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under the aspects of flexibility and technological progress

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AC	Alternating current
ASHP	Air source heat pump
BEV	Battery Electric Vehicle
BOS	Balance of System
CCS	Carbon Capture and Storage
CHP	Combined Heat and Power
DC	Direct Current
EV	Electric Vehicle
FCEV	Fuel Cell Electric Vehicle
GDP	Gross domestic product
GHG	Greenhouse Gas
GSHP	Ground Source Heat Pump
Gt	Giga tonne (10^{12} kilogram)
GW	Gigawatt (10^{9} watt)
HAWT	Horizontal Axis Wind Turbine
HEV	Hybrid Electric Vehicle
kW	Kilowatt (10^{3} watt)
kWp	Kilowatt peak rated PV power
Mt	Megatonne (10^{9} kg)
MW	Megawatt (10^{6} watt)
PEM	Polymer Electric Membrane
PHEV	Plugin Hybrid Electric Vehicle
PV	Photovoltaics
SOFC	Solid Oxide Fuel Cell
t	Tonne (10^{3} kg)
UK	United Kingdom
US	United States
USD	United States Dollar
W	Watt

1 INTRODUCTION

Within the REFLEX project, several partners are performing modelling activities of different areas in the energy sector, including heat and power supply and demand, residential and industrial energy demand, and the transport sector. Since these modelling activities require accurate cost estimations of different technologies in these sectors, Work Package 3 (WP3) of the REFLEX project focused on gathering empirical data to make these future cost estimations using so-called experience curves. Aside from the application within the REFLEX project, the results of this exercise are themselves valuable for researchers, policymakers and other stakeholders.

Experience curves are based on the concept in economics that the production costs (or other parameters relating to the economic performance) of a technology improve significantly as producers gain experience with production of this technology. Within the REFLEX project, we apply the single-factor experience curve (SFEC):

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

Where C(cum) is the cost of a technology as a function of the cumulative production cum, C_1 is the cost of production for $cum = 1$, and b is the experience parameter. For each technology investigated in REFLEX WP3, we gather empirical data for C and cum, and use these data to estimate parameters C_1 and b by means of curve-fitting.

In this report, the findings of REFLEX WP3 are presented. In the following chapter, data gathering, processing, and parameter estimation methods are presented. Chapter 3 presents the main results of WP3, and thus gives an overview of the experience curves devised. In Chapter 4, these results are briefly compared and interpreted. Chapter 5 gives an overview of the model implementation of the experience curves for the models considered within REFLEX. The final chapter presents recommendations for further research and implications for policy makers and other stakeholders.

2 METHODS AND APPROACH

2.1 SELECTION OF TECHNOLOGIES

Table 1 below shows the technologies selected at the start of the REFLEX project, the technologies for which model implementation was performed and a list of technologies presented in this report. The original list of selected technologies was established by means of a survey of key technologies in the different models used by the REFLEX consortium. Since the focus of the REFLEX project is an analysis of integration of increased levels of flexibility in electricity grids, including amongst others the high penetration of renewables, electricity storage, demand side management, these technologies are well represented in the original selection. Furthermore, upcoming technologies that allow for decarbonisation of other sectors like heat supply, industry, and transport were originally selected.

A second survey conducted when data collection was nearly finished, and model implementation was scheduled to start was performed to assess which technologies were to be implemented in the different models. Since the scenarios analysed in REFLEX determine the penetration levels of e.g. renewable electricity generation technologies beforehand, future costs do not affect the investment decisions in these technologies and thus experience curves for these technologies will not be implemented, but only used ex post to analyse the cost developments of these technologies. Since we consider these to be key technologies for future energy systems, we still present them in this report.

Several other technologies are not reported here for different reasons. For some technologies, empirical data that can be used as input for devising experience curves is simply lacking. Examples are biofuels, compressed air energy storage, and overhead wiring trucks. Considerable effort by the partners of REFLEX has been made to collect data on other technologies (e.g. Solar Thermal, Air Conditioning, Industrial Heat pumps) resulting in large datasets that unfortunately at this moment do not show price trends that agree with sensible or usable experience curves. These datasets and technologies, together with the technologies that are already part of this report, will be analysed further to include them in the book that is planned as a final publication of the work on experience curves in the REFLEX project.

Table 1: Overview of considered technologies

	Original Selected Technologies	Model implemented	In this report
Electricity Generation	CCS (Membrane, Oxyfuel, Pre, Post)	Gas + CCS	Gas + CCS
	CCGT (Gas)	NGCC + CCS	NGCC + CCS
	EFCC (Gas)	Hard Coal + CCS	Hard Coal + CCS
	Biomass: digestion	Lignite + CCS	Lignite + CCS
	Biomass: gassification		
	Biomass: combustion		
	Concentrated Solar Power (CSP)		
	Geothermal: (dry, flash, binary)		
	Photovoltaics: modules (mono/poly, CdTe)		PV modules, BOS, systems
	Photovoltaics: system level costs		
	Wind: onshore and offshore		Wind: onshore and offshore
	CHP		
	micro-CHP	Fuel cell micro-CHP	Fuel cell micro-CHP
Electricity Storage	Battery: Lithium-(Ion/Polymer, Air)	Li-ion (utility, residential)	Li-ion (utility, residential)
	Battery: Redox-Flow	Redox-Flow	Redox-Flow
	CAES		
Heating/cooling	Electric boiler (P2H)		
	Heat Pump (air/air)		
	Heat Pump (air/water/ground)	Heat pump air/water	Heat pump air/water
	Solar Thermal (process heat or large scale)		
	Air conditioning		
	Thermal Energy Storage		
Industry	Industrial heat pumps (large scale)	Industrial Heat pumps	Industrial Heat pumps*
	Industrial heat/steam	Industrial CCS	Industrial CCS
	Industrial CCS		
Mobility	Battery electric vehicles	EV Lithium-ion battery	EV Lithium-ion battery
	Fuel Cell vehicles	EV Fuel Cell stack	EV Fuel Cell stack
	Hybrid electric car	HEV NiMH battery	HEV NiMH battery
	Plug-in hybrid electric car		
	Flexifuel car		
	Overhead wiring trucks		
	Biofuels (jet, vehicle, marine)		
Power to X	Power to Hydrogen	Power to H2 (alkaline electr.)	Power to H2 (alkaline electr.)
	Power to Methane		
	Power to Methanol		
Electricity end-use (DSM)	Lighting: LED		
	Elevators/escalators		
	Data centers		
	Building Energy Management/Automation		

**scaled from small scale heat pump data*

2.2 DATA GATHERING AND PROCESSING

In order to be able to devise experience curve, at minimum two datasets for each technology need to be gathered:

- The development of technology production costs over time
- The development of cumulative production of the technology over time

The specific application of a technology determines what kind of data was gathered. E.g. for energy supply technologies, production cost data per unit of electrical capacity is needed, and cumulative production in terms of total capacity. Since the production costs of technologies are commonly not publicly available, for most technologies it was expected to use technology (market) price instead.

