REflex

Analysis of the European energy system

Policy Brief

# Technological Learning in Energy Modelling: Experience Curves

Atse Louwen
Martin Junginger
Anand Krishnan
Utrecht University

This project has received funding from the European Union's Horizon 2020 research and innovation programme [GA-No. 691685].

# Bibliographical data

Atse Louwen, Martin Junginger, Anand Krishnan
Utrecht University, Copernicus Institute of Sustainable Development

Reviewed by:

Andrea Herbst, Fraunhofer ISI

Katrin Seddig, Karlsruhe Institute of Technology (KIT)

# Table of Contents

# 1 Introduction

Within the REFLEX project, a large effort is ongoing to model the transitioning layout of the European energy system. A set of energy models, representing all sectors of the energy system, are coupled to analyse especially how technologies that offer energy flexibility can play a role in the future energy system. A large part of this modelling activity is determining which technologies will see increased diffusion, and which technologies will be phased out. A key consideration here is how the future costs of both incumbent and upcoming technologies will develop in the future.

Technology costs can decrease through a variety of mechanisms, mainly learning-by-doing, learning-by-researching (R&D), product upscaling (larger products) and production upscaling (larger production facilities). Through a variety of methods, production cost decreases resulting from these mechanisms can be established. Experience curves, although not without drawbacks, are one of few methods that use empirical data to derive a mathematical function that relates cost decreases of a technology to cumulated production experience. Using experience curves, one can estimate the future costs of a technology, given some exogenously derived development of cumulative production.

Since the modelling activities within REFLEX require accurate cost estimations of different technologies in the future energy system, a part of the REFLEX project focused on gathering empirical data to make these future cost estimations using experience curves that were derived from this empirical data. Aside from the application within the REFLEX project, the results of this exercise are themselves valuable for researchers, policy makers and other stakeholders, since accurate cost trends and outlooks for energy technologies are valuable information in the context of the ongoing transition towards a sustainable energy system.

Experience curves are based on the concept in economics that the production costs of a technology (or other parameters relating to the economic performance) improve significantly as producers gain experience with production of this technology.

The experience curve in the form discussed here was developed by the Boston Consulting Group (BCG, 1968), as an evolution of previously known learning effects in manufacturing (Junginger et al., 2010). BCG presented the experience curve as a means to describe the reduction of total product cost as a function of cumulative production of this product:

$$C(cum) = C_1 \cdot cum^b \tag{1}$$

Where $C(cum)$ is the cost $C$ of the product at cumulative production $cum$, $C_1$ is the cost of the first unit produced, and $b$ is the experience parameter. The experience curve is normally plotted on a double-logarithmic scale, and can also be expressed as a linear equation by expressing it in a logarithmic form:

$$\log C(cum) = \log C_1 + b \cdot \log cum \tag{2}$$

The experience curve parameter $b$ thus represents the slope of the linear representation of the experience curve in a double-logarithmic graph. Since the slope of this line indicates the rate at which a technology's cost decreases, two terms have been connected to the experience parameter $b$: the progress ratio (PR) and the learning rate (LR):

$$PR = 2^b \tag{3}$$

$$LR = 1 - 2^b \tag{4}$$

**At a learning rate of 20% (PR of 80%), the cost of a product decreases with 20% for every doubling of cumulative production $cum$.** Hence these parameters are a more meaningful expression of the experience parameter $b$.

An example of an experience curve, for solar photovoltaic (PV) modules, is given in Figure 1. Shown in this figure is the raw, empirical data collected, the derived experience curve, and an example of plotting this data on normal, linear scales and on double-logarithmic or log-log scales. For this dataset, a learning rate of 23.9% was derived, indicating a decline in price of 23.9% for every doubling of cumulative production of PV modules.

