of natural gas power plants in the Mountain States of the USA between 1949 and 1968. However, this study has a very narrow definition of the learning system boundary (only Mountain States of the USA) and neglects any learning acquired by building natural gas power plants prior to 1949. The more recent study by Colpier and Cornland [108] takes global experience into account and analyses specific investment costs solely for combined cycle gas turbines (CCGT) built between 1981 and 1997. It distinguishes between two periods, deriving a learning rate of -13% for the period 1981 to 1991 and a learning rate of 25% for the period 1991 to 1997.

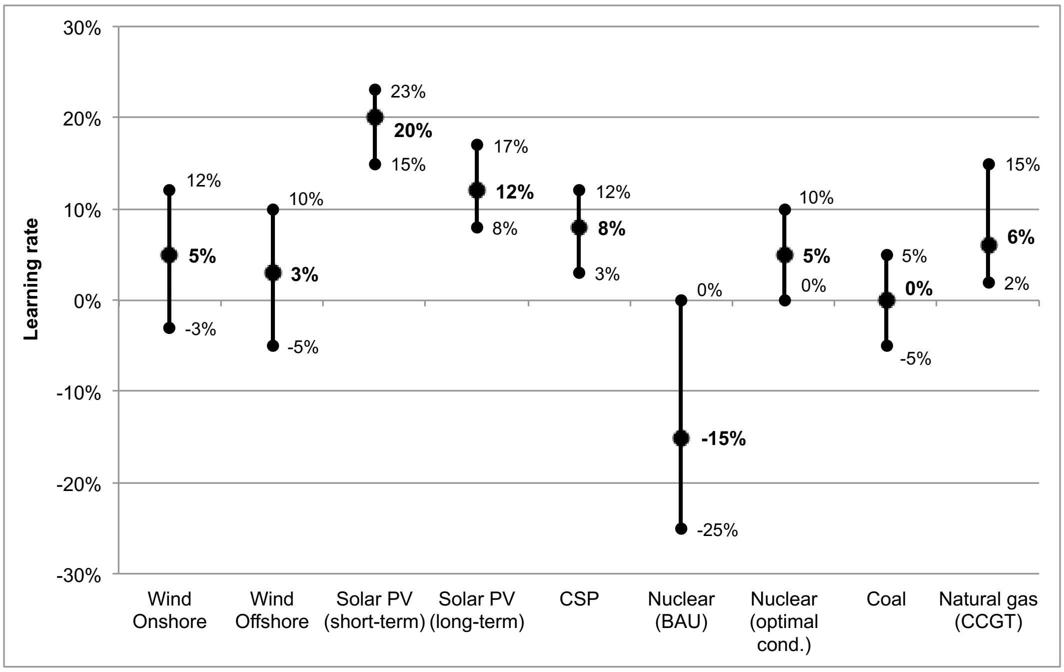
The study by Colpier and Cornland [108] also derives a learning rate for the specific generation costs of CCGT power plants over the entire period (1981 to 1997) of 15%. The authors note that if the natural gas price reductions observed over the analysed period had not occurred, the learning rate would have only been 6%.

4. Deriving plausible future learning rates for electricity generation technologies

This section provides estimates of future one-factor learning rates for electricity generation technologies. The estimates are based on the findings from the literature review of historic learning rates discussed in Section 3, as well as on the findings from a complementary literature review [43] which looked at factors beyond experience that affect these technologies' costs. "Best guess" estimates for the future learning rates of individual technologies are provided. In addition, for each technology a range is derived which provides a lower and upper estimate and which aims to reflect the uncertainty associated with estimating future learning rates. Both the "best guess" estimates and the full ranges can be used by energy system modellers to parameterize their models.

It should be noted that the learning rates provided in this section refer to the specific investment costs of a technology's capacity, as opposed to a technology's electricity generation cost. Learning rates for capacity and for electricity generation can diverge if a technology's typical load factor changes over time. This could be the case in the future for wind turbines, which may be further developed with the aim of increasing their average load factor. At the same time, the possible future use of less optimal wind sites may decrease the average load factor of wind turbines. The typical load factors of other types of power plants may also change over time; this could be due, for example, to changes in a system's capacity mix and the associated merit order. A divergence of the learning rates for capacity and for electricity generation is also possible if the non-investment costs are particularly relevant and if these costs do not move in parallel with specific capacity costs. Fuel costs for technologies using fossil fuels are especially relevant in this regard. Therefore, for deriving possible future electricity generation costs, further assumptions (beyond the assumptions behind the following learning rates) need to be made.

Figure 2: Estimates of plausible future learning rate ranges for several important electricity generation technologies



For the future cost of onshore wind turbines, the key question is whether the relatively low one-factor learning rates observed during the past few years will persist, or whether the rate will rebound. The answer to this question will depend on future material input prices, on the efforts required by manufacturers to adjust their turbines to deteriorating average turbine locations and on the future potential to better exploit economies of manufacturing scale as turbine designs become increasingly more mature (and design changes become less frequent as a result). Assuming no sharp long-term increase in material costs, it is reasonable to predict that wind turbine costs will decrease moderately in the future with a learning rate of about 5%. Learning rates of 10% to almost 20%, as observed in the literature for periods in the 1980s and 1990s, are not likely to return as manufacturers no longer benefit from economies of unit scale [80,109] and turbine design increasingly needs to be adjusted to work optimally at locations with less-than-optimal wind quality.

While in the past 10 to 15 years specific investment cost increases have been observed for offshore wind farms [91], it seems plausible to assume that moderate cost decreases can be expected in the future. There are indications that increased investment costs in the past were driven, in part, by the growth of profits along the supply chain. These profits can be expected to return to lower levels as the global market for offshore wind continues to grow and as competition along the entire supply chain increases as a result. Furthermore, engineering studies [110,111], as well as the results of several auctions held in 2016 in Europe for constructing offshore wind farms [112], indicate that the potential for considerable cost decreases exist. It can also be argued that future offshore wind farms will not move indefinitely into locations further from the coast and into deeper waters, so the past cost increases attributed to this trend can be expected to eventually level off. All these considerations indicate that, provided material input prices do not increase considerably in the future, moderate cost decreases are likely for offshore wind power. However, the site-specific nature of offshore wind, in comparison with onshore wind and especially solar PV, suggests that even under favourable conditions very high learning rates (e.g. learning rates of more than 10%) are unlikely for this technology.

Including data from more recent years, the global learning rate for PV modules shows no signs of levelling off and remains around 20%. Furthermore, engineering analysis indicates significant further cost reduction potential [113]. It therefore seems plausible to assume a continuation of the learning rate observed in the past, at least in the short to medium term. However, a number of studies suggest that increased economies of manufacturing scale was a key driver of past PV cost decreases. If this is the case, the one-factor learning rate can be expected to decrease once either organisational or market limits make it no longer economic to increase PV factory sizes. Furthermore, the relatively high learning rate and high growth rates for PV technology mean that the physical limits to cost decreases may be reached relatively quickly, making it likely that the learning rate will decrease well before this limit is reached. However, exactly when such a decrease in the learning rate will occur, and to what extent, is difficult to assess a priori.[9] Additional research on the future learning rate of PV technology, modelling the future evolution of PV manufacturing plant sizes and the potential effects of approaching floor costs, could shed light on this question.

Regarding CSP plants, the modular design of the mirror technology should allow for significant learning opportunities, while the thermal power generation units used in CSP plants are similar in design to those used in conventional power plants, offering little potential for additional learning. Based on the limited number of existing studies on CSP cost developments, a learning rate of around 8% appears to be plausible for the entire plant technology.