2.2.1 FUNCTIONAL UNITS

Table 1 shows the technologies that were initially selected, that were finally implemented in the different models, and that are presented in this report. For each technology, cost data was gathered for the unit that best describes the technology's function, e.g. the *functional unit*. The technology characteristics determine the functional unit. The most important considerations when determining the unit for which the data is collected are:

- the role of the technology in the model
- the means by which the model makes investment decisions on whether to increase the share of the technology
- the optimisation target of the model
- data availability

As an example, the decision on whether to implement for instance Solar PV systems in the energy system of a certain model will likely be determined by the cost of the PV system per unit of rated capacity in EUR/kW (combined with non-experience curve related information like the expected yield of PV in a certain location). For other technologies or products, for instance Power-to-X, some models might consider the cost per unit of output product (EUR/kg), or the cost per unit of Power-to-X power (EUR/kW).

The availability of data can also determine which functional unit is used. The aim was to gather data on production costs, but in most cases, accurate data for production costs are not available. Hence, the next best option is to gather data on the price of the desired unit. In this case, it is important to take into account that prices not always reflect technological learning, as they are affected also by supply and demand of the product and its' components, and other constraints. Nevertheless, using price as a proxy for cost is usual practice in experience curve analysis. For some cases, using price data will result in unclear or even upward trends of technology cost. These cases will be highlighted in Chapter 3.

A final important consideration regarding the functional unit is whether to use curves for complete systems, or curves per component of a system. This relates to data availability, but also to cost developments for the separate components. In the simplified case that total system costs are the sum of two components that currently represent an equal cost share, but have very different learning rates, the system costs in total do not follow a single experience curve, e.g. plotted on double-logarithmic chart the line is no longer straight. For the work within

REFLEX, no multi-component technologies were found that were implemented in the different models.

2.2.2 *Time Resolution*

To establish experience curves, it is most common to gather annual cost/price data and annual (cumulative) sales or production data. There is no specific requirement of the data we gather for the WP3 technologies in terms of temporal resolution. In some cases, the energy models from REFLEX might operate at different temporal resolutions. For time-resolutions higher than 1 year, it was proposed to take only one cost-estimate from the devised curve for each year.

2.2.3 *Geographical Area*

Some of the gathered datasets will likely present production costs or installed capacity costs for specific geographical areas. In this context, two considerations are important to take into account:

- The focus of the models of REFLEX is the European region
- We assume technological learning to be a global phenomenon

This means that cost data is available for e.g. installed wind turbines in Europe, the decline in cost will likely still be a function of the global cumulative capacity development. Or rather, if it is assumed costs of a product to go down as a function of cumulative production, production cost of e.g. a European wind turbine manufacturer go down as a function of this manufacturer's sales in Europe and globally. Hence, the aim is to approximate global experience curves, we would need cost datasets from different parts of the world, but even if the focus of cost decline is on Europe, we still need global cumulative production data assuming the European turbines are sold globally. In the end, price data for EU countries is preferred, but if data is scarce, data from other regions/countries (e.g. the US) is obviously also of use but will need to be converted to Euro's (see below).

2.2.4 *Data harmonisation*

It is likely that for each of the technologies in the list we will encounter different datasets, which do not necessarily present the same cost/price developments over time, thus for a certain year we can have multiple different costs/prices. If we consider these reported data to be estimates, measurements or approximations of reality, we can still use all the data points for fitting the experience curves, as long as we are sure that the different datasets report costs or prices for the same specific implementation of the considered technology. For instance, the price of wind turbines is affected not only by installation location (country, onshore or offshore) but also by the scale (rated capacity) of the turbines.

Other issues with using different datasets is that the data can be of different age, currency, etc. To be able to combine these different datasets we need to convert them to a single currency, valid for a certain year, which was agreed for REFLEX to be EUR 2014. This harmonisation is suggested to be done as follows:

- Correct for inflation using a GDP deflator for the local currency
- Convert the currency to EUR using exchange rate of the given currency year
- If needed: correct for PPP using 2014 as a base year

Data sources for these economic statistics include the IMF, OECD and World Bank (data.imf.org; stats.oecd.org, data.worldbank.org).

For some technologies, it might be necessary to correct local prices for purchasing power, for instance for consumer products like PV modules, BEVs and home appliances. For more large scale technologies purchasing power likely does not affect the data significantly.

To be able to account for differences between multiple datasets per technology, it is important to have a list of meta-data alongside the datasets themselves. These meta-data include

- a reference to the source of the data,
- a description of the technology implementation,
- the scope (temporal and geographical) for which the data is valid,
- the currency and currency year of the presented data, and the
- economic indicators used to convert the data to the desired currency (EUR 2014).

2.2.5 DATA GATHERING ISSUES AND WORKAROUNDS

During data gathering, there are several possible issues to be expected. Table 2 shows a list of possible issues and methods to resolve these issues. In each of the technology chapters (see chapter 3) an overview of issues regarding data gathering and methodological issues encountered are presented.

Table 2: Overview of possible data gathering issues

Issue	Resolution
Data is not for cost but for price	Use price data as indicator for costs
Data not available for desired cost unit	Convert data to desired unit if possible Use available data as a proxy
Data is valid for limited geographical scope	Convert currency and adjust for PPP Combine with other datasets from various geographical scopes
Cumulative production figures not available	Calculate from annual production figures Calculate from annual sales figures
Data is in incorrect currency or currency year	Convert currency and correct for inflation and PPP
Early cumulative production figures are not clear or available	Restrict the dataset to time horizon for which reasonable cumulative production figures are available
Supply/demand affecting costs significantly	If due to material prices, correct for using multi-factor experience curves (if required data is available) Otherwise, decide whether to discard this data, or keep data as is
Lack of empirical (commercial scale) data	Use proxy technologies, use expert estimates

2.3 EXPERIENCE CURVES

With the data gathered according to the methods described in section 2.2, experience curves will be devised. 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 way to describe the reduction of total product cost as a function of cumulative production of this product:

$$C(cum) = C_1 \cdot cum^b \#(1)$$

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:

$$\log C(cum) = \log C_1 + b \cdot \log cum \#(2)$$

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):

$$PR = 2^b \#(3)$$

$$LR = 1 - 2^b \#(4)$$

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.

Since the total costs of a product are developing as a function of different learning mechanism (e.g. R&D, learning-by-doing, upscaling), but are also influenced strongly by input material prices, the experience curve has been extended to include multiple independent variables, in two- or multi-factor experience curves. In some cases, an extension of the single-factor experience curve is better able to describe the cost developments of a technology (Yu et al., 2011; Kittner et al., 2017) by taking into account material prices and e.g. R&D expenditures, but thus requires more data inputs. In a similar manner (as discussed in section 2.2.1), complete technology costs might be the sum of multiple components with different learning rates. In this latter case, the input data requirements will be larger as well. In the REFLEX project, the experience curves will be implemented in energy models which are not always able to produce all needed input variables for multi-factor experience curves. Hence, for this report we do not take into account two- or multi-factor experience curves. Further analysis will be performed for publication of a book based on the work in REFLEX WP3 where these issues *will* be addressed.

2.4 Determining experience curves

From the data collected, experience curves were determined by fitting the data to the experience curve model described in section 2.3. Fitting was performed by least-squares optimisation of the gathered data to the nonlinear model described in equation (1) in section 2.3. The fitting was performed within *Python*, using the add-on package *scipy*. With this software package, the standard error of the parameter estimate was calculated by taking the square-root of the diagonal of the variance-covariance matrix.