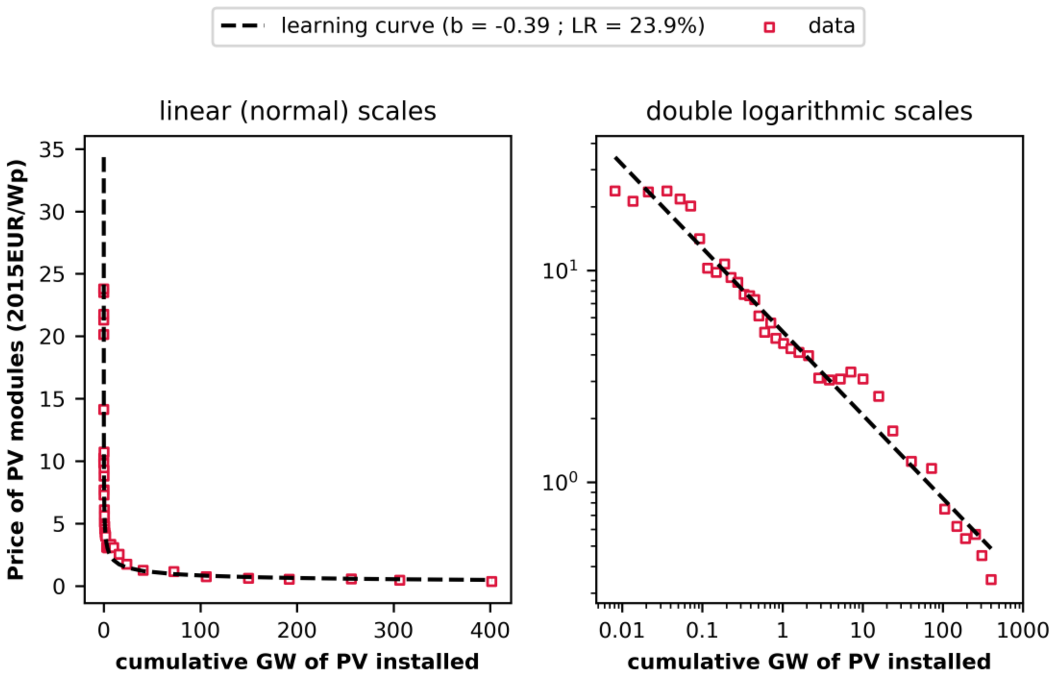


**Figure 1: Example of experience curves on two different graph scales: normal, linear scales (left) and double logarithmic or log-log scales (right). Data from Fraunhofer ISE (2016), Fraunhofer ISE (2017), Fraunhofer ISE (2018).**

# 2 Overview and technology highlights

## 2.1 Overview

In Table 1 below, an overview is given of the learning rates found for the technologies investigated within the REFLEX projects. A number of general observations are made:

With the exception of onshore wind and electricity with CCS, the value of learning rates ranges from about 10% to 21%. Errors in the learning rate range from very low (0.8% for PV modules) to very high (6.1% for utility redox-flow storage). This has direct implications for their application for extrapolation and use in models for future deployment, as will be discussed in the next section.

Furthermore, we note that earlier studies found a normal distribution of average learning rates for manufacturing technologies of about 20% (Argote and Epple, 1990) and more specifically for both energy supply and demand technologies of around 16% (Junginger et al. 2010; chapter 19). The learning rates presented in Table 1 below show an average of 15% (the learning rates of 24.5 and 25.8% for onshore wind were excluded from this average[1]).

Thus, it appears as if the majority of experience curves and learning rates identified are in line with earlier findings. Nevertheless, there are several issues and limitations with the (set of) experience curve(s) for each technology, which are discussed in the following section.

**Table 1: Overview of learning rates and their errors. At a learning rate of 20%, the cost of a product decreases with 20% for every doubling of cumulative production.**

| Technology | Learning rate | Error | Cumulative data unit | Functional unit | Remarks |
|---|---|---|---|---|---|
| Solar PV: modules | 21.4% | 0.8% | MW installed | Wp | |
| Solar PV: BOS | 12.9% | 1.7% | MW installed | Wp | |
| Solar PV: systems | 18.6% | 1.0% | MW installed | Wp | |
| Power-to-H2 (alk. electrolysis) | 17.7% | 5.3% | GW installed | kW | |
| Heat pumps | 10% | | Units sold | kW | Estimate |
| Gas + CCS | 2.2% | | MW installed | kW | From Rubin et al, 2007 |
| NGCC + CCS | 2.2% | | MW installed | kW | From Rubin et al, 2007 |
| Coal + CCS | 2.1% | | MW installed | kW | From Rubin et al, 2007 |
| Industrial CCS | 11%<br>12% | | Na. | Na. | From Rubin et al, 2007 proxy for capture only |
| Residential li-ion storage | 12.5% | 3.0% | GWh sold | kWh | |
| Utility li-ion storage | 15.2% | 3.7% | GWh installed | kWh | |
| Utility redox-flow storage | 14.3% | 6.1% | GWh installed | kWh | |
| BEV battery packs | 15.2% | 2.9% | GWh sold | kWh | |
| FCEV fuel cell stacks | 18.0% | 1.7% | GWh sold | kWh | |
| HEV battery packs | 10.8% | 0.6% | GWh sold | kWh | |
| Wind – offshore system | 10.3% | 3.3% | GW installed | MW | |
| Wind – onshore system | 5.9% | 1.3% | GW installed | MW | 1982-2016 data |
| PEFC micro-CHP | 19.3% | 1.6% | Units sold | kW | |

Source: REFLEX project

[1] The high values of 24.5% / 25.8% for onshore wind were excluded from this overview, as these learning rates are not considered to be representative.

## 2.2 Technology highlights, comparison and discussion

The experience curves shown in the previous section are the basis for the implementation of technological learning and cost reductions with cumulative deployment in a number of the energy models included in the REFLEX project. However, implementation if these models should be done with care, as each technology and experience curve have specific peculiarities and points of attention. Below, we first discuss the overview of experiences curves found, and the briefly zoom in on the individual technologies.

A first point observation is that all experience curves show production (or price) decline; not a single technology was identified with constant or increasing costs -at least not over several cumulative doublings of deployment.  In some cases, especially onshore and offshore wind, *prices* have remained stable or even increased of a number of years, but this can (almost always) be attributed to market effects and does not imply that actual production cost did not decline. Nevertheless, it is also a reminder that experience curves can only be used to project production costs of technologies, but these do not (necessarily) reflect market prices (which also depend on demand, subsidies, competition with other technologies, and other exogenous factors). As such, their use in *optimisation* models (where typically all technologies are assumed to be available at lowest possible costs) makes more sense than in simulation models.

