CHAPTER 16

Synthesis, conclusions, and recommendations

Martin Junginger[1] and Atse Louwen[1,2]

[1]*Copernicus Institute of Sustainable Development, Utrecht University, Utrecht, The Netherlands,* [2]*Institute for Renewable Energy, Eurac Research, Bolzano, Italy*

Abstract

The past 15 chapters provide an overview of the technological development and cost reductions achieved from a number of major energy technologies that are expected to be deployed as part of the ongoing energy transition. At the same time, these chapters highlight how future cost reductions and subsequent deployment of these technologies may shape the future mix of the electricity, heat, and transport sectors. In this final chapter, we discuss both methodological issues that appeared throughout the book and present a synthesis of the outlook of the technologies investigated. We discuss amongst others general lessons and recommendations for policy makers, industry, and academics, focusing on what technologies may require further policy support in the short term to have a major impact later on, which investments will be needed, and what scientific knowledge gaps remain for future research.

Chapter outline

16.1 Introduction

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deployed as part of the ongoing energy transition. At the same time, these chapters highlight how future cost reductions and subsequent deployment of these technologies may shape the future mix of the electricity, heat, and transport sectors.

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16.2 Methodological considerations

Many papers have been published in the past on the methodological limitations of experience curves. This section does not aim to summarize these findings, but mainly focuses on issues emerging from the current book.

16.2.1 Cost of capacity versus LCOE and other metrics

A common theme emerging from various technology chapters is the need for metrics that focus on the feature of a technology for which optimization is carried out. This is for most energy supply technologies the ability to deliver energy (electricity, heat, or transport fuels) at the lowest possible cost. For demand-side technologies, other factors typically play a role as well (e.g., safety, reliability, and comfort of use, see the example of LED lamps later). Still, for most technologies, the upfront investment cost was used as a proxy to reflect the technological learning and associated cost reductions of the energy delivered. While this yielded acceptable results in the past [especially for situations where the capital expenditures (Capex) remained a substantial part of the levelized cost of electricity (LCOE), such as photovoltaics (PV)] for many other technologies, increasingly the need is emerging to focus more on the assessment of LCOE in order to accurately capture and forecast cost trends. In this book, this need was particularly identified for onshore and offshore wind, where the increasing capacity factor but also lower weighted average cost of capital (WACC) and Opex have contributed to the overall reduction of LCOE, and experience curves solely based on Capex are increasingly less suitable to provide accurate trends.

Also for hydrogen production the levelized cost of hydrogen (LCOH) would be a more appropriate metric than stack costs. For electric cars, studies beyond battery pack costs focusing on total cost of ownership and cost per passenger-kilometer traveled will also help better understand diffusion and adoption of electric vehicles. Similarly, for heat pumps, the increases in coefficient of performance (COP) have led to substantial reductions in the cost of heat delivered compared to the reductions in the investment cost alone. However, as discussed above, data availability limits the possibilities to take these developments adequately into account.

Last but not the least, for LED lamps (as a typical consumer product), a correct assessment depends on many factors: the rapid evolution in LED lighting products also introduced a wide variety of new product features that also affect price, posing a challenge for determining a single, well-defined price at any given point in time, and confounding efforts to measure the underlying learning dynamics for the base technology. For instance, the earliest LED lighting products intended for general illumination had relatively low light output, while over time, products with higher output were introduced in the market at a substantial price premium (that eased with time). It is thus essential for any price-trend analysis to control for lumen output, to account for the varying maturity, and market penetration of bulbs with different output. Additional features that can impact the price of LED lighting products, of which relative market penetration varied significantly during the 2010s, include lifetime, color temperature, color rendering, dimmability, color tunability, remote controllability, and the esthetic appearance of the light bulb itself.

16.2.2 Component-based assessments

As was highlighted in Chapter 5, for photovoltaic systems, experience curves for a system, which is an aggregate of several components, should ideally be based on separate experience curves for each component of this system. We observed that the learning rate for PV modules was substantially higher than that for the so-called balance-of-system components. Future price extrapolations should be made on the basis of using separate experience curves for these components, rather than based on a single experience curve for the whole system. As we highlighted in Chapter 5, using this single system-based experience curve will likely lead to an overestimation of future cost reductions. A similar discussion is also made in Chapter 8, where an overview is given of the components of a battery storage system. From this discussion, it is clear that the potential for cost reduction varies for each component; hence, it is argued that it is feasible to assume the aggregate learning rate for battery systems will decrease over time as the relative cost shares of components with high learning rates decrease more quickly.