As discussed by Van Sark et al. in (Junginger et al., 2010), many statistical tools transform the input data by taking the logarithm before performing the fit of a power curve model. Hence, the result is that a linear regression is performed of the transformed data. This transformation is often performed in experience curve studies but is not commonly well supported. In general, reasons to perform this transformation would be to e.g. prevent a skewness of the regression residuals. For this report we use a direct fitting of the non-linear model to the non-transformed data, to prevent any transformation bias.

While it is common to present the R^2 value when performing model fits, we follow the recommendation of Van Sark et al. in (Junginger et al., 2010) to rather use the error in the progress ratio as an indicator of accuracy. Since we report the learning rate rather that the progress ratio, we present the error of the learning rate. As mentioned above, we use the fitting software to establish the covariance of the experience curve parameter and calculate the parameter errors as the square root of the diagonal of the covariance matrix.

2.5 MODEL IMPLEMENTATION

2.5.1 *BASICS*

The implementation of the experience curves in the various energy models would ideally consist of programming the equation shown above into the energy models and allow for endogenous modelling of technological learning, where the parameters will be supplied by Utrecht University for each technology. For endogenous modelling, the models should provide the development of cumulative production. As an example, to model the cost developments of photovoltaic (PV) installations, in principle the models will need to supply the development of cumulative installed PV capacity to the experience curve function, and it will return the development of PV system costs, through which the levelised cost of electricity (LCoE) can be derived.

In practical cases however, this endogenous approach might not be possible for various reasons (among others): the mathematics and optimisation approach of the respective model might not allow for implementation and optimisation of a power curve; the model is restricted in its geographical scope; or the model does not produce the cumulative production data in the required units. Below, possible solutions to these issues are shown.

2.5.2 *CHALLENGES FOR MODEL IMPLEMENTATION*

Including learning rates in energy system models faces a number of challenges. These are different depending on the type of model. For optimisation models, an issue is that the models tend to choose technologies with high learning rates, as these models by definition have "perfect foresight", while this is not happening in the real world. Further, optimisation models have problems including non-linear functions as the learning function (see section 5.2 for an example). In simulation models technologies might never start their learning process, although in the long-term they might be very promising. Including policy instruments like investment grants in the model can address this issue.

Other challenges are relevant for both types of models. This includes the lack of empirical data. For many technologies hardly any data on learning rates is available, while for others data quality is not sufficient. Obviously this can be addressed with more empirical research. Empirical research should also provide generic rules that can be used by modelers to make consistent learning assumptions on learning rates. Geographical scale of energy models raises the issues of how to integrate global technological learning in regional/local models. In this sense, also sectoral models have problems including cross-sectoral learning.

The experience curve function could in theory supply a cost figure at any time resolution, however, we recommend limiting the cost estimations to an annual time resolution, unless there is strong information that the cost decreases for the respective technology occur at a higher time resolution.

Not all models will likely model the cumulative production of all technologies (or any technologies) endogenously in the required. For instance, some models might calculate the developments in *electricity production* from a certain technology. In this case, there are at least two options to estimate the development of costs for a technology as well as approaches that use elements of both options:

- For endogenous modelling: Using these developments as a proxy for development of cumulative production in the desired unit, to calculate cumulative production (approach to be determined per technology)
- Exogenous modelling: Estimating the costs of a technology based on cumulative production development data from an external source (for instance another energy model that gives development of cumulative production for congruent scenarios as modelled in REFLEX). This would be the least optimal option, as it means that the developments of the technologies in the model are not accounted for in the cost estimation.

2.5.3 Summary

The considerations above are visualised in the figure below. Although this figure is not complete, it shows a few different approaches of implementation of experience curves in energy models. With a green arrow, the direct, endogenous implementation is indicated. Here, the energy model produces the required datum (cumulative production) to calculate the technology cost, which is then applied in the energy model. With red arrows, the case is shown where technology demand or penetration is modelled, requiring some form of conversion to cumulative production. If this can be a direct proxy, the modelling is still considered to be endogenous. It is possible however that the modelled technology demand must be coupled to exogenous cumulative production data. With the blue arrow, a completely exogenous case is shown; the energy model only supplies the year for which the technology cost should be calculated, and external data describing cumulative production over time is used to determine the correct input for the experience curve function.

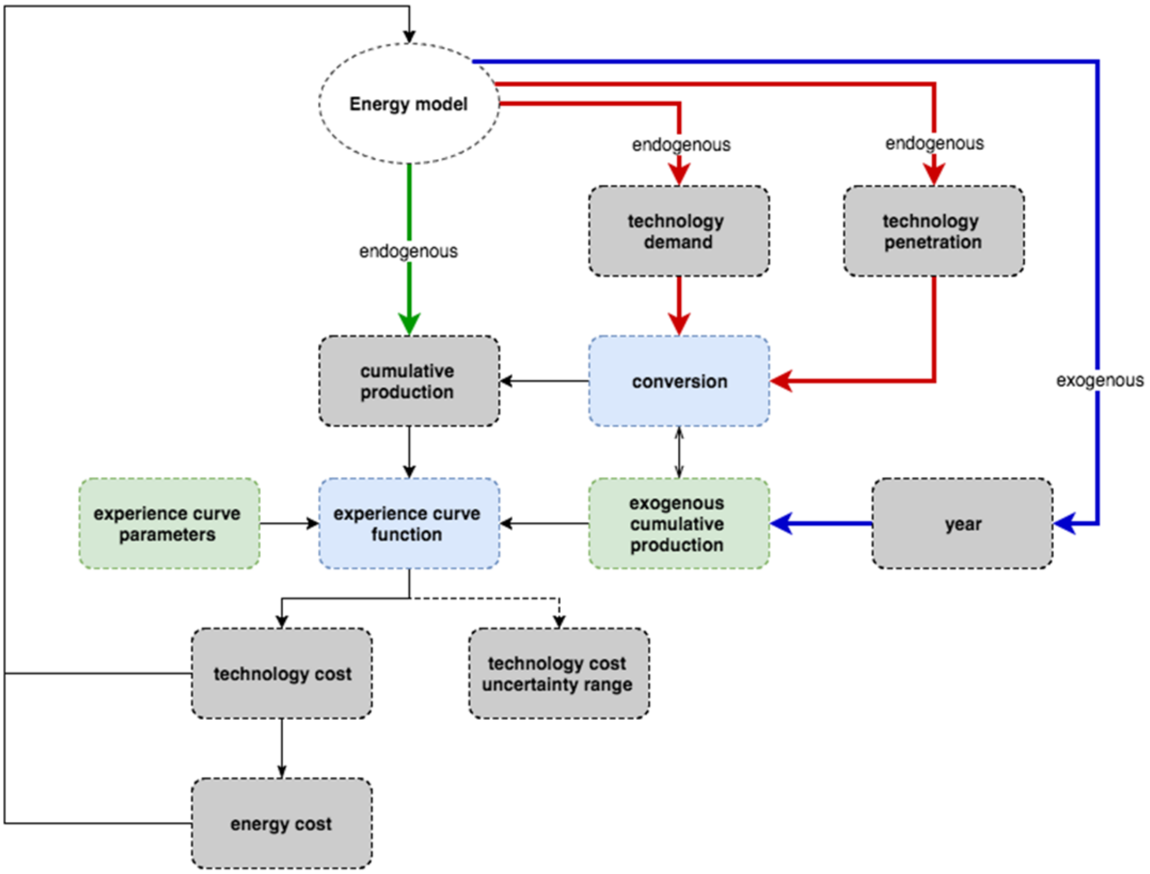

Figure 1: Schematic overview of possible model implementation routes for experience curves. Grey boxes indicate model-produced data points, green boxes represent external data sources, blue boxes represent functions.