The highest rates observed are for PV modules, which also show the lowest error term[2] and thus can be extrapolated with fairly high confidence. On the other hand, the error in e.g. the experience curve slope for utility redox-flow storage is significant, and extrapolation over 2-3 cumulative doublings would already result in a large range of possible costs. These aspects will need to be taken into account when evaluating the model results.

Second, for all technologies, one or several issues were identified (as shown at the end of each technology chapter). For several issues, it was possible to apply a standard solution, but in many cases, one or several points remained that need to be considered when interpreting these curves and using them in energy models. These are also briefly discussed below for each (set of) technologies.

When looking at individual technologies, ***PV modules*** have been the prime example of demonstration the experience curve principle – within the energy sector, they are undisputedly the technology following most closely and consistently an experience curve (Figure 2). Even despite minor price fluctuations due to market effects, the curve is declining steadily at a learning rate of 21.4±0.8% over 3.5 decades and about 16 doublings of cumulative production – a truly impressive accomplishment, with no signs of slowing down. It has however become apparent that the balance-of system costs need to be modelled separately, as these learn with a different learning rate (about 13%). The balance-of-system or BOS costs represent all costs aside from the modules, like the inverter and mounting structure, but also installation costs (labour) and other costs.

[2] The error term indicates the uncertainty margin of the established learning rate, and is a result of variations of the collected data from the fitted experience curve model.

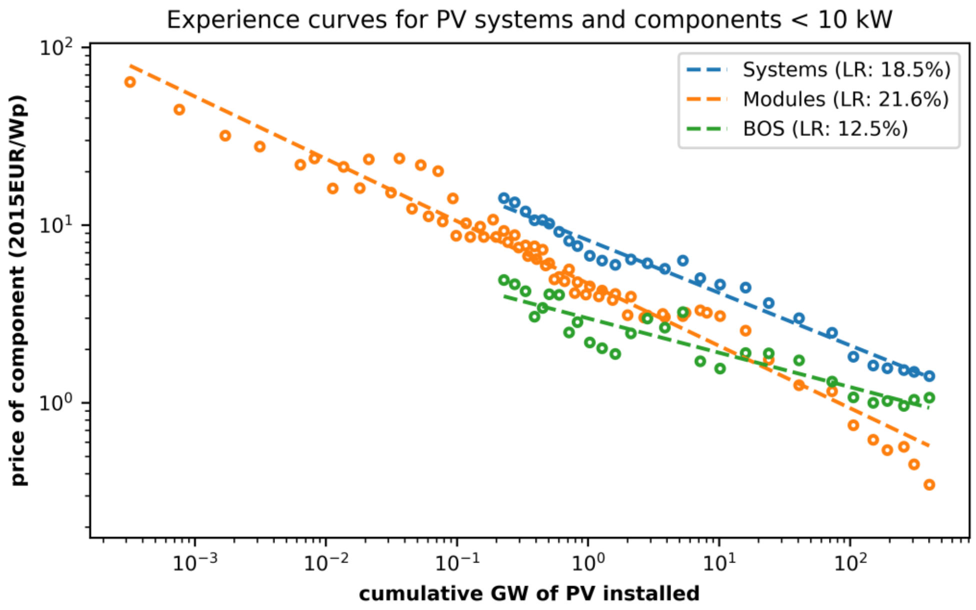


**Figure 2: Experience for PV systems, Modules and Balance-of-system components. Data sources: Fraunhofer ISE (2016), Fraunhofer ISE (2018), Van Sark (2008), IEA PVPS (2017).**

On the other hand, there are several peculiarities for the second technology that is expected to provide a major share of renewable electricity: ***onshore (and offshore) wind energy.*** Studies analysing price trends over the period 1980-2000 already found varying estimates for learning between about 10-18%, depending amongst others on the chosen system boundaries (Neij et al. 2003). However, steep price increases were observed between 2002-2009, only to be followed by strong decreases again between 2009-2016. The 25.8 / 24.5% values for two separate datasets for onshore wind shown for the 2009-2016 period are excluded from the range cited above, as this trend is only established over a rather short period of time, in which few doublings of cumulative capacity occurred. Also, this decline had in 2016 not reached 2002 levels. This means that the average capacity costs in 2016 were still higher than those of 2002. No clear reasons were found for why price levels had not returned to the level found 14 years earlier. Due to this anomaly between 2002-2016, the long-term experience curve from 1981-2016 shows a learning rate of only 5.9%, which is much lower than previous estimates. While this value is deemed most reliable for the time being, it is possible that actual production costs are still (far lower) than current prices, and that prices could decline much below the 2002 levels in the future. This is also supported by recently reported record-lows for costs of electricity from onshore (and offshore) wind farms (Pfeifer, 2018). Thus, models using learning rates for onshore wind should explore how outcomes are affected by higher (i.e. more optimistic) learning rates.

Similar problem were encountered for offshore wind (Figure 3): even though the weighted average prices for large offshore wind farms has been declining, underlying prices differed largely by country, and e.g. in Denmark have also increasing significantly over time. But also here, various (market) effects have been influencing these trends, and also for offshore wind, dramatic cost reductions have recently been reported, with claims that wind farms can be built without subsidy (Pfeifer, 2018). Thus, the learning rates found should be considered as uncertain, and offshore learning rates used in energy models should be subjected to sensitivity analysis.