16.2.3 Two- and multifactor experience curves

In Chapters 5 and 8, the concept of multifactor experience curves is discussed. Multifactor experience curves attempt to expand the single-factor experience curve, by including additional parameters aside from cumulative production. These parameters commonly include R&D activities, by means of a variety of proxy datasets, and input material prices. We observed in Chapter 5, that the price of silicon is highly correlated with the observed cost developments of crystalline silicon PV modules, while it is difficult to separate the effects of cumulative production and R&D efforts, as the developments over time of these two parameters are highly correlated. For battery storage systems (Chapter 8), material input prices show little correlation with the observed cost reductions, a result of battery designs being highly diversified in terms of material compositions and having design features that are resilient to strong short-term price changes in, for instance, lithium and cobalt.

The use of multifactor experience curves in price extrapolations and energy modeling activities would address several issues that arise from the application of single-factor experience curves, for example, it would be possible to take into account changes in input material prices, the effects of policy measure that enhance R&D efforts, and possibly also take into account knowledge (and production experience) spillover activities from one product to the other. This would especially be true if a combination is made of component-based and multifactor experience curves. Endogenous implementation of multifactor curves in energy modeling is however still a developing field. The successful implementation faces some tough methodological challenges, as the data requirements for multifactor and component-based experience curves are much larger compared to single-factor curves. First, much more detailed data needs to be collected, validated, and verified. Second, the endogenous application of multifactor and component-based experience curves in energy models requires that these models produce a much larger set of input data for the curves, such as raw material prices, R&D activities, and cumulative production for each separate component of a product. Still, if further research were to be successful in addressing these issues, multifactor experience curves have the potential to improve the accuracy of modeling future cost trajectories of technologies.

16.2.4 Environmental experience curves and social learning

As pointed out both in Chapter 4, and in the chapter on electricity storage (Chapter 8), monitoring cost developments may not be the only application of the experience curve. There are clear indications that with decreasing use of materials, next to cost, also the environmental impacts during the production phase of, for example, solar cells or wind turbines, decrease. Likewise, higher efficiencies of demand-side technologies reduce the demand for fuels or electricity, and thus lower again the environmental impacts in the use phase of many technologies. So far, deploying the experience curve concept to both assess the historical environmental impacts and extrapolate such trends for future projections has been very limited, partly also due to data limitations. One promising technology where a historical analysis may be promising is onshore wind (given data availability), but also other technologies could be scrutinized. After all, with massive deployment of these technologies, assessing environmental impacts is equally important as describing the overall cost of deployment.

Another application of the concept of technological learning is discussed in Chapter 4, where social learning mechanisms are investigated in a case study on the market diffusion of electric vehicles. By taking into account a set of social dynamics, a more realistic model can be derived on the uptake of these novel technologies in society, which includes more than only fully rational decisions a consumer would make based on total cost of ownership of a technology. Here, social learning represents the change in risk perception consumers have of novel technologies, for instance, due to first adopters buying into these novel technologies and essentially demonstrating the technologies' value and capability to replace incumbent technologies.

16.2.5 Application in energy and climate models

Implementation of technological learning processes in energy modeling is nowadays common, yet not without its issues and drawbacks. As discussed in Chapter 3, a variety of model characteristics can hamper endogenous implementation. Many energy models are restricted in geographical scope, while technological progress is most often considered a global process. In these cases, it is likely that an (at least partly) exogenous cost trajectory based on experience curves is necessary, but a feedback between development within the model under study and technological learning is in this case only possible to a limited extent.

Other issues are encountered relate to technical or practical considerations in energy modeling, such as the mathematical layout of the model, computation time, or the ability of models to produce the required input parameters for endogenous (multifactor) experience curves. When comparing an endogenous versus exogenous approach of implementing technological learning in different energy system models, it appears that especially top-down models allow easier implementation.