3 RESULTS – DATA COLLECTION AND DERIVED EXPERIENCE CURVES

3.1 SOLAR PHOTOVOLTAICS

3.1.1 DESCRIPTION OF TECHNOLOGY

Solar Photovoltaic (PV) systems convert solar energy in the form of light directly into electricity (Twidell & Weir, 2015). Photovoltaic cells are the main component in PV systems. These cells are made of semiconductor material and function as small electricity generation devices by producing electricity from absorbing electromagnetic radiation, such as sunlight. Figure 2a shows a schematic overview of a solar cell (see for more information Twidell & Weir, 2015). Common photovoltaic materials used for solar cells are mono- and polycrystalline silicon and thin films, such as cadmium telluride, gallium arsenide, and indium gallium phosphide, while major upcoming technologies are based on perovskites or organic materials. Photovoltaic cells are combined to form modules (Khan & Arsalan, 2016).

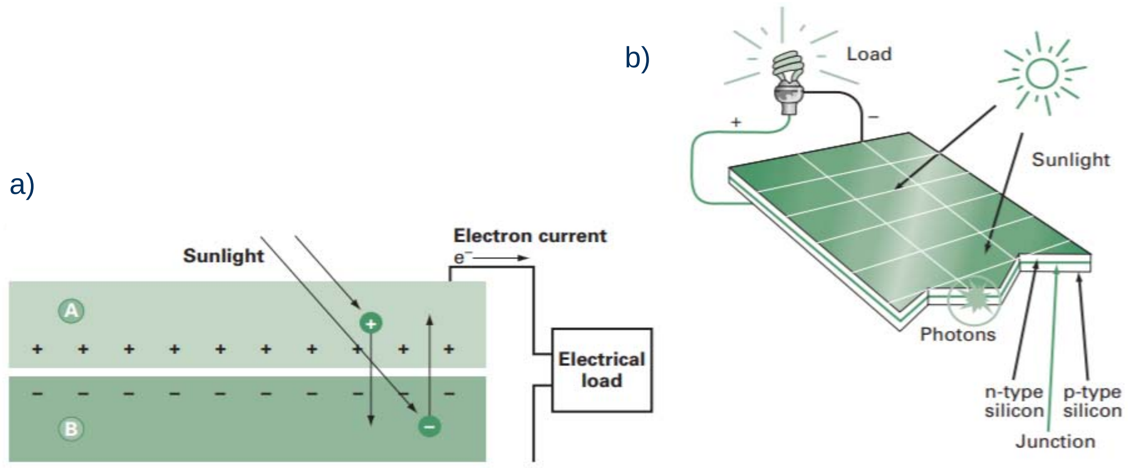

Figure 2: Schematic overview of photovoltaic cell (a) and photovoltaic array (b). Source: Twidell & Weir (2015).

PV modules are connected into a PV array (Figure 2b), which can differ in size dependent on the desired power output (Khan & Arsalan, 2016). Other elements in the PV system are mechanical and electrical connections, an inverter for converting direct current (DC) to alternating current (AC), and a regulator for the electrical power output (Parida et al., 2011). These other elements are generally denoted by the word Balance-of-System (BOS) and have an effect on the overall PV system efficiency. In addition to direct solar irradiation, PV systems are able to utilise the diffused components of irradiation, which makes the panels suitable for areas characterised by both high and low direct irradiance (Khan & Arsalan, 2016).

The efficiency of PV modules is dependent on various aspects. Best full-module lab efficiencies for PV modules range from 11% for amorphous silicon modules to 24.4% for monocrystalline silicon PV modules under standard test conditions. Cadmium telluride, copper indium gallium selenide and multicrystalline silicon modules have very comparable efficiencies at 18.6%, 19.2% and 19.9%, respectively (Fraunhofer ISE, 2018). System efficiency is affected by weather conditions, such as irradiation level or temperature (Singh, 2013). Another factor influencing efficiency is the presence of a tracking system that enables the panel to follow the path of the sun during the day and thus decreases efficiency losses related to the angular response of PV modules. Tracking systems consume electricity, but because they enable the panel capturing more sunlight during the day, PV systems that include one are more efficient. A disadvantage of using tracking systems is that the solar panel takes up more space (Khan & Arsalan, 2016), and that installation and BOS costs, as well as O&M costs are much higher compared to static PV systems. PV systems are rated in peak kilowatts (kWp), which denotes the capacity of power under standard conditions (STC)[1]. Concentration PV systems combine the two-axis tracking system with optical components that concentrate the normal-incident irradiation onto a solar cell (Hinzer et al, 2017), increasing the efficiency of power conversion, but resulting in high temperatures being generated. Currently, the deployment of concentration PV is very limited compared to conventional PV systems.

3.1.2 Market developments

Although commercial PV modules are on the market since at least the 1970's, cost have been prohibitively high for the majority of time between then and now. However, since the 2000s, PV systems are used for centralised and decentralised, grid-connected power generation (Twidell & Weir, 2015). Especially the last ten years, the solar PV market has grown tremendously, which can be seen in Figure 3.

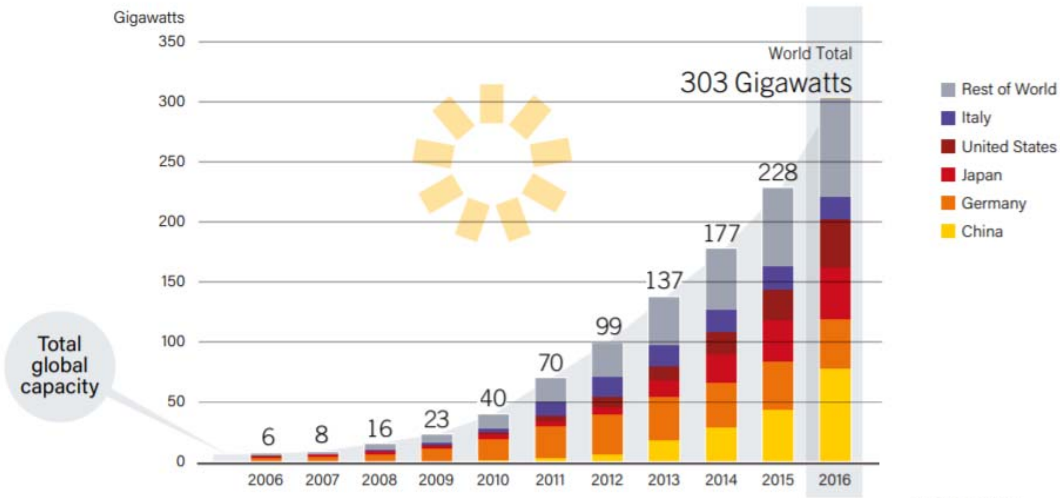

Figure 3: Global installed solar PV capacity, by country and region, 2006-2016. Source: REN21 (2017).