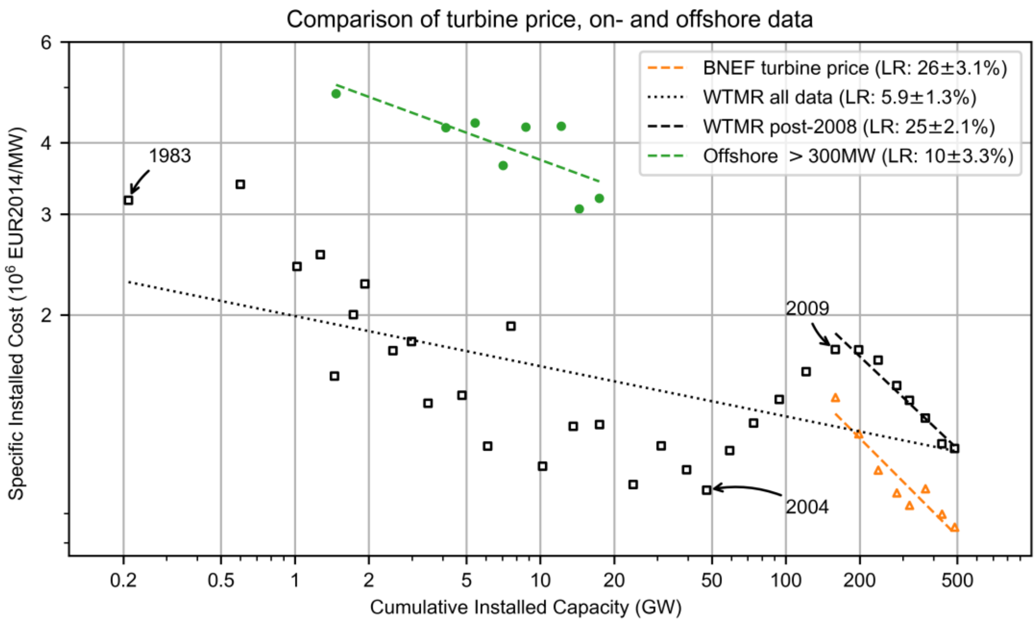


**Figure 3: Comparison of experience curve data for wind energy: onshore systems, offshore systems and turbine price indices. Data sources: Own data collection (offshore), WTMR (Wyser & Bolinger, 2016; Wyser & Bolinger, 2017), BNEF turbine price (Wyser & Bolinger, 2017).**

Another energy-producing technology covered by the REFLEX project's work on experience curves is the Proton Exchange Membrane Fuel Cell (***PEFC*) *micro-CHP***. For this technology, only one dataset from Japan was found, which however shows a constant decline of costs with a learning rate of about 19%. This trend has also a fairly low error, and so is recommended to be sued in models. However, ideally more studies (also for other type of fuel cells) are needed to validate this trend.

With the expected strong increase of electricity from intermitted sources, assessment of storage technologies becomes more and more important. ***Production of hydrogen*** (and other power-to-X technologies) may play an important role to buffer excess electricity supply and produce green fuels and chemicals. As alkaline electrolysis is a technology that has been increasingly deployed since the 1980's, it was possible to establish an experience curve, revealing learning curves of about 18%. However, the (so far) limited amount of data – especially for the early phases of production, makes this trend somewhat uncertain, and warrants more investigation into the underlying reasons for cost reductions and additional data points.

***Lithium and Redox-Flow batteries*** are also increasingly deployed on a global level, and are expected to become even more important both for stationary use and in electric cars (see below). Learning rates found by recent studies and own analysis are in the range of 12-18% (with most values around 15%). The results are shown in Figure 4. While these cannot always be compared directly with each other (e.g. due to varying size and application), data availability is high and trends are deemed fairly robust, thus making them suitable for implementation in energy models.

Closely linked to battery costs, the future cost development of ***electric cars*** will be of major important for models focussing on transport. The experience curves and datasets for the three vehicle types considered (BEVs, HEVs and FCEVs) are showing learning rates (for the battery-part only of the car) between 10-18%. The highest learning rate is observed for fuel cell stacks (18%), while hybrid EV batteries only have a learning rate of 10%, and full electric EV batteries are estimated to have a learning rate of 15.2±2.9%. Give the limited error found for these learning rates, they are deemed applicable in energy models, even though the datasets on which they are based are quite small.