As noted above, for nuclear power the learning rate concept is widely regarded as unsuitable for describing past cost developments or predicting future cost developments. Experience-driven learning does not seem to be the main factor

[9] If it is assumed that the average size of PV manufacturing plants will stop increasing once the global PV market is no longer growing, looking at global energy scenarios can shed light on how much longer PV manufacturing plants could continue to grow in size. The annual global demand for PV modules was around 50 GW in 2015 [114]. In the 2DS scenario of the IEA's Energy Technology Perspectives 2015 study [115], global PV capacity reaches 2,755 GW by 2050, while it reaches 9,295 GW in the Advanced Energy [R]evolution scenario commissioned by Greenpeace International, Global Wind Energy Council and SolarPower Europe [116]. Assuming that the PV capacity in 2050 is the long-term capacity required for a sustainable energy system and further assuming a 25 year lifespan for PV systems [96], this would mean that the global PV market will grow until it reaches 110 GW annually in the 2DS scenario and 372 GW annually in the Advanced Energy [R]evolution scenario.

determining the development of this technology's cost. If the future cost developments of nuclear power were nonetheless to be described by a one-factor experience curve, a negative learning rate would probably need to be assumed based on the experience of the past few decades. Specific costs may carry on rising due to reactor designs continuing to change frequently (as security requirements become increasingly stringent) and material input prices and labour prices continuing to increase. However, it can also be argued that under good conditions (e.g. a predictable and steady deployment programme and stable safety standards allowing for the construction of many reactors of identical or very similarly design), nuclear power plants are likely to exhibit positive learning rates, as under such conditions learning effects that have been identified at company level would not be negated by the cost-increasing effects of various other factors [79].[10]

Since the 1970s, the investment costs of coal power plants appear to have increased, due to a large extent to increasing environmental standards. The future learning rate for coal power plants can equally be expected to depend largely on changes in environmental standards. Assuming that any future changes in these standards will only have modest cost-increasing effects, and further assuming that material input prices and labour prices will not grow considerably, stable specific costs (i.e. a learning rate of around 0%) can probably be expected for the future. Of course, any requirements to equip new coal power plants with CCS technology would considerably increase specific investments costs, but for these kinds of plants specific learning rates would need to be derived [117].

Compared to coal power plants, higher learning rates for natural gas power plants have been observed – especially since the 1970s. However, few literature sources deal with learning rates for natural gas power plants and the few studies available do not cover the more recent years. This makes it difficult to estimate a plausible range for the future learning rate of natural gas power plants. Based on the available literature, a future learning rate of about 6% (with a range of 2% to 15%) appears to be reasonable .

5. Conclusion

This article has reviewed the vast volume of literature on the theory and application of experience curves for electricity generation technologies. It has provided a systematic overview of the different ways in which such experience curves can be constructed and has discussed the learning rates derived from 67 empirical studies released between 1979 and 2017 for several electricity generation technologies. The article has also provided a structured discussion of the limitations of the experience curve theory and its application, deriving suggestions on how to adequately address these limitations when constructing experience curves and making use of the associated learning rates. Finally, based on the extensive literature review, the article has derived plausible future ranges for one-factor learning rates for several electricity generation technologies.

This conclusion first summarises key insights gained from the review and then suggests how additional research could help to further improve our understanding of past and possible future cost developments of electricity generation technologies.

[10] Such a stable environment for the future construction of nuclear power plants is probably difficult to achieve, at least in those countries in which there is considerable public opposition to nuclear power.

5.1. Key insights gained from the review of the experience curve literature

For most technologies using renewable energy sources, the literature finds clear statistical support for a strong negative correlation between experience and costs. The limited number of literature sources establishing learning rates for fossil fuel technologies also find negative correlations for the most part, although these correlations tend to be weaker than for renewable energy technologies. For nuclear power plants, on the other hand, learning effects in the past seem to have been low and these have been negated in many countries by other factors influencing technology costs. As several authors have noted [for example 78,79], it is doubtful whether the experience curve theory is a useful tool for explaining the past cost developments of nuclear power plants or the anticipated future costs.

For PV modules, the correlation between experience and technology costs has been remarkably stable for many decades. The observed learning rate of around 20% is also exceptionally high compared to other electricity generation technologies. These empirical findings concerning the strong cost decline in PV modules are in line with theoretical considerations. Small-scale modular technologies, which can be mass-produced in manufacturing plants and whose installation is largely independent of site-specific characteristics, are expected to have the largest potential to benefit from learning effects during the design, manufacture and use stages of a technology.

Despite the apparent relevance of experience to the development of renewable and fossil fuel technology costs, the literature review has also shown that additional factors may play a considerable role [see also 43]. Commodity price fluctuations, for example, have had a significant influence since the mid-2000s, especially on wind turbine costs. Stricter environmental and safety regulations have also apparently led to upward pressure on the costs of coal power and especially nuclear power in the past decades. In many cases, these other factors can be reasonably accurately identified, although some uncertainty remains when attempts are made to quantify them; for example, to construct multi-factor experience curves.

Overall, however, the empirical and theoretical insights from the reviewed literature suggest that learning does indeed take place as experience is accumulated by a technology. It is important to note that not only can experience directly reduce costs through experience-induced learning, but it can also indirectly reduce costs through its potential effects on other cost-influencing factors. These include both private and public RD&D expenses, as well as the potential for realising economies of manufacturing and unit scale (upsizing), all of which are likely to be positively related to a technology's experience. This consideration also puts into perspective the findings stressed by some authors that not only experience, but also other factors such as RD&D and economies of scale, can considerably influence technology costs. This is probably true, but it does not necessarily mean that focusing primarily on experience as the variable for informing about costs is unjustified.

However, it is important for researchers to keep in mind the limitations of the experience curve concept and the uncertainties associated with using observed learning rates to anticipate future cost developments. Modellers should contemplate if and how other potentially relevant factors (besides experience) can be taken into consideration in their modelling. If possible, modellers should also use *ranges* of future learning rates for individual technologies (see Figure 2) to reflect the associated uncertainties, especially given the key role that learning rate estimates can play in determining the results of energy system modelling [62,118].

5.2. Suggestions for further research

The literature review reveals several areas in which further research could help to better understand past and possible future cost developments of electricity generation technologies.

- Most available studies derive learning rates in relation to a technology's capacity. In the cases of onshore and offshore wind power, it would be informative to have more studies investigating the historic learning rates related to electricity generation. This would ensure that efforts made by turbine developers to increase a turbine's full load hours are fully reflected in the technology's learning rates.
- Future research could investigate whether it would be worthwhile deriving separate experience curves for individual components of a technology. To date, only a very few such studies exist. CSP power plants could lend themselves to this approach.
- Future research could also investigate whether the correlation between experience and specific costs can be improved, for some technologies at least, by taking floor costs into consideration, i.e. by using an assumed floor cost component that does not learn [74].
- A few of the more recent studies have attempted to improve the explanatory power of learning rates by correcting for past commodity price changes, and future research should continue this approach. Similar attempts could be made to correct the prices observed for market power; for example, by using an industry's average annual profit rate to adjust the observed prices and so possibly obtain prices that are more in line with the actual costs.
- As many new CSP power plants were built in recent years, collecting comprehensive, reliable and long-term cost data for this technology could be enlightening. Specifically, the role of public R&D and time relative to the role of experience could be analysed for this technology, given the long pause in the construction of new CSP plants during the 1990s and early 2000s.
- Finally, it can be expected that the costs of integrating electricity generation from fluctuating renewable energy sources (especially wind and solar) will play an increasingly important role in the coming years and decades in determining the overall costs of electricity supply. It could, therefore, be worthwhile for future research to investigate historic and potential future learning rates of technologies such as batteries, large-scale storage devices or fuels cells.[11]

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[11] A few studies on learning rates for batteries [119,120] and fuels cells [121] were published in recent years.

Appendix

Note: In the following tables, learning rates provided by the original studies that refer to a limited part of the whole time period considered in the respective studies are indicated in light font.

Table A-1: Learning rates found in the literature for *onshore wind power plants*

Literature source	Geographical domain	Experience (in cumulative terms)	Costs or prices [a] (in specific terms)	Period	Learning rate (%)	R^2	Number of doublings of experience	Additional independent variable(s) controlled for
[87]	Denmark	Capacity sales	Wind turbine prices	1982-1995	**4**	0.83	10	
	Denmark	Capacity sales	Generation costs	1980-1991	**9**	n.s.	n.s.	
[86]	Global/USA [c]	Number of turbines installed	Generation costs	1985-1995	**18**	0.99 [b]	1	R&D
[49]	Denmark	Capacity sales	Wind turbine prices	1982-1997	**8**	n.s.	n.s.	
[59]	USA	Electricity generation	Generation costs	1985-1994	**32**	n.s.	4	
	EU	Electricity generation	Generation costs	1980-1995	**18**	n.s.	10	
[44]	Denmark	Installed capacity	Generation costs	1984-1999	**8**	n.s.	6	
	Denmark	Installed capacity	Generation costs	1984-1988	**12**	n.s.	3	
	Denmark	Installed capacity	Generation costs	1988-1999	**7**	n.s.	3	
	UK	Installed capacity	Generation costs	1991-1999	**25**	n.s.	4	
[122]	Germany	Installed capacity	Wind turbine prices	1990-2001	**6**	n.s.	7	
	Germany	Installed capacity	Wind turbine prices	1990-1992	**-2**	n.s.	1	
	Germany	Installed capacity	Wind turbine prices	1992-1996	**11**	n.s.	3	
	Germany	Installed capacity	Wind turbine prices	1996-2001	**-3**	n.s.	3	
	Germany	Electricity generation	Wind turbine prices	1990-2001	**9**	n.s.	8	
[123]	Denmark	Number of turbines	Wind turbine prices	1983-1998	**18**	0.82 [b]	4	