In 2016, a little over 300 GW of PV was installed globally, compared to only 6 GW in 2006. During these ten years PV capacity experienced an average annual growth of 50% (REN21, 2017). At the end of 2017, global capacity is estimated to have increased to over 400 GW (SolarPower Europe, 2017; IEA PVPS, 2017). Total cumulative capacity is largest in China. With a total of 77.4 GW the country leaves any other country behind. In 2016, Japan and the United States passed Germany for the first time with total installed capacity (REN21, 2017).

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[1] Solar irradiance of 1000 W/m^{-2} perpendicular to the cell, a temperature of 25°C, and an air mass (which is a measure for the pathlength of light through the atmosphere) of 1.5 (Twidell & Weir, 2015)

Current growth of installed PV systems is dominated by Asia, and especially by China which is estimated to account for almost 50% of new PV installations in 2016. The EU saw a decline of 24% in solar PV growth in 2016 compared to 2015, mainly due to a market decline in the United Kingdom. Still, the United Kingdom added most capacity in absolute terms. Together with Germany and France, it accounted for 70% of EU newly installed capacity. Other countries that added capacity were Belgium, Italy and the Netherlands. Even though France did not see much growth in 2016, it remains the fourth country in the EU in terms of total capacity (REN21, 2017).

China is the main actor at the production side as well, followed by Japan. The two countries together accounted for approximately 70% of global PV module production in both 2015 and 2016 (IRENA, 2018b). Before 2007, the majority of production took place in Japan and Europe, and ten years earlier the USA was the main producer of PV modules (Fraunhofer ISE, 2018; Louwen, 2016). The main PV technology on the market is silicon PV, representing roughly 95% of installed PV capacity, while thin-film PV technologies, especially cadmium telluride (CdTe) account for the remaining market share (Fraunhofer ISE, 2018). Traditionally, most PV systems installed were either grid-connected, decentralised PV systems, but in the last years the majority of installed capacity concerns centralised, grid-connected systems (IEA PVPS, 2017). The most common PV cell technology, multicrystalline silicon, represents ~70% of global production in 2016, while monocrystalline silicon has a ~25% market share (Fraunhofer ISE, 2018).

The rapid expansion of PV modules results from lower costs, increasing demand for electricity and increasing interest in sustainable electricity sources. Prices for PV modules have decrease significantly, on average by 83% between March 2010 and March 2017. Prices for PV modules in 2016 were lowest in China and India with 0.43 USD/W and 0.44 USD/W respectively. The highest prices were seen in California, 0.61 USD/W, and Japan, 0.59 USD/W. In 2017, modules were sold for as low as 0.3 USD/W, and 0.4 USD/W for higher quality and sustainable produced modules (IRENA, 2018b).

In the World Energy Outlook 2017 of the International Energy Agency (IEA) the exponential growth of solar PV is expected to continue when currently existing and announced policy plans are included. A global installed capacity of 939 GW is forecasted in 2025 and over 2000 GW in 2040. In a scenario where global temperature increase remains below two degrees by 2100 in line with the 2015 Paris Agreement, solar PV capacity increases to 1846 GW in 2030 and 3245 GW in 2040 (OECD/IEA, 2017c). For the two degrees case, the International Renewable Energy Agency (IRENA) 7122 GW of solar PV by 2050 (IRENA, 2018a). With the current growth rate, solar PV is on track of meeting targets under a two degrees scenario (OECD/IEA, 2017a).

3.1.3 Experience curves

Figure 4 shows the results of our analyses, with experience curves for complete PV systems, PV modules, and balance of system (BOS) components for different markets. The figure illustrates that local market maturity and dynamics and dataset time horizon can substantially affect the established learning rates.

An aggregated dataset with a long time-horizon from Germany (Fraunhofer, 2016) combined with global average module selling prices (Van Sark, 2006; Fraunhofer, 2016) results in a learning rate of 21% for modules and 19% for systems, while the learning rate for BOS components (price inferred as difference between modules and systems) was found to be considerably lower at just 13%. As can be seen in Figure 4a, module prices declined in price quite rapidly between 2012 and 2015 to below the experience curve, but have since somewhat stabilised. The module price data in this top graph also indicates some noticeable deviations from the experience curve, the first leading up to 1985, the second from 2005-2008. The latter was due to a shortage in silicon production leading to a sharp increase in silicon feedstock prices.

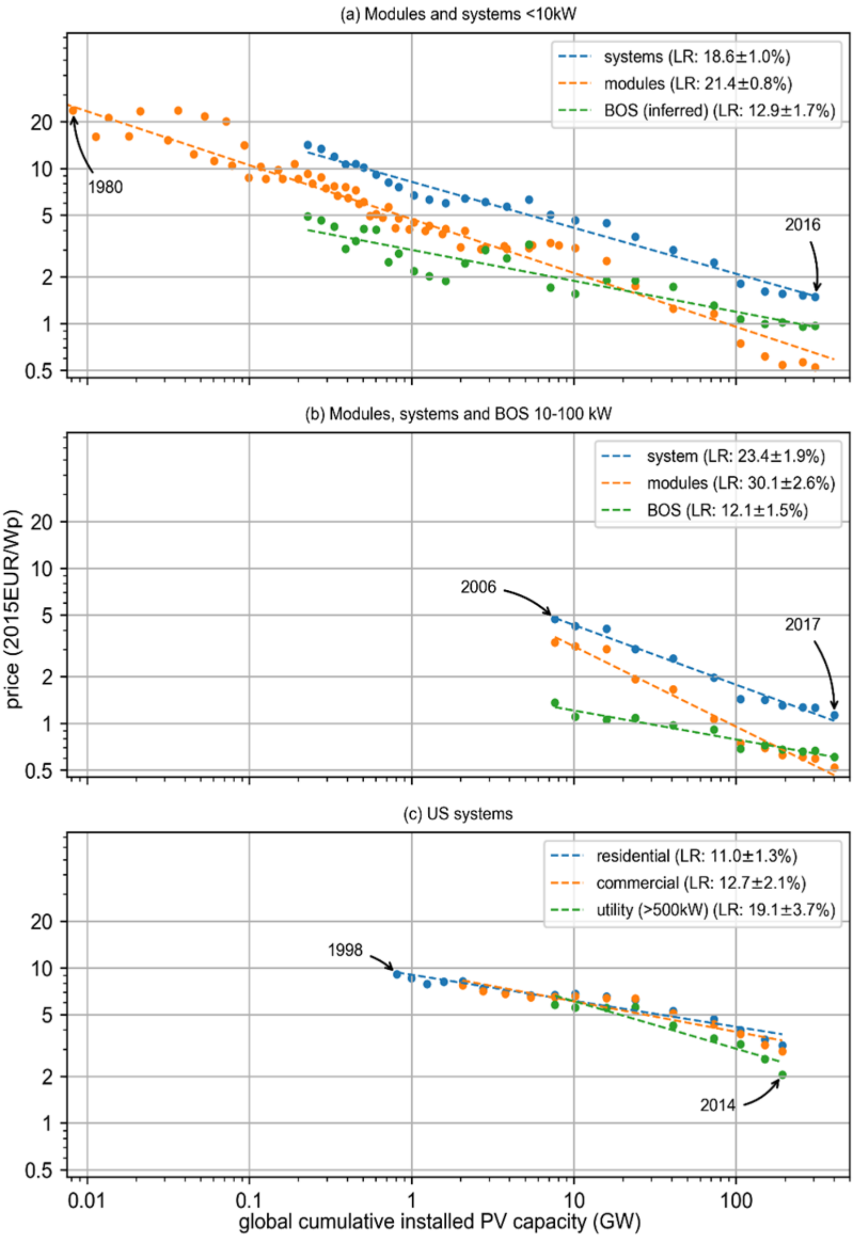

Figure 4: Experience curves for PV modules, systems and BOS components in different markets. Data sources: Fraunhofer ISE (2016), Fraunhofer ISE (2018), Feldman et al. (2016), Van Sark (2006), IEA PVPS (2017).