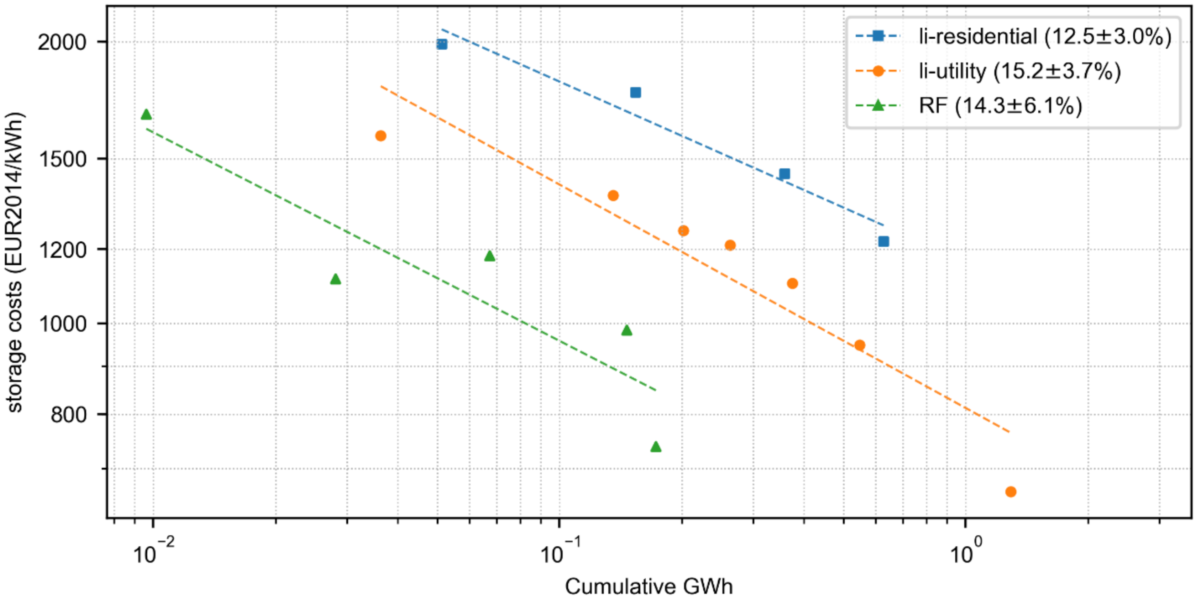


**Figure 4: Experience Curves for energy storage technologies. Data source: Schmidt et al, 2017; Sandia National Laboratories, 2015; IRENA, 2017a.**

***Heat pumps*** are another important energy-demand technology, expected to play a major role in future heating applications. Despite this expected increase, and the fact that heat pumps have been around for decades, only one study by Weiss et al. (2008) was found. The study by Weiss et al. revealed a very constant decline of costs with a learning rate of 26% (±0.36%). However, own investigation for heat pump prices in the Netherlands showed that the heat pump price in the Netherlands for the year 2011 was higher by a factor of 1.2 than the Swiss heat pump price in the year 2004, and also the learning rate found (11%) was far lower than the Swiss rate (but also measured over a *much* shorter time period). This shows again that prices may differ significantly between countries, and use of learning rate form just one study/country in global or European energy models is not generally recommended. More data for heat pumps should be gathered, and at the same time application in energy models of these learning rates should be subject to thorough sensitivity analysis.

Finally, various ***CCS-related energy production technologies*** are expected to be deployed widely in the coming decades according to the projections of many integrated assessment models. However, due to the (almost) complete lack of actual CCS projects developed over the past decade, there is little more than studies that try to anticipate the potential cost reductions using proxy technologies. While this may be the only feasible way until more empirical data becomes available, it also means that any learning rates used to project future cost reductions should be used with care.

Overall, we conclude that for most technologies, experience curves can be implemented in energy models, but due care needs to be taken, assessing amongst other things the impact of uncertainty of the various learning rates.

## 2.3 Cost Outlook for Selected Technologies

Using the experience curves derived from the data gathered within REFLEX, it becomes possible to extrapolate future costs of technologies, using exogenous data that describes the future developments of cumulative deployments of the respective technologies. Several energy outlook scenarios, which are often the result of complex modelling activities, describe what these future developments will look like. Some of these outlook scenarios, such as the International Energy Agency's "World Energy Outlook" (IEA WEO), attempt to model global, total energy demand and supply (IEA, 2018). Many other models exist that develop scenarios on smaller geographical scales and/or for sub-sectors of global or local energy systems. Finally, technology specific scenarios are very common, developed by industry collaborations such as SolarPowerEurope, financial institutions, energy research institutes and data and statistics firms, among others. In this section we highlight some of the previously discussed technologies, being PV systems, electricity storage, and electric vehicle li-ion batteries, and extrapolate current costs to 2030, based on several scenarios. All mentioned prices are in 2015 Euros.

For PV we analyse two PV system scales: under 10 kW, and between 10 and 100 kW. In the IEA WEO "Sustainable Development Scenario", which aims to achieve climate and sustainability targets, the projected cumulative PV capacity in 2030 would be 2346 GW, as opposed to 401 GW at the end of 2017. As a result of this strong increase in PV capacity, prices are expected to drop to 0.77-0.89 EUR/Wp for residential systems under 10 kW, and to 0.46-0.62 EUR/Wp for systems between 10 and 100 kW. This latter figure should be scrutinised however, since it is based on the total system price developments for systems as shown in Figure 2.The extrapolations are shown in Figure 5 and Table 2. Extrapolating these costs based on the experience curves for modules and BOS components separately, results in a 2030 PV system cost of 0.72-0.86 EUR/Wp. This mainly results from the much smaller