		produced						
	Denmark	Produced capacity	Wind turbine prices	1983-1998	**9**	0.95 [b]	7	Time trend and annual export share
	Denmark	Number of turbines produced	Wind turbine prices	1983-1998	**11**	0.94 [b]	4	Time trend and annual export share
	Denmark	Number of turbines produced	Wind turbine prices	1983-1998	**9**	0.95 [b]	4	Time trend, annual export share and project scale
[42]	Global	Installed capacity	Investment costs	1971-1997	**10**	0.8	n.s.	R&D
[88]	Denmark	Installed capacity	Investment costs	1981-2000	**10**	0.92	8	
	Denmark	Installed capacity	Wind turbine prices	1981-2000	**9**	0.94	8	
	Denmark	Produced capacity	Wind turbine prices	1981-2000	**8**	0.84	10	
	Denmark	Produced capacity	Generation costs	1981-2000	**17**	0.97	10	
	Germany	Installed capacity	Wind turbine prices	1987-2000	**6**	0.88	11	
	Germany	Produced capacity	Wind turbine prices	1987-2000	**6**	0.74	8	
	Spain	Installed capacity	Investment costs	1984-2000	**9**	0.85	15	
	Sweden	Installed capacity	Investment costs	1994-2000	**4**	0.32	5	
[14]	Global/Spain [c]	Installed capacity	Investment costs	1990-2001	**15**	0.89	4	
	Global/UK [c]	Installed capacity	Investment costs	1992-2001	**19**	0.98	3	
[124]	Germany, Denmark, UK	Installed capacity	Investment costs	1986-2000	**5**	0.72 [b]	7	R&D
[125]	Japan	Installed capacity	Investment costs	1990-2003	**11**	0.42	8	
	Japan	Installed capacity	Investment costs	2000-2003	**8**	0.59	2	
[80]	Global/ Germany [c]	Installed capacity	Wind turbine prices	1991-2003	**11**	n.s.	4	
	Global/	Installed capacity	Wind turbine prices	1991-2003	**13**	n.s.	4	Turbine scale and higher wind

	Germany [c]							speeds at higher tower heights
	Germany	Installed capacity	Wind turbine prices	1991-2003	**7**	n.s.	7	
[126]	Germany, Denmark, UK	Installed capacity	Investment costs	1986-2000	**5**	0.72 [b]	n.s	R&D
	Germany, Denmark, UK, Spain	Installed capacity	Investment costs	1986-2000	**7**	0.83 [b]	n.s	R&D
	Germany, Denmark, UK, USA	Installed capacity	Investment costs	1986-2002	**7**	0.50 [b]	n.s	R&D
	Germany, Denmark, UK, Spain, USA	Installed capacity	Investment costs	1986-2002	**7**	0.65 [b]	n.s	R&D
[81]	Global	Installed capacity	Investment costs	1981-1997	**14**	0.95 [b]	n.s.	R&D
[58]	Germany	Installed capacity	Wind turbine prices	1987-2000	**5**	0.71 [b]	n.s	
	Germany	Electricity generation	Wind turbine prices	1987-2000	**7**	0.76 [b]	n.s	
	Denmark	Installed capacity	Wind turbine prices	1987-2000	**11**	0.83 [b]	n.s	
	Denmark	Electricity generation	Wind turbine prices	1987-2000	**13**	0.96 [b]	n.s	
[127]	Germany, UK, Denmark, Spain	Installed capacity	Investment costs	1986-2000	**3**	0.81	7	R&D, turbine scale and feed-in tariff level
[65]	Germany, UK, Denmark, Spain	Installed capacity	Investment costs	1986-2000	**5**	0.64 [b]	7	
	Germany, UK, Denmark, Spain	Installed capacity	Investment costs	1992-2000	**8**	0.67 [b]	4	
	Germany, UK, Denmark,	Electricity generation	Investment costs	1986-2000	**6**	0.67 [b]	n.s.	

	Spain							
	Germany, UK, Denmark, Spain	Installed capacity	Investment costs	1986-2000	**4**	0.73 [b]	7	R&D
	Germany, UK, Denmark, Spain	Installed capacity	Investment costs	1986-2000	**2**	0.74 [b]	7	R&D and turbine scale
	Germany, UK, Denmark, Spain	Installed capacity	Investment costs	1986-2000	**8**	0.96 [b]	7	R&D and identified endogeneity between cost and deployment
[72]	Global/ California [c]	Installed capacity	Wind turbine prices	1981-2004	**11**	0.75	12	
[128]	EU/Denmark	Installed capacity	Wind turbine prices	1990-2009	**7**	0.65	7	
	EU/Denmark	Installed capacity	Wind turbine prices	1990-2001	**9**	0.95	5	
	EU/Denmark	Installed capacity	Price of electricity	1998-2009	**10**	0.97	3	
[57]	Global/ Germany, Denmark, Spain, Sweden, UK [c]	Installed capacity	Investment costs	1986-2002	**17**	0.88	4	R&D and turbine scale
[129]	China	Installed capacity	Price of electricity	2003-2007	**8**	0.44	3	
	China	Installed capacity	Price of electricity	2003-2007	**4**	0.63	3	Steel price, project size, wind quality and localisation rate
[89]	India	Installed capacity	Investment costs	2006-2011	**17**	0.56 [b]	n.s.	Project size, capacity factor, steel price, exchange rate, time trend and region
	India	Installed capacity	Generation costs	2006-2011	**18**	0.67	n.s.	Project size, capacity factor, steel price, exchange rate, time trend and region

[38,130]	Global/USA [c]	Installed capacity	Investment costs	1982-2014	**7**	n.s.	12	
	Global/USA [c]	Installed capacity	Investment costs	1982-2004	**14**	n.s.	9	
[11]	Global	Installed capacity	Wind turbine prices	1990-2012	**4**	0.80	7	
	Global	Installed capacity	Wind turbine prices	1990-2012	**2**	0.84 [b]	7	R&D
[131]	China	Installed capacity	Generation costs	2004-2011	**4**	0.65	6	
[132]	China	Installed capacity	Generation costs	1997-2012	**5**	n.s.	n.s.	
[15]	China	Installed capacity	Wind turbine prices	1998-2012	**8**	0.80 [b]	8	
	China	Installed capacity	Wind turbine prices	1998-2012	**9**	0.99	8	R&D, turbine scale, labour price, cost of capital, steel price, fibre/resin price
[67]	Global/Eight EU countries	Installed capacity	Investment costs	1991-2008	**8**	0.37 [b]	6	Steel price
	Global/Eight EU countries	Installed capacity	Investment costs	1991-2008	**7**	0.36 [b]	6	Steel price, cumulative installed national capacity
	Global/Eight EU countries	Installed capacity	Investment costs	1991-2008	**6**	0.39 [b]	6	Steel price, R&D
	Global/Eight EU countries	Installed capacity	Investment costs	1991-2008	**5**	0.43 [b]	6	Steel price, R&D, feed-in-tariff level

[a] For reasons of clarity, the term “investment costs” as used in this table also covers the dependent variables referred to in the literature sources which refer to “total installation costs” [88], “turnkey investment costs” [14], “(total) project costs” [38,125,130] or “capital costs” [81]. The (limited) information provided by the studies in relation to the cost elements included suggests that there are no major differences between their respective cost definitions.

[b] Numbers refer to the *adjusted* R^2. Unlike R^2, the adjusted R^2 does not automatically increase as more explanatory variables are added. Instead, the adjusted R^2 only increases when additional explanatory variables improve the R^2 more than would be expected by chance.

[c] The geographical domains of the dependent and the independent variables differ in these experience curves. The region named first refers to the independent variable, while the state, country or countries named after the slash refer(s) to the geographical domain of the dependent variable.

Table A-2: Learning rates found in the literature for *offshore wind power plants*

Literature source	**Geographical domain**	**Experience** (in cumulative terms)	**Costs or prices** [a] (in specific terms)	**Period**	**Learning rate (%)**	**R^2**	**Number of doublings of experience**	**Additional independent variable(s) controlled for**
[45]	Global	Installed capacity [b]	Investment costs	1991-2007	**3**	0.06	8	
	Global	Installed capacity [b]	Investment costs	1991-2001	**10**	0.62	6	
	Global	Installed capacity [b]	Investment costs	2001-2007	**-13**	0.17	2	
[90]	Denmark, the Netherlands, Sweden, UK	Installed capacity	Investment costs	1991-2008	**0**	0.31	8	
	Denmark, the Netherlands, Sweden, UK	Installed capacity	Investment costs	1991-2008	**3**	0.49	8	Copper and steel prices
	Denmark, the Netherlands, Sweden, UK	Installed capacity	Investment costs	1991-2005	**5**	0.57	7	Copper and steel prices

[a] For reasons of clarity, the term “investment costs” as used in this table covers the dependent variables referred to in the literature sources as “total installation cost” [45] or “turbine production plus installation cost” [90]. The (limited) information provided by the studies in relation to the cost elements included suggests that there are no major differences between their respective cost definitions.