A dataset with a shorter time horizon shown in Figure 4b, for PV systems between 10 and 100 kW, indicates fast price declines for PV systems (LR of 23%), mainly due to a very high learning rate of 30% for PV modules. This fast decline is likely related to market dynamics rather than only being a result of technological progress in manufacturing, which is supported by the fast, downward trend for modules discussed earlier and shown in Figure 4a.

Data from the US (Feldman et al., 2015) for residential, commercial and utility-scale systems seem to indicate that the residential and commercial markets in the US are not as mature as most European markets, with relatively high prices and low learning rates (11-13%) for residential and commercial systems. Utility scale systems show stronger price declines in the past 5 years and a higher learning rate of 19%, which is reasonably comparable with the data from Germany. Furthermore, for all three of the system scales investigated, price declines seem to be accelerating near the end of the dataset.

3.1.4 DATA COLLECTION AND METHODOLOGICAL ISSUES

An overview of the general data collection issues applicable to photovoltaics is given in Table 3 (next page). As is apparent from the datasets shown in Figure 4, two of the generalised issues for data collection describe in Chapter 2 affect the obtained results. First of all, by comparing datasets from different locations (e.g. Europe in Figure 4a and Figure 4b compared to the USA in Figure 4c), we see that although PV modules are traded as an international commodity, other components in total installed PV system costs show considerable variation depending on the country of installation. Especially for residential systems soft costs (including overhead, labour, and procurement) represent over 50% of total system costs in the US in 2017 (Fu et al., 2017). Secondly, the long-term dataset for PV modules in Figure 4a shows signs of market dynamics affecting the price trends, resulting in large temporary deviations from to long-term experience curve trend. A related issue, shown in Figure 4b, is that of short-term datasets exhibiting very different behaviour compared to long-term trends. Because of the short time horizon of the dataset in Figure 4b, the established learning rate for PV modules is much higher (30%) compared to what is found for long-term datasets (21%).

Aside from these issues, it also becomes clear that single-factor learning curves for PV systems as a whole will likely not be able to accurately estimate future costs of PV, since the data in Figure 4 shows that PV modules and BOS components have a substantially different learning rate (21% vs 13%), and the contribution of BOS components to overall system costs is now roughly equal to that of the PV modules. Hence, more accurate PV systems cost can be obtained by separately modelling BOS and PV module cost using their separate experience curves.

Table 3: General data collection issues for photovoltaics.

Issue	Resolution applied	Applicability
Data is not for cost but for price	Use price data as indicator for costs	☑
Data not available for desired cost unit		
Data is valid for limited geographical scope	Convert currency Combine with other datasets from various geographical scopes	☑
Cumulative production figures not available		
Data is in incorrect currency or currency year	Convert currency and correct for inflation and PPP	☑
Early cumulative production figures are not clear or available		
Supply/demand affecting costs significantly	Keep data as is	☑
Lack of empirical (commercial scale) data		

3.2 WIND ON- AND OFFSHORE

3.2.1 DESCRIPTION OF TECHNOLOGY

Wind turbines are based on the principle of converting kinetic energy of wind resource into mechanical work, such as water pumping, or via mechanical work into electricity via a generator (Da Rosa, 2005). Nowadays, wind turbines produced worldwide are almost solely of the electricity generating type. Nevertheless, mechanical work turbines used for water pumping are still of essential use in some areas (Twidell & Weir, 2015). Wind turbines come in various types. The most common type of wind turbine for electricity generation, both on- and offshore, are horizontal axis turbines with three blades (IRENA, 2018b).

Modern-day conventional (horizontal axis) wind turbines are built up of a steel or concrete tower, a yaw system between the tower and the nacelle (the housing of the rest of the wind turbine) that orientates the wind turbine towards the wind, a drivetrain (gearbox or direct drive generator), a convertor, and the rotor with the blades (Twidell & Weir, 2015). The inner structure of a wind turbine is shown in Figure 5.

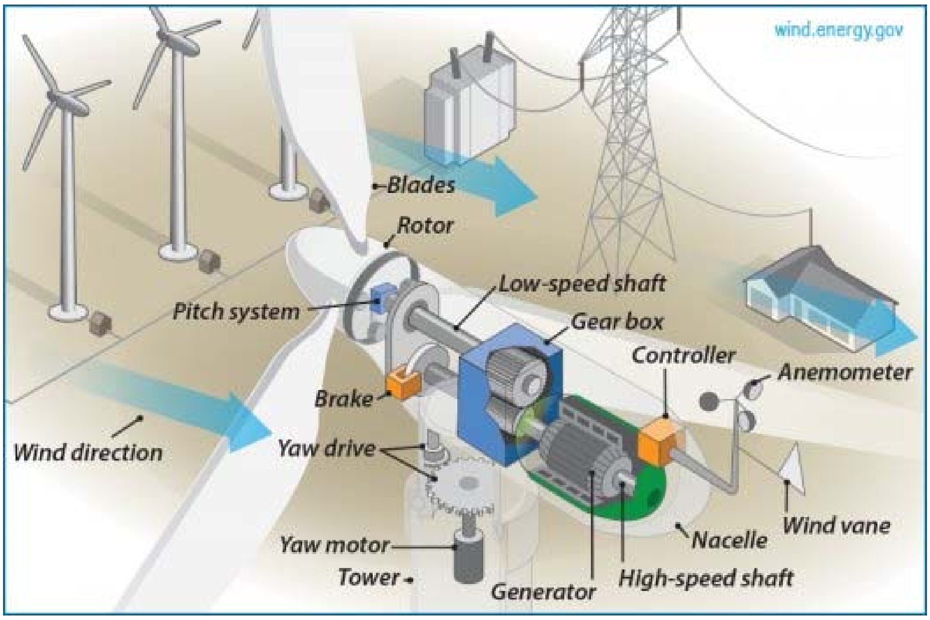

Figure 5: The inside of a wind turbine. Source: EERE (n.d.).

The power generated by a wind turbine is related to the quality of the wind, height of the tower (hub height), the rotor diameter and management of operation and maintenance. In general, wind turbines are able to generate electricity at windspeeds between 3-5 m/s and 25 m/s. The maximum of electricity generation is usually achieved from 11 m/s up to 25 m/s (IRENA, 2018b).