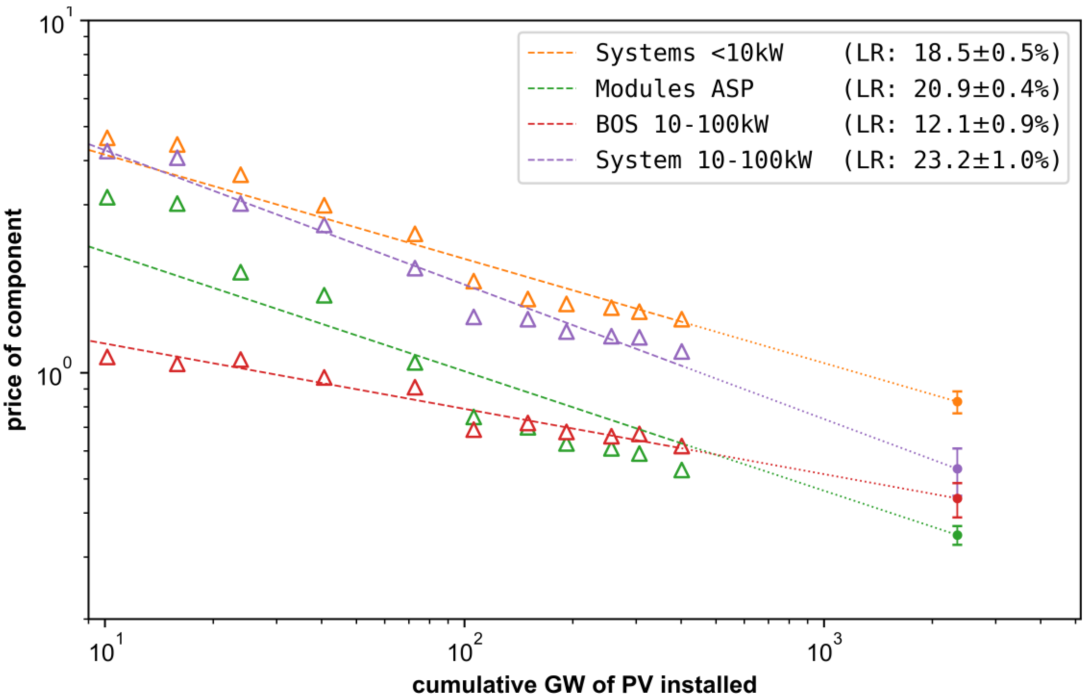


**Figure 5: Cost extrapolations for PV systems. All prices are in 2015EUR/Wp.**

learning rate for BOS components, but also from the fact that in this case the lower learning rate obtained for modules over a longer period was used. A similar approach should be used for the residential data.

**Table 2: Overview of cost extrapolations for selected technologies**

| Technology | 2030 deployment | Baseline extrapolation (2015EUR) | Range | |
|---|---|---|---|---|
| PV System <10kW | 2346 GWp[a] | 0.83 | 0.77-0.89 | EUR/Wp |
| PV System 10-100 kW[b] | 2346 GWp[a] | 0.53 | 0.46-0.62 | EUR/Wp |
| PV System 10-100 kW[c] | 2346 GWp[a] | 0.79 | 0.72-0.86 | EUR/Wp |
| PV BOS 10-100kW system | 2346 GWp[a] | 0.44 | 0.39-0.49 | EUR/Wp |
| PV modules 10-100kW system | 2346 GWp[a] | 0.35 | 0.33-0.37 | EUR/Wp |
| Li-ion Residential | 280 GWh[d] | 363 | 304-430 | EUR/kWh |
| Li-ion Utility | 180 GWh[e] | 274 | 220-340 | EUR/kWh |
| Redox-Flow Utility | 60 GWh[e] | 351 | 316-388 | EUR/kWh |
| Li-ion Electric Vehicles | 2195 GWh[d] | 90 | 65-123 | EUR/kWh |

[a]Based on IEA WEO "Sustainable Development Scenario" (IEA, 2018)
[b]Calculation based on whole system experience curve
[c]Calculation based on experience curves of BOS and modules separately
[d]Based on the S-curve approach as shown in Schmidt et al., 2017
[e]Based on the S-curve approach as shown in Schmidt et al., 2017; assuming a market share of 75% for li-ion and 25% for Redox-Flow in utility applications

For batteries (stationary and electric vehicle li-ion batteries), significant cost reductions can be expected for 2030. As shown in Figure 6 and Table 2, especially the forecasted growth of the electric vehicle market is large. As a result, EV battery prices are expected to drop to 90 EUR/kWh, with an uncertainty range from 65-123 EUR/kWh. Residential and utility scale stationary li-ion storage systems are extrapolated to drop in price to 304-430 EUR/kWh and 220-340 EUR/kWh, respectively, while Redox-Flow utility scale storage systems extrapolate to 316-388 EUR/kWh. Apparent clearly in Figure 6, when examining the last 3-4 data points for utility li-ion storage and EV batteries, is that it seems the price decrease is accelerating. This could be due to market dynamics (e.g. balance between supply and demand), but could also be a result of spillover effects in different li-ion markets.