[b] This source includes mostly historic cost data, but also a few data sources based on the forecast costs for offshore wind farm projects that had not been realised at the time of writing.

Table A-3: Learning rates found in the literature for *solar photovoltaic (PV) technology*

Literature source	Geographical domain	Experience (in cumulative terms)	Costs or prices (in specific terms)	Period	Learning rate (%)	R^2	Number of doublings of experience	Additional independent variable(s) controlled for
[133]	Global	Produced capacity	Module prices	1976-1992	**18**	n.s.	10	
[134]	USA	Sold capacity	Module prices	1976-1988	**22**	0.98	9	
[59]	European Union	Electricity generation	Generation costs	1985-1995	**35**	n.s.	5	
	Global	Produced capacity	Module prices	1976-1984	**16**	n.s.	7	
	Global	Produced capacity	Module prices	1987-1996	**21**	n.s.	2	
[135]	Global	Produced capacity	Module prices	1968-1998	**20**	n.s.	13	
[136]	Global	Produced capacity	Module prices	1976-2000	**20**	0.99	12	
[137]	Global	Produced capacity	Module prices	1981-2000	**23**	0.99	7	
	Global	Produced capacity	Module prices	1981-1990	**20**	0.98	4	
	Global	Produced capacity	Module prices	1991-2000	**23**	0.98	2	
[138]	Global	Produced capacity	Module prices	1976-2002	**25**	n.s.	9	
	Global	Produced capacity	Module prices	1989-2002	**19**	n.s.	3	
[19]	Global	Produced capacity	Module prices	1976-2001	**20**	0.99	12	
	Global	Produced capacity	Module prices	1987-2001	**23**	0.93	4	
	Europe	Installed capacity	Balance of system prices	1992-2001	**21**	0.78	5	
	The Netherlands	Installed capacity	Balance of system prices	1992-2001	**19**	0.93	9	
[139]	Global	Produced capacity	Module prices	1976-2003	**20**	n.s.	13	

[94]	Global/ Germany [d]	Produced capacity	Module prices	1992-2002	**16**	0.73	3	
	Global/ Germany [d]	Produced capacity	Generation costs	1992-2002	**35**	0.95	3	
	Germany	Installed capacity	Generation costs	1992-2002	**19**	0.97	6	
	Germany	Installed capacity	System prices	1992-2002	**24**	0.92	3	
[81]	Global	Produced capacity	Module prices	1975-2000	**18**	0.99	10	R&D
[29] [a]	Global	Produced capacity	Module prices	1978-2001	**26**	n.s.	11	
	Global	Produced capacity	Module prices	1976-2001	**17**	n.s.	10	
[140]	Global	Produced capacity	Module prices	1979-2005	**19**	n.s.	7	
[58]	USA	Produced capacity	Module costs	1990-2000	**23**	0.97 [b]	n.s.	
	USA	Produced capacity	Module prices	1990-2000	**20**	0.95 [b]	n.s.	
	USA	Installed capacity	Module prices	1992-2000	**32**	0.93 [b]	2	
	Germany	Installed capacity	Module prices	1992-2000	**15**	0.95 [b]	5	
	Switzerland	Installed capacity	Module prices	1992-2000	**10**	0.82 [b]	2	
	USA, Germany, Switzerland	Installed capacity	Module prices	1992-2000	**17**	0.82 [b]	2	
	USA, Germany, Switzerland	Installed capacity	Module prices	1992-2000	**10**	0.84 [b]	2	Time trend
[95]	Global	Installed capacity	Module prices	1975-2003	**23**	0.99	12	
	Global	Installed capacity	System prices	1991-2004	**27**	0.88	4	
[71]	Global	Produced capacity	Module prices	1976-2006	**21**	0.99	15	
	Global	Produced capacity	Module prices	1991-2000	**30**	0.98	2	
	Global	Produced capacity	Module prices	1997-2006	**12**	n.s.	4	

[141]	Global	Produced capacity	Module prices	1976-2010	**19**	n.s.	16	
	Global	Produced capacity	Module prices	1976-2003	**23**	n.s.	12	
[92]	Global	Produced capacity	Module prices	1976-2010	**23**	n.s.	14	
	Global	Produced capacity	Module prices	1976-1988	**30**	n.s.	6	
	Global	Produced capacity	Module prices	1988-2010	**17**	n.s.	8	
	Global	Produced capacity	Module prices	1988-2010	**14**	n.s.	8	PV module efficiency
[24]	Global	Produced capacity	Module prices	1976-2006	**20**	0.98	15	
	Global	Produced capacity	Module prices	1976-2006	**14**	0.99	15	Economies of manufacturing scale, silver and silicon prices, R&D
[41]	Global	Produced capacity	Module prices	1990-2011	**20**	n.s.	9	Silicon prices [c]
[142]	Global	Installed capacity	Module prices	1976-2010	**21**	0.91	13	
	Global	Installed capacity	Module prices	1991-2010	**15**	0.84	9	
[35]	Global	Installed capacity	Module prices	1988-2006	**14**	0.87	5	
	Global	Installed capacity	Module prices	1988-2006	**8**	0.97	5	Silicon prices
[143]	South Korea	Electricity generation	Generation costs	2004-2011	**3**	0.93	n.s.	
	South Korea	Electricity generation	Generation costs	2004-2011	**2**	0.96 [b]	n.s.	R&D
[11]	Global	Installed capacity	Module prices	1992-2012	**17**	0.78	8	
	Global	Installed capacity	Module prices	1992-2012	**10**	0.82 [b]	8	R&D, PV module overcapacities (2011, 2012)
	Germany	Installed capacity	System costs	1991-2012	**13**	0.75	15	
[132]	China	Installed capacity	Generation costs	1976-2009	**25**	n.s.	n.s.	
[144]	Taiwan	Installed capacity	Installation costs	2000-2014	**10**	0.87 [b]	n.s.	
	Taiwan	Installed capacity	Installation costs	2000-2014	**12**	0.97 [b]	n.s.	Silicon prices

[99]	Global	Installed capacity	Module prices	1976-2014	**21**	n.s.	19	
[17]	Global	Installed capacity	Module prices	1981-2013	**24**	0.97 [e]	12	
	Global	Installed capacity	Module prices	1981-2013	**23**	0.98 [e]	12	Silicon prices
	Global	Installed capacity	Module prices	1993-2013	**25**	0.98 [e]	8	Silicon prices
	Global	Installed capacity	Module prices	1993-2013	**35**	n.a. [e]	8	Silicon prices, fossil fuel energy prices

[a] The two different learning rates provided by this source are based on two different sets of historic data on cost and experience.

[b] Numbers refer to the *adjusted* R^2. Unlike R^2, the adjusted R^2 does not automatically increase as more explanatory variables are added. Instead, the adjusted R^2 only increases when additional explanatory variables improve the R^2 more than would be expected by chance.

[c] The study tests the explanatory power of three additional variables (silver prices, economies of scale in manufacturing and R&D) in various combinations but finds the specification with only experience and silicon prices as the independent variables to be the best.

[d] The geographical domains of the dependent and the independent variables differ in these experience curves. The region named first refers to the independent variable, while the country named after the slash refers to the geographical domain of the dependent variable.

[e] These R^2 values were kindly provided by the author of the article [17], Ignacio Mauleón, based on personal communication in February 2017. In his article, Mauleón does not report any R^2 values, but instead reports for each of his models the sum of squared residuals and the standard deviation of the errors. These are more meaningful indicators of the goodness of fit of each model than the R^2, according to Mauleón. However, in this table only the values for R^2 are reported, as R^2 is the value that is by far the most common in the reviewed literature sources. The fourth model listed here from [17] does not have a proper R^2, since it is the reduced form of a two equations structural model.