Testing the impact of the uncertainty of learning rates in in three different bottom-up models (see Chapter 14) revealed that the diffusion of different technologies is not impacted equally: heat pump diffusion for residential heating is only moderately affected, as installation rates are also dependent on, for example, technology preferences independent of pure cost parameters and policy preferences (e.g., support of centralized vs decentralized systems). On the other hand, assuming higher learning rates for batteries may significantly determine the diffusion of electric vehicles (see Chapter 15) in the transport sector and may shift new investments from gas turbines to redox-flow batteries (see Chapter 14) in the power sector. Similarly, the assumption whether CCS technologies do or do not learn largely determines investment in CCS plants by 2050. Unfortunately, there is considerable uncertainty for many of the learning rates applied in these models, amongst others, due to the limited availability of reliable learning rates and experience curves for many new energy technologies such as CCS. Thus these model results should also be handled with care, and sensitivity of the models to variation in learning rates should always be tested.

16.2.6 Data availability and future data collection

Based on the nine technology chapters, we conclude that data availability and quality differ strongly between the individual technologies investigated. For some technologies, data availability is excellent, such as onshore wind, offshore wind, solar PV, and batteries. Especially for the electricity supply technologies, data availability is high for the United States and Europe, often due to excellent long-term publicly funded bodies that systematically collect these data.

For other technologies, there is surprisingly little public data available. For example, LEDs have been around for many years, are currently rapidly gaining market share, and are generally considered as *the* lighting technology for the coming decades. Yet, other than the data presented in this chapter, there are surprisingly little time series on LED price developments available—possibly due to the large amount of data to be collected in order to correctly assess and compare LED lamps. Likewise, heat pumps for space heating and cooling have been deployed for decades (and in the form of air conditioning units on massive global scale) and are generally seen as one of the most promising technologies to provide low-temperature heat for residential buildings—yet, systematic collection of data on capital costs and COP is largely missing. Hydrogen production through electrolysis has been carried out on a large scale in the middle of the 20th century, but documentation of the declining cost of hydrogen has been minimal. Given the fact that these technologies are expected to play a major role in coming years, more comprehensive data collections on Capex and other variables (see earlier) is of vital importance to better monitor and asses future cost trends.

Similarly, there is also an actual lack of experience and data to make quality forecasts for electricity storage technologies. The rapid pace of advances on the battery chemistry front introduces new challenges that are novel and cannot be compared with other technologies such as hydropower dams or natural gas combined cycle plants. Technological learning studies should also incorporate alternative indices related to the life cycle of greenhouse gas emissions from storage options, materials availability of emerging battery chemistries, and cost indicators that incorporate multiple services and applications provided by storage. Also here, we call for transparency, and public access of data remains key to validating new learning curve models.

On green hydrogen production through alkaline electrolysis—one of the key technologies to decarbonize the energy system—relatively little public data is available, and often the data is incomplete or unclear (e.g., what parts are included, the size of the system). For future data collection, we recommend collecting data for the separate components of electrolyzers (stack, gas dryer, compressor, etc.) and generating experience curves for each component that makes up the system, similarly as performed for PV (see Chapter 5). This may be particularly useful for proton exchange membrane (PEM) electrolyzers. PEM—due to is flexibility with dynamic operation—might play an important role in hydrogen production in the future.

16.3 Technology outlook till 2030

This section provides an outlook for the various technologies covered in this book until 2030, including likely cost reduction levels.

At the time of writing, three out of four *electricity production technologies* covered in this book (solar PV, onshore wind, and offshore wind) reported that production cost levels could (at least in some instances) outcompete the fossil reference technology:

- Given the already low cost of PV systems, especially for large-scale systems, the LCOE from PV is already competitive with fossil generation in high irradiance locations and has achieved grid parity for private consumers years ago in a much larger geographical region. Chapter 5, shows that there is still substantial room for further system cost reductions, and so it is likely that electricity generation with PV will be cost-competitive in many more locations, even those with relatively low solar irradiance.
- Also, onshore wind is rapidly gaining market share and pushing out incumbent fossil generation in many parts of the world. As shown in Chapter 6, onshore wind has shown cost reductions for more than three decades, but the importance of underlying factors has varied over time. Next to lower upfront Capex, the capacity factor has also increased significantly. While Capex and LCOE have also temporarily increased between 2005 and 2011, the overall learning rate for LCOE for data between 1990 and 2017 is 11.4%. Combining this learning rate with anticipated growth in global onshore wind deployment yields a projected LCOE of about 33€/MWh by 2030, a reduction of approximately 25% from 2018 levels, making it highly competitive with expected prices of new coal and natural gas generation.
- After an increase between 2000 and 2015, the LCOE of offshore wind has declined dramatically from 190€/MWh in 2015 to about 100€/MWh at the end of 2018, with average projections for 2021 reaching as low as 70€/MWh. Especially, the increase in capacity factor has been a major driver in reducing the LCOE. Given the strong fluctuations in the past and many factors influencing the LCOE of offshore wind projects, it was not possible to derive meaningful one-factor experience curves and