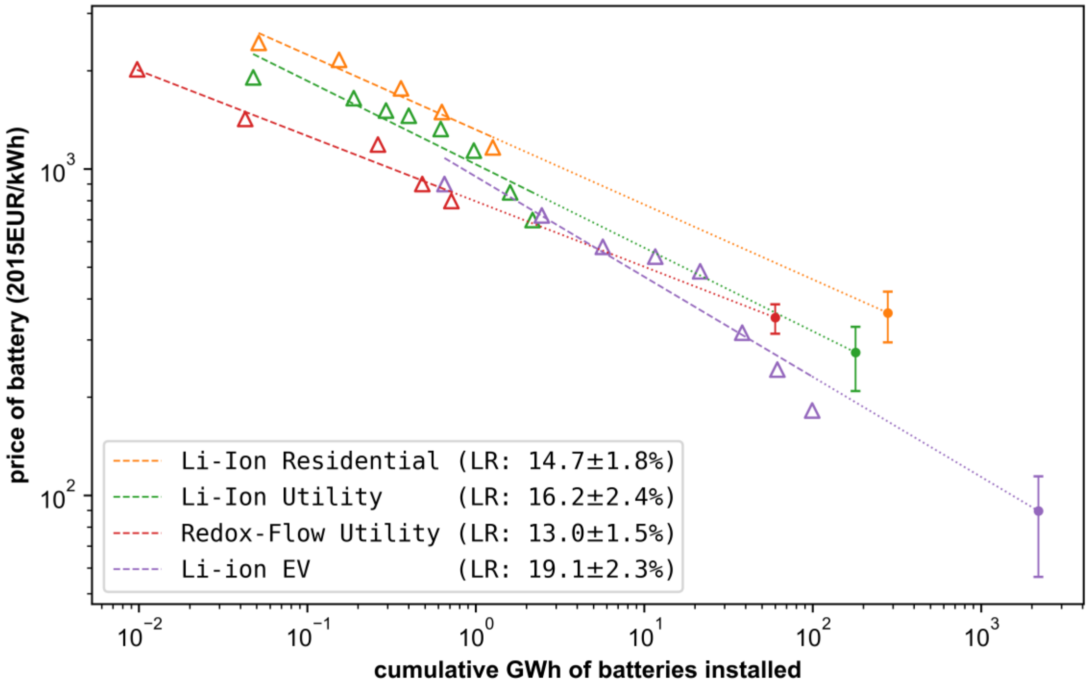


**Figure 6: Experience curves and cost extrapolations for different types of batteries. Data source: Schmidt et al, 2018.**

# 3 Conclusions and policy recommendations

Within the REFLEX project, historical cost data was collected for several energy technologies. From this data, where possible, experience curves were derived. In this policy brief, an overview is given of the work performed and results obtained. The experience curves have been implemented in different energy models that will analyse the future of the European energy system in different sectors, including power supply and demand for industry and residences, heat supply and demand, and transportation. Further research will be performed on the datasets that were produced by the REFLEX consortium for technologies not reported here, for dissemination in a follow-up publication from the REFLEX project.

Although experience curves are typically based on historical data, they offer one of few methods that can be used for evidence-based cost projections for the future. Especially for upcoming technologies, however, there are often issues with data availability and/or accuracy of the devised experience curve parameters. The work performed has found several issues in this respect, which have been systematically assessed, resulting in several recommendations to take into account for further research as well as when applying the results obtained. These recommendations are detailed below.

For many technologies, availability of consistent time series data for cost developments is an important issue. Many of the technologies that are often named as key in meeting greenhouse gas emission reduction targets, like carbon capture and storage, wind power, electric transport and electricity storage, are sometimes characterised by a very limited availability of data. For carbon capture and storage, and some electricity storage technologies, there is even a complete lack of empirical, commercial scale data. As a result, establishing learning curves and using these for evidence-based cost estimations is still difficult (or even impossible), requiring approximations e.g. through the comparison with similar technologies. Since many of these and other upcoming and promising decarbonisation technologies are currently supported by policy makers in many different countries, there should be a push for more research in better estimating the likely production cost developments of these technologies.

Research has shown, and our results also indicate, that among other factors, market dynamics and raw material prices can significantly affect technology costs (and market prices) and thus established experience curve parameters are affected by these non-technological learning related factors. Further research should investigate how multi-factor experience can be implemented in energy modelling. Multi-factor learning curves may at least partially address market effects, e.g. by taking explicitly into account the increase of cost for raw materials (e.g. steel, gold and other metals, concrete, plastics etc.), scale effects and other factors. On the other hand there needs to be a balance between the additional modelling complexity and input data requirements vs. the possible increase of the accuracy with which technological learning can be modelled and cost estimations can be made. Within the REFLEX project, these issues will be investigated to be included in a follow-up publication.

Another issue related to implementing technological learning in energy modelling relates to the difficulty with which this process can be modelled endogenously. Since technological learning is normally considered to be a process that occurs on a global scale, experience curves should be derived based on global cost developments. Many of the energy models analysed within REFLEX are however of a smaller (EU or country-level) geographical scale. Hence, depending on the assumptions of the market shares of a certain technology for the geographical region within and outside of the model, fully endogenous modelling is basically not possible for most of these models, and requires assumptions on e.g. global developments of cumulative deployments.

For some of the technologies presented here, it is fair to assume that their cost developments influence each other. For instance, all technologies based on lithium-ion batteries in different applications (electronics, electric vehicles, electricity storage) likely benefit from each other's developments since they share common components. These spill-over effects are easy to theorise on, but difficult to account for in modelling and experience curve analysis. One way to approach it is to break down the costs of these related technologies to their components and devise experience curves on a component basis. This will however drastically increase modelling complexity, as well as having much broader data requirements to be able to establish experience curves. Furthermore, while time series of cost or price data for end products are already difficult to obtain, data on the cost of components of these products is even less transparently available. Further research should try to establish what kind of accuracy improvements could reasonably be expected with this more detailed approach, and weigh this against the added data requirements and increase of modelling complexity.