Table A-4: Learning rates found in the literature for *concentrating solar thermal power (CSP) plants*

Literature source	**Geographical domain**	**Experience** (in cumulative terms)	**Costs or prices** [a] (in specific terms)	**Period**	**Learning rate (%)**	**R^2**	**Number of doublings of experience**	**Additional independent variable(s) controlled for**
[145]	USA	Installed capacity	Investment costs	1984-1990	**12**	n.s.	5	
[95]	USA	Installed capacity	Investment costs	1985-1991	**3**	0.12	4	
	USA	Electricity generation	O&M costs	1992-1998	**35**	0.93	2	
[96]	Global	Installed capacity	Investment costs	1984-2010	**11**	n.s.	6	
[74]	Global	Installed capacity	Investment costs	2002-2013	**10**	n.s.	n.s.	Plant configuration (size of the solar field and the thermal storage)
[97]	Spain	Installed capacity (parabolic trough)	Investment costs	2006-2011	**16**	n.s.	3	Plant configuration (size of the solar field and the thermal storage)

[a] For reasons of clarity, the term “investment costs” as used in this table also covers the dependent variables referred to in the literature sources as “capital costs” [95,145].

Table A-5: Learning rates found in the literature for *biomass power plants*

Literature source	**Geographical domain**	**Experience** (in cumulative terms)	**Costs or prices** (in specific terms)	**Period**	**Learning rate (%)**	**R^2**	**Number of doublings of experience**	**Additional independent variable(s) controlled for**
[59]	European Union	Electricity generation	Generation costs	1980-1995	**15**	n.s.	2	
[23]	Sweden	Electricity generation	Generation costs	1990-2002	**8**	0.88	n.s.	
[69]	China	Installed capacity	Investment costs	2005-2012	**6**	0.27	2	
	China	Installed capacity	Investment costs	2005-2012	**6**	0.35	2	Plant size, steel price, company ownership
	China	Installed capacity	Generation costs	2005-2012	**2**	0.12	2	
	China	Installed capacity	Generation costs	2005-2012	**6**	0.23	2	Time trend
	China	Installed capacity	Generation costs	2005-2012	**6**	0.41	2	Plant size, company ownership, labour cost, fuel price, location, time trend

Table A-6: Learning rates found in the literature for *nuclear power plants*

Literature source	**Geographical domain**	**Experience** (in cumulative terms)	**Costs or prices** [a] (in specific terms)	**Period**	**Learning rate (%)**	**R^2**	**Number of doublings of experience**	**Additional independent variable(s) controlled for**
[46]	USA	Number of plants built	Investment costs	1960-1973	**22**	0.2	5	
[102]	USA	Capacity installed and being built	Investment costs	1971-1978	**-49**	0.91 [b]	2	Plant location, architect-engineer experience, unit scale, multiple units at the same site and need for cooling towers [c]
[68]	France	Number of plants built	Investment costs	1978-2002	**-17**	n.s.	6	Unit scale, labour costs, reactor group/type experience, plant reliability/safety

[a] As in the other tables, the term "investment costs" covers the dependent variables referred to in the literature sources that relate to the costs of power plant projects. Ostwald and Reisdorf [46] and Komanoff [102] use the term "capital costs", while Rangel and Lévêque [68] use the term "construction cost".

[b] Number refers to the *adjusted* R^2. Unlike R^2, the adjusted R^2 does not automatically increase as more explanatory variables are added. Instead, the adjusted R^2 only increases when additional explanatory variables improve the R^2 more than would be expected by chance.

[c] The study tests the explanatory power of five additional variables (reactor type (boiling or pressurised water reactor), reactor manufacturer, regional seismic potential, proximity to centres and licensing time) but does not find any of these to correlate significantly with nuclear costs.

Table A-7: Learning rates found in the literature for *coal power plants*

Literature source	Geographical domain	Experience (in cumulative terms)	Costs or prices [a] (in specific terms)	Period	Learning rate (%)	R^2	Number of doublings of experience	Additional independent variable(s) controlled for
[46]	Mountain States of the USA [b]	Number of plants built	Investment costs	1957-1976	**8** [c]	0.12	5	
	Mountain States of the USA [b]	Number of plants built	Investment costs	1957-1973	**13** [c]	n.s.	4	
	Mountain States of the USA [b]	Number of plants built	Investment costs	1973-1976	**-13** [c]	n.s.	< 1	
[30]	Global/USA [d]	Installed capacity (pulverised coal power plants only)	Cost of subcritical PC boiler [d]	1942-1999	**6**	n.s.	9	
	Global/USA [d]	Installed capacity (pulverised coal power plants only)	Non-fuel O&M costs [e]	1929-1997	**8**	n.s.	13	
[107]	USA	Number of plants built	Investment costs	1902-2006	**12**	n.s.	9	

[a] As in the other tables, the term "investment costs" covers the dependent variables referred to in the literature sources that relate to the costs of power plant projects. The two literature sources listed here that refer to project costs use the terms "capital costs" [46] or "construction costs" [107].

[b] The Mountain States of the USA consist of Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah and Wyoming.

[c] In deriving this learning rate, the study neglects the experience gained from coal power plants built prior to 1957.

[d] The geographical domains of the dependent and the independent variables differ in these experience curves. The region named first refers to the independent variable, while the country named after the slash refers to the geographical domain of the dependent variable.

[e] Cost data is taken from 12 actual US plants constructed between 1942 and 1973 and from one hypothetical plant described in a 1999 study by the U.S. Department of Energy.

Table A-8: Learning rates found in the literature for *natural gas power plants*

Literature source	**Geographical domain**	**Experience** (in cumulative terms)	**Costs or prices** [a] (in specific terms)	**Period**	**Learning rate (%)**	**R^2**	**Number of doublings of experience**	**Additional independent variable(s) controlled for**
[46]	Mountain States of the USA [b]	Number of plants built	Specific investment costs	1949-1968	**15** [c]	0.48	5	
[108]	Global/Europe and North America [d]	Installed capacity (CCGT only)	Investment costs	1981-1991	**-13**	0.41	2	
	Global/Europe and North America [d]	Installed capacity (CCGT only)	Investment costs	1991-1997	**25**	0.9	2	
	Global/Europe and North America [d]	Electricity generation (CCGT only)	Generation costs	1981-1997	**15**	n.s.	4	
	Global/Europe and North America [d]	Electricity generation (CCGT only)	Generation costs	1981-1997	**6**	n.s.	4	Natural gas price

[a] As in the other tables, the term "investment costs" covers the dependent variables referred to in the literature sources that relate to the costs of power plant projects. The two literature sources listed here use the terms "capital costs" [46] or "investment prices" [108].

[b] The Mountain States of the USA consist of Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah and Wyoming.

[c] In deriving this learning rate, the study neglects the experience gained from natural gas power plants built prior to 1949.

[d] The geographical domains of the dependent and the independent variables differ in these experience curves. The region named first refers to the independent variable, while the regions named after the slash refer to the geographical domain of the dependent variable.

References

[1] IEA. World Energy Outlook 2016 – Electricity Access Database 2016.

[2] United Nations. Transforming our World: The 2030 Agenda for Sustainable Development. New York, NY: 2015.

[3] SDSN, IDDRI. Pathways to deep decarbonization 2015 report. 2015.

[4] Köhler J, Grubb M, Popp D, Edenhofer O. The Transition to Endogenous Technical Change in Climate-Economy Models: A Technical Overview to the Innovation Modeling Comparison Project. The Energy Journal 2006;27:17–55.

[5] Grubb M, Köhler J, Anderson D. Induced Technical Change in Energy and Environmental Modeling: Analytic Approaches and Policy Implications. Annual Review of Energy and the Environment 2002;27:271–308. doi:10.1146/annurev.energy.27.122001.083408.

[6] Löschel A. Technological change in economic models of environmental policy: a survey. Ecological Economics 2002;43:105–26. doi:10.1016/S0921-8009(02)00209-4.

[7] Mattsson N, Wene C-O. Assessing New Energy Technologies Using an Energy System Model with Endogenized Experience Curves. Int J Energy Res 1997;21:385–93. doi:10.1002/(SICI)1099-114X(19970325)21:4<385::AID-ER275>3.0.CO;2-1.

[8] Messner S. Endogenized technological learning in an energy systems model. J Evol Econ 1997;7:291–313. doi:10.1007/s001910050045.

[9] Gillingham K, Newell RG, Pizer WA. Modeling endogenous technological change for climate policy analysis. Energy Economics 2008;30:2734–53. doi:10.1016/j.eneco.2008.03.001.

[10] Clarke L, Weyant J, Birky A. On the sources of technological change: Assessing the evidence. Energy Economics 2006;28:579–95. doi:10.1016/j.eneco.2006.05.004.

[11] Wiebe KS, Lutz C. Endogenous technological change and the policy mix in renewable power generation. Renewable and Sustainable Energy Reviews 2016;60:739–51. doi:10.1016/j.rser.2015.12.176.