3.2.2 MARKET DEVELOPMENT

Simple devices exploiting the energy available in wind date back thousands of years ago. The first large wind device for electricity generation was a 12 kW turbine introduced in 1888 in Cleveland, United States. As with many other technologies, renewed interest in wind energy was stimulated by the 1973 oil crisis. While the first developments of wind energy were mainly in the United States (most notably California), market activity shifted to Europe from 1990 onwards (Kaldellis & Zafirakis, 2011). More recently, the United States regained a leading position, together with China (REN21, 2017).

The last ten years wind energy has grown from an installed capacity of 74 GW in 2006 to 487 GW in 2016, representing an average annual growth rate of 22%. The current market is dominated by Asia, and especially China (see Figure 6), being the largest regional market for eight years straight. China is largest in terms of both installed capacity and capacity growth. However, the growth in China in 2016 was much smaller due to problems with grid integration and diminishing demand for electricity, which is also mainly responsible for declining growth globally. The top 5 of installed capacity per inhabitant consist of EU countries only: Denmark, Sweden, Germany, Ireland, and Portugal. In the EU, about 10% of electricity demand in 2016 was met by wind energy (REN21, 2017).

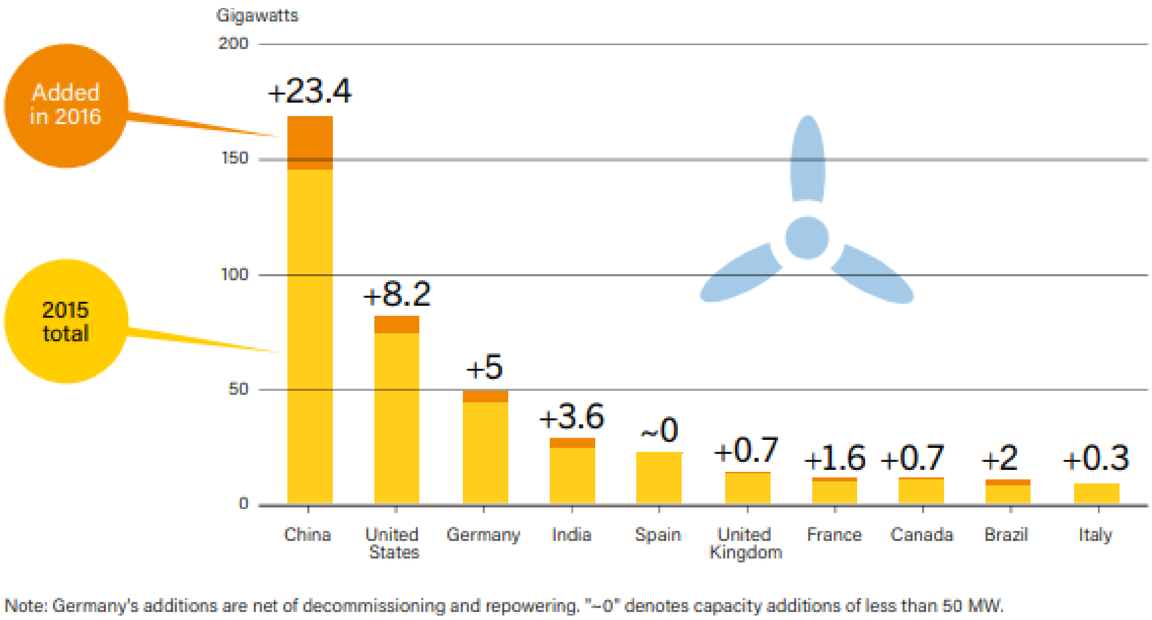

Figure 6: Wind power capacity (on- and offshore) and additions of the top 10 countries, 2016. Source: REN21 (2017).

On the supplier side of onshore wind turbines, activities are concentrated at a number of manufacturers in China, the EU, India and the United States. Key players are Vestas (Denmark), GE (United States), Goldwind (China), Siemens Gamesa (Germany/Spain), Enercon (Germany) and Suzlon (India).

Different trends are visible in the offshore industry. The offshore wind industry is dominated by Europe (see Figure 6). Newly added offshore wind capacity in Europe in 2016 (1.6 GW) accounted for 70% of total global additions. Capacity was added only in Germany, the Netherlands and the United Kingdom. Outside Europe, offshore wind capacity was added mainly in China (0.6 GW). In terms of total installed capacity by 2016, Germany takes the lead (4.15 GW), followed by China (1.9 GW), Denmark (1.3 GW), the Netherlands (1.1 GW) and Belgium (0.7 GW). The main offshore turbine producers are Siemens (Germany) and Sewind (China) (REN21, 2017).

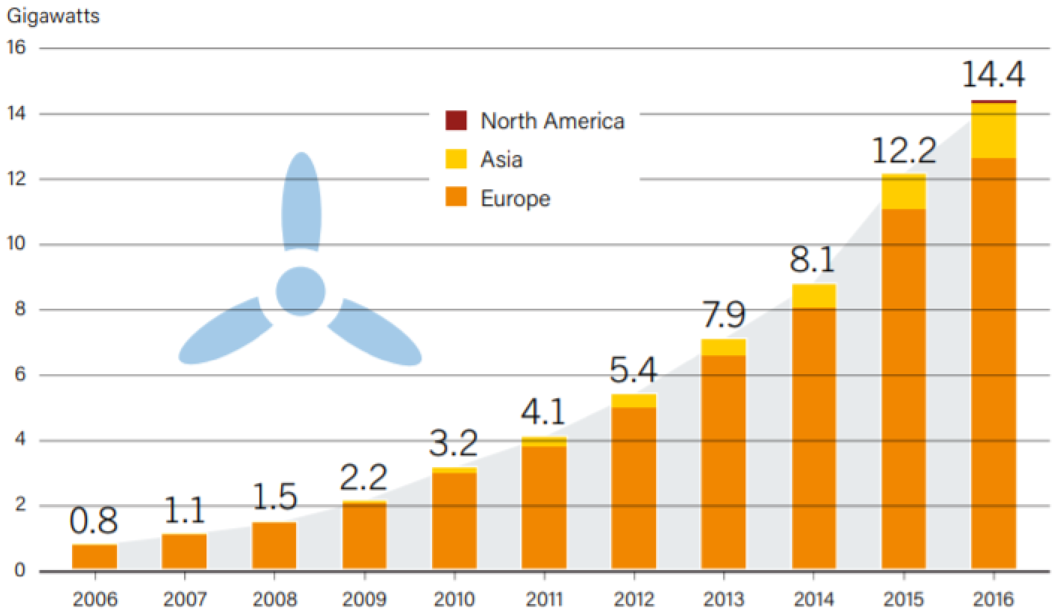

Figure 7: Global capacity offshore wind, by region, 2006-2016. Source: REN21 (2017).

The costs of turbines generally represent 64-84% of total system costs for onshore wind farms and 30-50% for offshore farms. Besides turbines, major cost components include construction and foundation works, grid connection, land and project costs. Prices of wind turbines were lowest in 2000-2002, and rose afterwards. The rise occurred because of increasing material and labour costs related to the financial crisis, higher demand than supply, and development of larger wind turbine technologies leading to higher construction costs. After prices peaking between 2007 and 2010, a downward trend started again. Between 2009 and 2017, turbines with rotor diameters smaller than 95 meter, prices decline by 53%, and turbines with greater rotor diameter by 41%. In 2017, average wind turbine prices were below 1000 USD/kW in most markets, reaching levels from 2002 (IRENA, 2018b).