In terms of policy implications, we highlight the following issues:

- As a prime and major conclusion, we can state that **all energy technologies investigated show production cost declines with cumulative production**. **Many of these technologies have been supported both by public R&D and deployment support**. Without such support, technologies such as wind and solar energy would not have the level of (near) competitiveness with fossil electricity production, and their major role in the energy transition would not have been possible**. For the coming decades, further cost reductions can be expected, and as such, learning investment will very likely be earned back.** Continued support may, however, still be needed for technologies which have not reached full parity yet with their fossil fuel counterparts, e.g. heat pumps and alkaline electrolysis.

- Especially for CCS technologies in both the power sector and industry, accurate cost data for experience curves is lacking, as there are hardly any large-scale plants except from some (very site-specific) pilot programmes. Since CCS technologies are one of the main ways to decarbonise especially industrial processes, **policy makers should push for more pilots on industrial CCS while specifically making sure that transparent cost data will be made available**.

- Similarly, data for existing technologies (such as heat pumps, alkaline hydrolysis) should in principle be available but is often hard to obtain. Thus **(renewable) energy support programs (e.g. tenders, R&D support) by governments should be designed as such that aside from finding the lowest bid/furthering research and development etc., they also create a transparent database of cost data**.

- By using the data presented for batteries, electric vehicles, governments can establish the best target for incentives, and make estimations on total required government investments to attain a certain level of competitiveness. However, they do need to take into account the uncertainty associated with the small datasets that are currently available, hence keep track of this and push producers to give transparent cost data.

# References


1. Argote and Epple, 1990. Learning curves in manufacturing. Science, 247(4945), 920-24.

2. BCG (1968). Perspectives on Experience. Boston, MA: Boston Consulting Group Inc.

3. Fraunhofer ISE, 2016. Photovoltaics report. Freiburg, Germany: Fraunhofer Institute for Solar Energy Systems (ISE).

4. Fraunhofer ISE, 2017. Photovoltaics report. Freiburg, Germany: Fraunhofer Institute for Solar Energy Systems (ISE).

5. Fraunhofer ISE, 2018. Photovoltaics report. Freiburg, Germany: Fraunhofer Institute for Solar Energy Systems (ISE).

6. IEA, 2018. World Energy Outlook. Available from: http://www.iea.org/weo2018

7. IEA PVPS 2017. Trends 2017 in Photovoltaic Applications. International Energy Agency Photovoltaic Power Systems (IEA PVPS) program task 1. Retrieved from: http://www.iea-pvps.org/?id=256

8. IRENA, 2017. Electricity storage and renewables: costs and markets to 2030. International Renewable Energy Agency (IRENA). Retrieved from http://www.irena.org/-/media/Files/IRENA/Agency/Publication/2017/Oct/IRENA_Electricity_Storage_Costs_2017.pdf

9. Junginger et al. 2010. Technological learning in the energy sector: lessons for policy, industry and science. Cheltenham, UK/Northampton, USA: Edward Elgar Publishing.

10. Neij et al. 2003. Final report of the EXTOOL project – experience curves: a tool for energy policy programme assessment. Lund, Sweden.

11. Pfeifer, 2018. Subsidy-free renewable projects on ‘cusp of breakthrough’. Financial Times, March 28, 2018, Retrieved from https://www.ft.com/content/1960c6fe-2dea-11e8-a34a-7e7563b0b0f4

12. Rubin, E. S., Yeh, S., Antes, M., Berkenpas, M., & Davison, J., 2007. Use of experience curves to estimate the future cost of power plants with CO2 capture. International journal of greenhouse gas control, 1(2), 188-197.

13. Sandia National Laboratories, 2015. DOE Global Energy Storage Database. Available at: http://www.energystorageexchange.org/. (Accessed: 1st May 2018)

14. Schmidt, O., A. Hawkes, A. Gambhir & I. Staffell, 2017. The future cost of electrical energy storage based on experience rates. Nature Energy, 2(8), 17110.

15. Oliver Schmidt, Sylvain Melchior, Adam Hawkes, Iain Staffell, 2018. Update to publication: O. Schmidt, A. Hawkes, A. Gambhir & I. Staffell. The future cost of electrial energy storage based on experience rates. Nat. Energy 2, 17110 (2017). DOI: 10.1038/nenergy.2017.110

16. van Sark, W. G., Alsema, E. A., Junginger, H. M., de Moor, H. H. and Schaeffer, G. J., 2008, Accuracy of progress ratios determined from experience curves: the case of crystalline silicon photovoltaic module technology development. Prog. Photovolt: Res. Appl., 16: 441-453. doi:10.1002/pip.806

17. Weiss et al. 2008. Learning energy efficiency: experience curves for household appliances and space heating, cooling and lightng technologies. Utrecht, The Netherlands: Utrecht University.

18. Wyser & Bolinger, 2016. 2015 Wind Technologies Market Report. US Department of Energy Office of Energy Efficiency and Renewable Energy, Washington, D.C., United States.

19. Wyser & Bolinger, 2017. 2016 Wind Technologies Market Report. US Department of Energy Office of Energy Efficiency and Renewable Energy, Washington, D.C., United States.