[12] McDonald A, Schrattenholzer L. Learning rates for energy technologies. Energy Policy 2001;29:255–61. doi:10.1016/S0301-4215(00)00122-1.

[13] Rubin ES, Azevedo IML, Jaramillo P, Yeh S. A review of learning rates for electricity supply technologies. Energy Policy 2015;86:198–218. doi:10.1016/j.enpol.2015.06.011.

[14] Junginger M, Faaij A, Turkenburg WC. Global experience curves for wind farms. Energy Policy 2005;33:133–50. doi:10.1016/S0301-4215(03)00205-2.

[15] Yu Y, Li H, Che Y, Zheng Q. The price evolution of wind turbines in China: A study based on the modified multi-factor learning curve. Renewable Energy 2017;103:522–36. doi:10.1016/j.renene.2016.11.056.

[16] Lindman Å, Söderholm P. Wind power learning rates: A conceptual review and meta-analysis. Energy Economics 2012;34:754–61. doi:10.1016/j.eneco.2011.05.007.

[17] Mauleón I. Photovoltaic learning rate estimation: Issues and implications. Renewable and Sustainable Energy Reviews 2016;65:507–24. doi:10.1016/j.rser.2016.06.070.

[18] Jaffe AB, Newell RG, Stavins RN. Technological change and the Environment. In: Vincent K-GM and JR, editor. Handbook of Environmental Economics, vol. 1, Elsevier; 2003, p. 461–516.

[19] Schaeffer GJ, Alsema E, Seebregts A, Beurskens L, de Moor H, van Sark W, et al. 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. 2004.

[20] Kamp LM, Smits REHM, Andriesse CD. Notions on learning applied to wind turbine development in the Netherlands and Denmark. Energy Policy 2004;32:1625–37. doi:10.1016/S0301-4215(03)00134-4.

[21] Koornneef J, Junginger M, Faaij A. Development of fluidized bed combustion—An overview of trends, performance and cost. Progress in Energy and Combustion Science 2007;33:19–55. doi:10.1016/j.pecs.2006.07.001.

[22] Gross R, Heptonstall P, Greenacre P, Candelise C, Jones F, Castillo Castillo A. Presenting the Future: Electricity Generation Cost Estimation Methodologies. London: UKERC; 2013.

[23] Junginger M, de Visser E, Hjort-Gregersen K, Koornneef J, Raven R, Faaij A, et al. Technological learning in bioenergy systems. Energy Policy 2006;34:4024–41. doi:10.1016/j.enpol.2005.09.012.

[24] Yu CF, van Sark WGJHM, Alsema EA. Unraveling the photovoltaic technology learning curve by incorporation of input price changes and scale effects. Renewable and Sustainable Energy Reviews 2011;15:324–37. doi:10.1016/j.rser.2010.09.001.

[25] Dutton JM, Thomas A. Treating Progress Functions as a Managerial Opportunity. The Academy of Management Review 1984;9:235–47. doi:10.2307/258437.

[26] Junginger M, van Sark W, Faaij A, editors. Technological Learning in the Energy Sector: Lessons for Policy, Industry and Science. Cheltenham, UK; Northampton, MA, USA: Edward Elgar Publishing; 2010.

[27] Weiss M, Junginger M, Patel MK, Blok K. A review of experience curve analyses for energy demand technologies. Technological Forecasting and Social Change 2010;77:411–28. doi:10.1016/j.techfore.2009.10.009.

[28] Wright TP. Factors Affecting the Cost of Airplanes. Journal of the Aeronautical Sciences 1936;3:122–8. doi:10.2514/8.155.

[29] Nemet GF. Beyond the learning curve: factors influencing cost reductions in photovoltaics. Energy Policy 2006;34:3218–32. doi:10.1016/j.enpol.2005.06.020.

[30] Yeh S, Rubin ES. A centurial history of technological change and learning curves for pulverized coal-fired utility boilers. Energy 2007;32:1996–2005. doi:10.1016/j.energy.2007.03.004.

[31] Joskow PL, Rozanski GA. The effects of learning by doing on nuclear plant operating reliability. Cambridge, Mass. : M.I.T. Dept. of Econonmics; 1977.

[32] Görig M, Breyer C. Energy learning curves of PV systems. Environ Prog Sustainable Energy 2016;35:914–23. doi:10.1002/ep.12340.

[33] Brown LR. World on the Edge - Supporting Data for Chapter 9 - Wind 2011.

[34] Earth Policy Institute. World Average Photovoltaic Module Cost per Watt, 1975-2006 2007.

[35] Gan PY, Li Z. Quantitative study on long term global solar photovoltaic market. Renewable and Sustainable Energy Reviews 2015;46:88–99. doi:10.1016/j.rser.2015.02.041.

[36] GWEC. Global Wind Statistics 2015. 2016.

[37] Wirth H. Aktuelle Fakten zur Photovoltaik in Deutschland. Freiburg: 2016.

[38] Wiser R, Bolinger M. 2014 Wind Technologies Market Report. US Department of

Energy; 2015.

[39] Wiser R, Bolinger M. 2015 Wind Technologies Market Report. US Department of Energy; 2016.

[40] Berry D. Innovation and the price of wind energy in the US. Energy Policy 2009;37:4493–9. doi:10.1016/j.enpol.2009.05.071.

[41] de La Tour A, Glachant M, Ménière Y. Predicting the costs of photovoltaic solar modules in 2020 using experience curve models. Energy 2013;62:341–8. doi:10.1016/j.energy.2013.09.037.

[42] Miketa A, Schrattenholzer L. Experiments with a methodology to model the role of R&D expenditures in energy technology learning processes; first results. Energy Policy 2004;32:1679–92. doi:10.1016/S0301-4215(03)00159-9.

[43] Samadi S. A Review of Factors Influencing the Cost Development of Electricity Generation Technologies. Energies 2016;9:970. doi:10.3390/en9110970.

[44] Ibenholt K. Explaining learning curves for wind power. Energy Policy 2002;30:1181–9. doi:10.1016/S0301-4215(02)00014-9.

[45] Isles L. Offshore Wind Farm Development - Cost Reduction Potential. Lund: 2006.

[46] Ostwald PF, Reisdorf JB. Measurement of technology progress and capital cost for nuclear, coal-fired, and gas-fired power plants using the learning curve. Engineering and Process Economics 1979;4:435–54.

[47] Berthélemy M, Escobar Rangel L. Nuclear reactors' construction costs: The role of lead-time, standardization and technological progress. Energy Policy 2015;82:118–30. doi:10.1016/j.enpol.2015.03.015.

[48] Canterbery ER, Johnson B, Reading D. Cost Savings from Nuclear Regulatory Reform: An Econometric Model. Southern Economic Journal 1996;62:554–66. doi:10.2307/1060879.

[49] Neij L. Cost dynamics of wind power. Energy 1999;24:375–89. doi:10.1016/S0360-5442(99)00010-9.

[50] Paik S, Schriver WR. The Effect of Increased Regulation on Capital Costs and Manual Labor Requirements of Nuclear Power Plants. The Engineering Economist 1980;26:223–44. doi:10.1080/00137918008902884.

[51] Watanabe C, Wakabayashi K, Miyazawa T. Industrial dynamism and the creation of a "virtuous cycle" between R&D, market growth and price reduction: The case of photovoltaic power generation (PV) development in Japan. Technovation 2000;20:299–312. doi:10.1016/S0166-4972(99)00146-7.

[52] Zimmerman MB. Learning Effects and the Commercialization of New Energy Technologies: The Case of Nuclear Power. The Bell Journal of Economics 1982;13:297–310. doi:10.2307/3003455.

[53] Ferioli F, Schoots K, van der Zwaan BCC. Use and limitations of learning curves for energy technology policy: A component-learning hypothesis. Energy Policy 2009;37:2525–35. doi:10.1016/j.enpol.2008.10.043.

[54] Viebahn P, Lechon Y, Trieb F. The Potential Role of Concentrated Solar Power (CSP) in Africa and Europe: a Dynamic Assessment of Technology Development, Cost Development and Life Cycle Inventories Until 2050. Energy Policy 2011;39:4420–30. doi:10.1016/j.enpol.2010.09.026.

[55] Garzón Sampedro MR, Sanchez Gonzalez C. Spanish photovoltaic learning curve. International Journal of Low-Carbon Technologies 2014. doi:10.1093/ijlct/ctu026.

[56] Shum KL, Watanabe C. Towards a local learning (innovation) model of solar photovoltaic deployment. Energy Policy 2008;36:508–21. doi:10.1016/j.enpol.2007.09.015.