learning rates that would allow extrapolation for future cost projections, but similarly to onshore wind and PV, it is expected that in the coming years, offshore wind will increasingly be able to compete with fossil fuels without direct economic support.

- In contrast, while concentrated solar power has also displayed cost decline in the past decades, current LCOE is still at an average of 210€/MWh; it cannot currently compete with PV, wind, and natural gas for electricity production.

Overall, with further opportunities to reduce LCOE, these technologies are set to deliver the large-scale diffusion needed in many energy scenarios (especially those with ambitious climate−change mitigation targets), delivering a surplus of electricity to provide energy for the mobility and heating sector. However, due to the increasingly intermittent availability of electricity in such systems, storage options will likely play a vital role.

Therefore past and future cost reductions of e*lectric mobility and electricity storage options* (EV, batteries, and H_2) have also been assessed in this book.

- For storage technologies, by 2030, stationary systems may cost between 200 and 440€/kWh, with pumped hydro and an electrolysis-fuel cell combination as minimum and maximum value, respectively. When accounting for experience rate uncertainty, the price range expands to 150−520€/kWh (min: utility-scale lithium-ion, max: electrolysis-fuel cell). For battery-based storage technologies, this means typically a cost reduction of more than 50% between 2018 and 2030.
- Similarly, the price of battery packs for transport applications is also expected to decline in a similar fashion from 50 to 190€/kWh in 2030 (40−200€/kWh with uncertainty), partly also depending on the level of diffusion of electric cars, which might reach between 100 and 240 million vehicles on the road by 2030. With the anticipated strong growth in uptake, our chapter suggests that by 2040, the cost could drop an additional 50% from today's level, ultimately reaching 50€/kWh. Such trajectories are feasible based on costs of new lithium-ion cathode chemistries and other battery pack materials. Meeting policy goals such as the EU's Strategic Energy Technology Plan cost target of 75€/kWh is feasible in both high and moderate growth scenarios This result, based on experience rates, indicates that aggressive targets may not be so difficult to meet, which can help as a transportation decarbonization strategy.
- For hydrogen production, a less clear picture emerged. The experience curve for alkaline electrolysis system between 1956 and 2016 shows a learning rate of 16% ± 6% with Capex decreasing from 2100 to 750$€_{2017}$/kW_{input} in 1956 to a range between 900 and 500$€_{2017}$/kW_{input} in 2016 but with a poor R^2 of 0.307, which can be attributed to discrepancies in the Capex composition of the gathered data and the wide spread in capacity (1−100 MW).

With regard to heating and cooling technologies, this book investigated both condensing natural gas boiler (the dominant fossil fuel−based heating technology in many EU countries) and heat pumps. Based on Swiss and Dutch case studies, the learning rate of the main cost components of heat pumps is 12%–22% and the one of the system as a whole about 20%, while their utility, in terms of less noise emission, system integration, and energy efficiency, improved over the past decades. This is equal or higher as compared to the LR of condensing gas boiler (13%). This holds for both countries assessed, although it should be kept in mind that the time series is quite short in the Dutch case. Moreover, a learning rate for the coefficient of performance was found, which is 5% in the case of ground-source heat pumps and 9% for air-to-water heat pump (HP). Thus heat pumps offer a high potential to improve their cost-effectiveness relative to reference systems in terms of cost of delivered heating energy, which depend on both specific investment costs and on the energy efficiency. Given the historical production and sales of heat pumps and condensing boilers, the cost reduction of heat pumps will likely be more dynamic as the cumulative production (or sales) will double faster, particularly in a climate mitigation scenario. Moreover, there is still a considerable technical potential to improve peak performance and energy efficiency (as opposed to gas condensing boilers where the technical potential is basically tapped). Therefore competitiveness particularly will be improved from a life-cycle-cost perspective, and from this perspective, heat pumps are already competitive for different use cases in many countries, also depending on the framework conditions.