[57] Ek K, Söderholm P. Technology learning in the presence of public R&D: The case of European wind power. Ecological Economics 2010;69:2356–62. doi:10.1016/j.ecolecon.2010.07.002.

[58] Papineau M. An economic perspective on experience curves and dynamic economies in renewable energy technologies. Energy Policy 2006;34:422–32. doi:10.1016/j.enpol.2004.06.008.

[59] IEA, editor. Experience Curves for Energy Technology Policy. Paris: 2000.

[60] Neij L. Cost development of future technologies for power generation—A study based on experience curves and complementary bottom-up assessments. Energy Policy 2008;36:2200–11. doi:10.1016/j.enpol.2008.02.029.

[61] Huenteler J, Niebuhr C, Schmidt TS. The effect of local and global learning on the cost of renewable energy in developing countries. Journal of Cleaner Production 2016;128:6–21. doi:10.1016/j.jclepro.2014.06.056.

[62] Nordhaus WD. The Perils of the Learning Model for Modeling Endogenous Technological Change. The Energy Journal 2014;35. doi:10.5547/01956574.35.1.1.

[63] Hall G, Howell S. The experience curve from the economist's perspective. Strat Mgmt J 1985;6:197–212. doi:10.1002/smj.4250060302.

[64] Jamasb T. Technical Change Theory and Learning Curves: Patterns of Progress in Electricity Generation Technologies. The Energy Journal 2007;28:51–71.

[65] Söderholm P, Sundqvist T. Empirical challenges in the use of learning curves for assessing the economic prospects of renewable energy technologies. Renewable Energy 2007;32:2559–78. doi:10.1016/j.renene.2006.12.007.

[66] Joskow PL, Rose NL. The Effects of Technological Change, Experience, and Environmental Regulation on the Construction Cost of Coal-Burning Generating Units. The RAND Journal of Economics 1985;16:1–27. doi:10.2307/2555585.

[67] Grafström J, Lindman Å. Invention, innovation and diffusion in the European wind power sector. Technological Forecasting and Social Change 2017;114:179–91. doi:10.1016/j.techfore.2016.08.008.

[68] Escobar Rangel L, Leveque F. Revisiting the Cost Escalation Curse of Nuclear Power: New Lessons from the French Experience. Economics of Energy & Environmental Policy 2015;4:103–25. doi:10.5547/2160-5890.4.2.lran.

[69] Lin B, He J. Learning curves for harnessing biomass power: What could explain the reduction of its cost during the expansion of China? Renewable Energy 2016;99:280–8. doi:10.1016/j.renene.2016.07.007.

[70] Loiter JM, Norberg-Bohm V. Technology policy and renewable energy: public roles in the development of new energy technologies. Energy Policy 1999;27:85–97. doi:10.1016/S0301-4215(99)00013-0.

[71] van Sark WGJHM, Alsema EA, Junginger HM, de Moor HHC, Schaeffer GJ. Accuracy of progress ratios determined from experience curves: the case of crystalline silicon photovoltaic module technology development. Prog Photovolt: Res Appl 2008;16:441–53. doi:10.1002/pip.806.

[72] Nemet GF. Interim monitoring of cost dynamics for publicly supported energy technologies. Energy Policy 2009;37:825–35. doi:10.1016/j.enpol.2008.10.031.

[73] Wene C-O. Energy Technology Learning Through Deployment in Competitive

Markets. The Engineering Economist 2008;53:340–64. doi:10.1080/00137910802482287.

[74] Pietzcker RC, Stetter D, Manger S, Luderer G. Using the sun to decarbonize the power sector: The economic potential of photovoltaics and concentrating solar power. Applied Energy 2014;135:704–20. doi:10.1016/j.apenergy.2014.08.011.

[75] Rout UK, Blesl M, Fahl U, Remme U, Voß A. Uncertainty in the learning rates of energy technologies: An experiment in a global multi-regional energy system model. Energy Policy 2009;37:4927–42. doi:10.1016/j.enpol.2009.06.056.

[76] Sark WGJHM van. Introducing errors in progress ratios determined from experience curves. Technological Forecasting and Social Change 2008;75:405–15. doi:10.1016/j.techfore.2007.03.006.

[77] Trancik JE. Scale and innovation in the energy sector: a focus on photovoltaics and nuclear fission. Environmental Research Letters 2006;1:1–7.

[78] Grubler A. The costs of the French nuclear scale-up: A case of negative learning by doing. Energy Policy 2010;38:5174–88. doi:10.1016/j.enpol.2010.05.003.

[79] Lovering JR, Yip A, Nordhaus T. Historical construction costs of global nuclear power reactors. Energy Policy 2016;91:371–82. doi:10.1016/j.enpol.2016.01.011.

[80] Coulomb L, Neuhoff K. Learning Curves and Changing Product Attributes: the Case of Wind Turbines. University of Cambridge, Electricity Policy Research Group; 2006.

[81] Kobos PH, Erickson JD, Drennen TE. Technological learning and renewable energy costs: implications for US renewable energy policy. Energy Policy 2006;34:1645–58. doi:10.1016/j.enpol.2004.12.008.

[82] IRENA. Wind Power. 2012.

[83] Lantz E, Wiser R, Hand M. IEA Wind Task 26: The Past and Future Cost of Wind Energy. Golden, CO: National Renewable Energy Laboratory; 2012.

[84] GWEC. Global Wind Report - Annual Market Update 2014. 2015.

[85] McDonald A, Schrattenholzer L. Learning curves and technology assessment. International Journal of Technology Management 2002;23:718–54.

[86] Cory KS, Bernow S, Dougherty W, Kartha S, Williams E. Analysis of Wind Turbine Cost Reductions: The Role of Research and Development and Cumulative Production, Burlington, VT: 1999.

[87] Neij L. Use of experience curves to analyse the prospects for diffusion and adoption of renewable energy technology. Energy Policy 1997;25:1099–107. doi:10.1016/S0301-4215(97)00135-3.

[88] Neij L, Andersen PD, Durstewitz M. Experience curves for wind power. International Journal of Energy Technology and Policy 2004;2:15–32. doi:10.1504/IJETP.2004.004585.

[89] Partridge I. Renewable electricity generation in India—A learning rate analysis. Energy Policy 2013;60:906–15. doi:10.1016/j.enpol.2013.05.035.

[90] van der Zwaan B, Rivera-Tinoco R, Lensink S, van den Oosterkamp P. Cost reductions for offshore wind power: Exploring the balance between scaling, learning and R&D. Renewable Energy 2012;41:389–93. doi:10.1016/j.renene.2011.11.014.

[91] Voormolen JA, Junginger HM, van Sark WGJHM. Unravelling historical cost developments of offshore wind energy in Europe. Energy Policy 2016;88:435–44. doi:10.1016/j.enpol.2015.10.047.

[92] Kersten F, Doll R, Kux A, Huljic DM, Göring MA, Breyer C, et al. PV Learning

Curves: Past and Future Drivers of Cost Reduction. Proceedings of the 26th European Photovoltaic Solar Energy Conference, Hamburg: 2011, p. 4697–702. doi:10.4229/26thEUPVSEC2011-6CV.1.63.

[93] Haysom JE, Jafarieh O, Anis H, Hinzer K, Wright D. Learning curve analysis of concentrated photovoltaic systems. Prog Photovolt: Res Appl 2015;23:1678–86. doi:10.1002/pip.2567.

[94] Staffhorst M. The Way to Competitiveness of PV: An Experience Curve and Break-even Analysis. kassel university press GmbH; 2006.

[95] Taylor M, Nemet G, Colvin M, Begley L, Wadia C, Dillavou T. Government Actions and Innovation in Clean Energy Technologies: The Cases of Photovoltaic Cells, Solar Thermal Electric Power, And Solar Water Heating. California Energy Commission; 2007.

[96] Hernández-Moro J, Martínez-Duart JM. Analytical model for solar PV and CSP electricity costs: Present LCOE values and their future evolution. Renewable and Sustainable Energy Reviews 2013;20:119–32. doi:10.1016/j.rser.2012.11.082.

[97] Platzer W, Dinter F. A learning curve for solar thermal power. AIP Conference Proceedings, vol. 1734, 2016, p. 160013. doi:10.1063/1.4949254.

[98] Köberle AC, Gernaat DEHJ, van Vuuren DP. Assessing current and future techno-economic potential of concentrated solar power and photovoltaic electricity generation. Energy 2015;89:739–56. doi:10.1016/j.energy.2015.05.145.

[99] Feldman D, Margolis R, Denholm P, Stekli J. Exploring the Potential Competitiveness of Utility-Scale Photovoltaics plus Batteries with Concentrating Solar Power, 2015–2030. Golden, CO: NREL; 2016.

[100] Hettinga WG, Junginger HM, Dekker SC, Hoogwijk M, McAloon AJ, Hicks KB. Understanding the reductions in US corn ethanol production costs: An experience curve approach. Energy Policy 2009;37:190–203. doi:10.1016/j.enpol.2008.08.002.

[101] van den Wall Bake JD, Junginger M, Faaij A, Poot T, Walter A. Explaining the experience curve: Cost reductions of Brazilian ethanol from sugarcane. Biomass and Bioenergy 2009;33:644–58. doi:10.1016/j.biombioe.2008.10.006.

[102] Komanoff C. Power Plant Cost Escalation: Nuclear and Coal Capital Costs, Regulation, and Economics. New York: 1981.

[103] MacKerron G. Nuclear costs: Why do they keep rising? Energy Policy 1992;20:641–52. doi:10.1016/0301-4215(92)90006-N.

[104] Escobar Rangel L, Lévêque F. Revisiting the Nuclear Power Construction Costs Escalation Curse. IAEE Energy Forum 2013:14–6.

[105] Navarro P. Comparative Energy Policy: The Economics of Nuclear Power in Japan and the United States. The Energy Journal 1988;9:1–15.

[106] Mooz WE. A Second Cost Analysis of Light Water Reactor Power Plants. 1979.

[107] McNerney J, Doyne Farmer J, Trancik JE. Historical costs of coal-fired electricity and implications for the future. Energy Policy 2011;39:3042–54. doi:10.1016/j.enpol.2011.01.037.

[108] Colpier UC, Cornland D. The economics of the combined cycle gas turbine—an experience curve analysis. Energy Policy 2002;30:309–16. doi:10.1016/S0301-4215(01)00097-0.

[109] Bolinger M, Wiser R. Understanding wind turbine price trends in the U.S. over the past decade. Energy Policy 2012;42:628–41. doi:10.1016/j.enpol.2011.12.036.

[110] Prognos AG, Fichtner Group. Cost Reduction Potentials of Offshore Wind Power in

Germany. 2013.

[111] The Crown Estate. Offshore Wind Cost Reduction Pathways Study. London, Edinburgh: 2012.

[112] Roland Berger. Offshore wind power: Takeaways from the Borssele wind farm. Munich: 2016.

[113] Fraunhofer ISE. Current and Future Cost of Photovoltaics. Long-term Scenarios for Market Development, System Prices and LCOE of Utility-Scale PV Systems. 2015.

[114] IEA PVPS. Snapshot of Global Photovoltaic Markets 2015. 2016.

[115] IEA. Energy Technology Perspectives 2015 2015. www.iea.org/etp2015.

[116] Teske S, Sawyer S, Schäfer O. energy [r]evolution - A Sustainable World Energy Outlook 2015 - 100% Renewable Energy for All. Hamburg: 2015.

[117] Rai V, Victor DG, Thurber MC. Carbon capture and storage at scale: Lessons from the growth of analogous energy technologies. Energy Policy 2010;38:4089–98. doi:10.1016/j.enpol.2010.03.035.

[118] Gritsevskyi A, Nakićenovi N. Modeling uncertainty of induced technological change. Energy Policy 2000;28:907–21. doi:10.1016/S0301-4215(00)00082-3.

[119] Nykvist B, Nilsson M. Rapidly falling costs of battery packs for electric vehicles. Nature Clim Change 2015;5:329–32. doi:10.1038/nclimate2564.

[120] Matteson S, Williams E. Residual learning rates in lead-acid batteries: Effects on emerging technologies. Energy Policy 2015;85:71–9. doi:10.1016/j.enpol.2015.05.014.

[121] Wei M, Smith SJ, Sohn MD. Experience curve development and cost reduction disaggregation for fuel cell markets in Japan and the US. Applied Energy 2017;191:346–57. doi:10.1016/j.apenergy.2017.01.056.

[122] Hoppe-Klipper M. Entwicklung der Windenergietechnik in Deutschland und der Einfluss staatlicher Förderpolitik - Technikentwicklung in den 90er Jahren zwischen Markt und Forschungsförderung. 2003.

[123] Madsen ES, Jensen C, Hansen JD. Scale in technology and learning-by-doing in the windmill industry. Journal for International Business and Entrepreneurship Development 2003;1:27–35. doi:10.1504/JIBED.2003.007824.

[124] Klaassen G, Miketa A, Larsen K, Sundqvist T. The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom. Ecological Economics 2005;54:227–40. doi:10.1016/j.ecolecon.2005.01.008.

[125] Sato T, Nakata T. Learning curve of wind power generation in Japan. Proceedings of the 28th IAEE International Conference, Taipei, Taiwan: 2005.

[126] Goff C. Wind energy cost reductions. 2006.

[127] Söderholm P, Klaassen G. Wind Power in Europe: A Simultaneous Innovation–Diffusion Model. Environmental and Resource Economics 2007;36:163–90. doi:10.1007/s10640-006-9025-z.

[128] Nielsen P, Lemming J, Morthorst PE, Clausen NE, Lawetz H, Lindboe HH, et al. Vindmøllers Økonomi. Aalborg: 2010.

[129] Qiu Y, Anadon LD. The price of wind power in China during its expansion: Technology adoption, learning-by-doing, economies of scale, and manufacturing localization. Energy Economics 2012;34:772–85. doi:10.1016/j.eneco.2011.06.008.

[130] Wiser R, Bolinger M. 2009 Wind Technologies Market Report. US Department of Energy; 2010.

[131] Yao X, Liu Y, Qu S. When will wind energy achieve grid parity in China? –

Connecting technological learning and climate finance. Applied Energy 2015;160:697–704. doi:10.1016/j.apenergy.2015.04.094.

[132] Zou H, Du H, Broadstock DC, Guo J, Gong Y, Mao G. China's future energy mix and emissions reduction potential: a scenario analysis incorporating technological learning curves. Journal of Cleaner Production 2016;112, Part 2:1475–85. doi:10.1016/j.jclepro.2015.08.012.

[133] Williams RH, Terzian G. A benefit/cost analysis of accelerated development of photovoltaic technology. Center for Energy and Environmental Studies; 1993.

[134] Cody G, Tiedje T. A learning curve approach to projecting cost and performance in thin film photovoltaics. Conference Record of the Twenty Fifth IEEE Photovoltaic Specialists Conference, 1996, 1996, p. 1521–4. doi:10.1109/PVSC.1996.564426.

[135] Harmon C. Experience Curves of Photovoltaic Technology. 2000.

[136] Williams RH. Facilitating Widespread Deployment of Wind and Photovoltaic Technologies. Energy Foundation, 2001 Annual Report, San Francisco: 2002, p. 19–30.

[137] Parente V, Goldemberg J, Zilles R. Comments on experience curves for PV modules. Progress in Photovoltaics: Research and Applications 2002;10:571–4. doi:10.1002/pip.458.

[138] Poponi D. Analysis of diffusion paths for photovoltaic technology based on experience curves. Solar Energy 2003;74:331–40. doi:10.1016/S0038-092X(03)00151-8.

[139] Surek T. Crystal growth and materials research in photovoltaics: progress and challenges. Journal of Crystal Growth 2005;275:292–304. doi:10.1016/j.jcrysgro.2004.10.093.

[140] Swanson RM. A vision for crystalline silicon photovoltaics. Progress in Photovoltaics: Research and Applications 2006;14:443–53. doi:10.1002/pip.709.

[141] Breyer, C., Birkner, C., Kersten, F., Gerlach, A., Goldschmidt, J.C., Stryi-Hipp, G., et al. Research and Development Investments in PV – a Limiting Factor for a Fast PV Diffusion?, 2010, p. 5385–408. doi:10.4229/25thEUPVSEC2010-6CV.5.22.

[142] Zheng C, Kammen DM. An innovation-focused roadmap for a sustainable global photovoltaic industry. Energy Policy 2014;67:159–69. doi:10.1016/j.enpol.2013.12.006.

[143] Hong S, Chung Y, Woo C. Scenario analysis for estimating the learning rate of photovoltaic power generation based on learning curve theory in South Korea. Energy 2015;79:80–9. doi:10.1016/j.energy.2014.10.050.

[144] Trappey AJC, Trappey CV, Tan H, Liu PHY, Li S-J, Lin L-C. The determinants of photovoltaic system costs: an evaluation using a hierarchical learning curve model. Journal of Cleaner Production 2016;112, Part 2:1709–16. doi:10.1016/j.jclepro.2015.08.095.

[145] Enermodal Engineering Limited. Cost Reduction Study for Solar Thermal Power Plants. 1999.