Last but not the least, the progress achieved with LED lamps has been scrutinized. The 2010 decade saw a steady and rapid decline in price for LED lighting products, with prices falling several folds from the high initial market-entry prices observed in 2010. For LED A-line lamps sold in the US market, a steady decline of 20%–30% per year was observed through the first half of the decade, in conjunction with fast growth in consumer uptake, resulting in a manyfold increase in cumulative production in the same period. This situation presented an unusual opportunity to observe significant technological learning effects in near real time as they occurred over a period of only a few years. For A-line lamps in the United States, a learning rate of 18% was found using only 2–3 years of data on price and lamp sales. With such a limited time period, this learning rate should be handled with care: manufacturers projected a 40% decline in costs from 2015 to 2020, while the price-based forecasts point to a fourfold price drop over the same period. The discrepancy may partly also be explained by changing margins for manufacturers. On the other hand, learning rates for PV modules (another modular technology) of between 18% and 21% have been observed for a period of over 50 years (see earlier); hence, this learning rate does not seem overly optimistic.

16.4 Final conclusions and recommendations

When reading through the previous section, it becomes clear that technological learning and associated cost reductions for most technologies covered have been impressive over the past two decades and are now important drivers for further large-scale diffusion as part of the transition to a low-carbon energy system. In many cases (onshore and offshore wind energy, PV, and LED lamps), these technologies have reached the stage where they are able to directly compete with some (e.g., coal, nuclear) or virtually all fossil/traditional energy technologies and thus are now entering the phase where society will reap learning benefits, that is, both lower costs (and thus economic benefits), lower greenhouse gas (GHG) emission, and thus lower environmental (and in consequence again economic) impacts. Even in the absence of stringent climate policies, these technologies now have the potential to rapidly displace fossil-based and inefficient technologies. This is mainly due to persistent learning investment by countries such as Denmark, Germany, the United States and Japan, but more recently also China.

In other cases, there is still a long way to go before this stage is reached. Green hydrogen production is seen by many as the ultimate way to decarbonize large parts of our energy system and has shown clear progress over the past decades, yet the production costs are still significantly higher than those of gray or blue hydrogen, and significant investments in both R&D and deployment will be needed to bring down the production costs, much like those of solar PV 50 years ago. The heat pump, as the technology to provide low-temperature heat using electricity, is already cost-competitive in some market segments; but the need for additional building insulation and the sheer size of the building stock to be covered implies that this will still be a process over decades.

Thus we do repeat a key lesson from the LED-lighting chapter: an appreciation for the effects of technological learning is essential for sound decision-making with regard to emerging technologies, both for market actors and for policymakers. Decisions that may seem bold, or even foolhardy, in the context of status quo market conditions may in fact appear wise and beneficial once the full effects of technological learning are considered.

Last but not the least, in this book, a selected number of technologies, which are deemed crucial for the ongoing transition to a low-carbon energy system, were highlighted. However, not all relevant technologies were covered: conversion technologies using fossil fuels and nuclear energy were barely touched upon, even though they will continue to play a major role for decades, and are also still learning. Carbon capture, utilization, and storage technologies of both fossil and biogenic carbon may be crucial in keeping global mean temperature increases below 2°C but were not included either. Advanced biofuels and solar fuels may provide a renewable fuel for aviation and shipping where little alternatives exist on the short term, but again did not feature in this book. This was partly based on time and resource constraints, partly on the fact that the deployment of fossil fuels will hopefully be phased out, but largely also because for many of these technologies, there is barely any public data available and/or little actual progress and deployment has been achieved. For example, both carbon cature, utilisation and storage (CCUS) and advanced biofuels have only seen marginal deployment in the past decade (for differing reasons), making it difficult to deploy experience-curve-based assessments. While many may favor technologies, such as wind, solar, and energy savings through efficiency measures, it remains very likely that we will have to rely on a wide portfolio of technological options to fully transition to a low-carbon energy system. Thus investing in these technologies to “push them down the experience curve” is likely equally important as pursuing deployment of those that have reached commercial maturity.