In the IEA World Energy Outlook 2017, the global installed wind capacity is expected to increase to 1174 GW in 2030 and 1664 GW in 2040, when accounting for current and announced policy plans. In the scenario of keeping global temperature increase lower than two degrees, installed capacity increases to 1706 GW in 2030 and 2629 GW in 2040. Together with solar PV, wind accounts for the largest share of renewables (OECD/IEA, 2017c). IRENA estimates a total wind capacity of 5445 GW is expected by 2050, of which 4923 GW onshore and 521 GW offshore (IRENA, 2018). With the current growth rates, onshore wind is on track of meeting targets in the two degrees case. Growth will mainly be driven by China and the United States. Progress for offshore wind has improved in Europe, but the current growth rate is not sufficient for meeting the two degrees target (OECD/IEA, 2017a).

3.2.3 EXPERIENCE CURVE

A plot of the data and fitted experience curves for wind turbines and systems is shown Figure 8-10 below. The figure shows clearly that the wind market (at least for onshore systems) is not behaving according to the experience curve theory. As shown in Figure 9, prices for onshore systems in the US almost double between a price minimum in 2004 and (local) maximum in 2008. Since 2009-2010, a strong and consistent decline in both onshore installed wind systems and the turbine price index is observed (Wyser & Bolinger, 2017; BNEF, 2017).

For offshore wind farms, data was collected on all wind farms installed offshore in Europe, with park sizes over 300 MW. After weighting and averaging, considerable variety remained in the dataset, but still a downward trend appears to be present. Recently, tendered offshore wind farm prices hit record lows in the Netherlands, Germany and Denmark. Since these farms have not been built yet, this data is not yet included in the data shown below. For offshore wind farms (Figure 8), a learning rate of 10% was determined, with an error of 3.3%-point. The offshore market and installed capacity is much smaller compared to the onshore market and capacity, as can also be determined from Figure 10.

Fits of short term data (2010-2017) show in Figure 9 (right) for onshore systems and wind turbine price indices show very high learning rates of 25%-26%. These high learning rates are not deemed realistic to establish future wind system and turbine prices, especially for medium to long term forecasts. A fit of the data from the Wind Technologies Market Report (WTMR) from Wyser & Bolinger (2017) for the whole period results in a learning rate of 5.9%, which is advised to be used as a conservative estimate for long term projections.

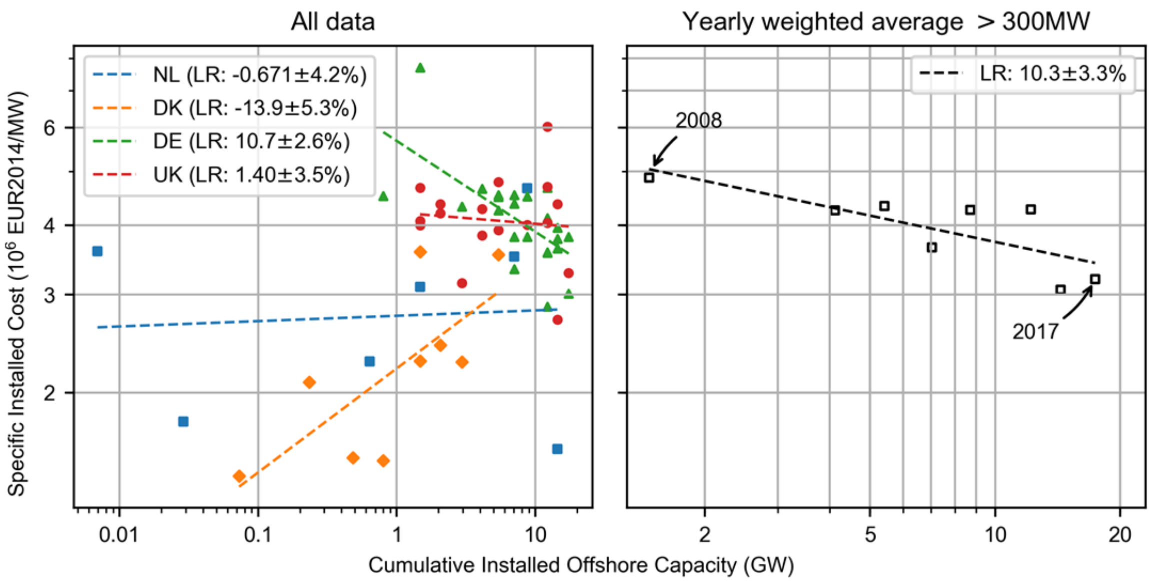

Figure 8: Data for all offshore wind farms (left) and processed yearly weighted average wind farm costs for wind farms over 300 MW of capacity (right). The average was weighted based on system capacity. Data source: own data collection.

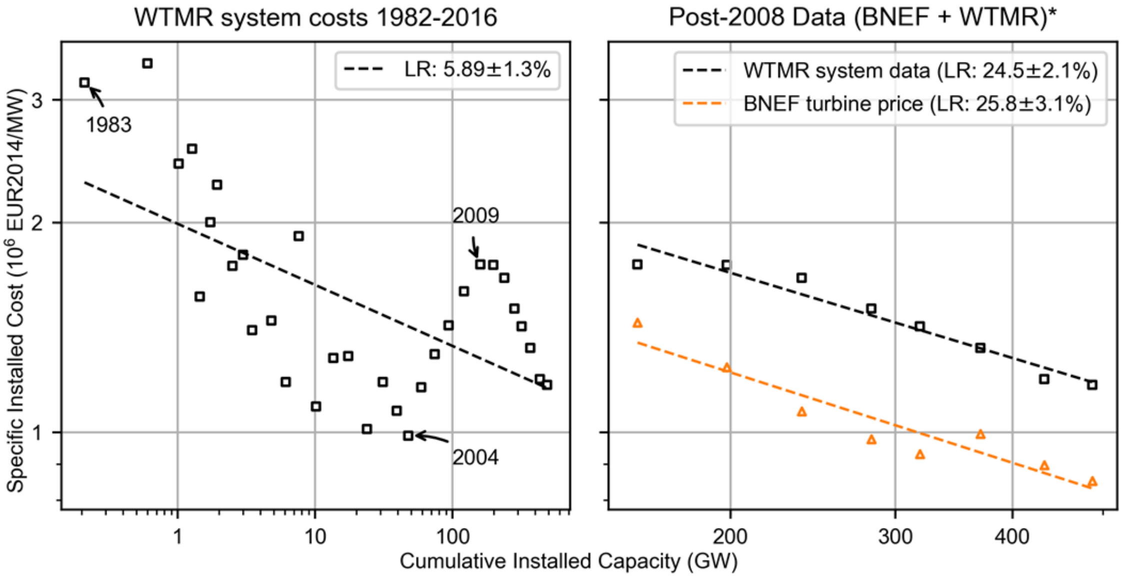

Figure 9: Overview of onshore system and turbine price data and experience curves. Left: whole dataset from WTMR (Wyser & Bolinger, 2017). Right: Post-2008 data from Wyser & Bolinger, 2017 and BNEF wind turbine price index (BNEF, 2017). *Note that the curves on the right are only shown as an example of short term datasets, and the learning rates shown are not recommended to be used in any modelling activity.

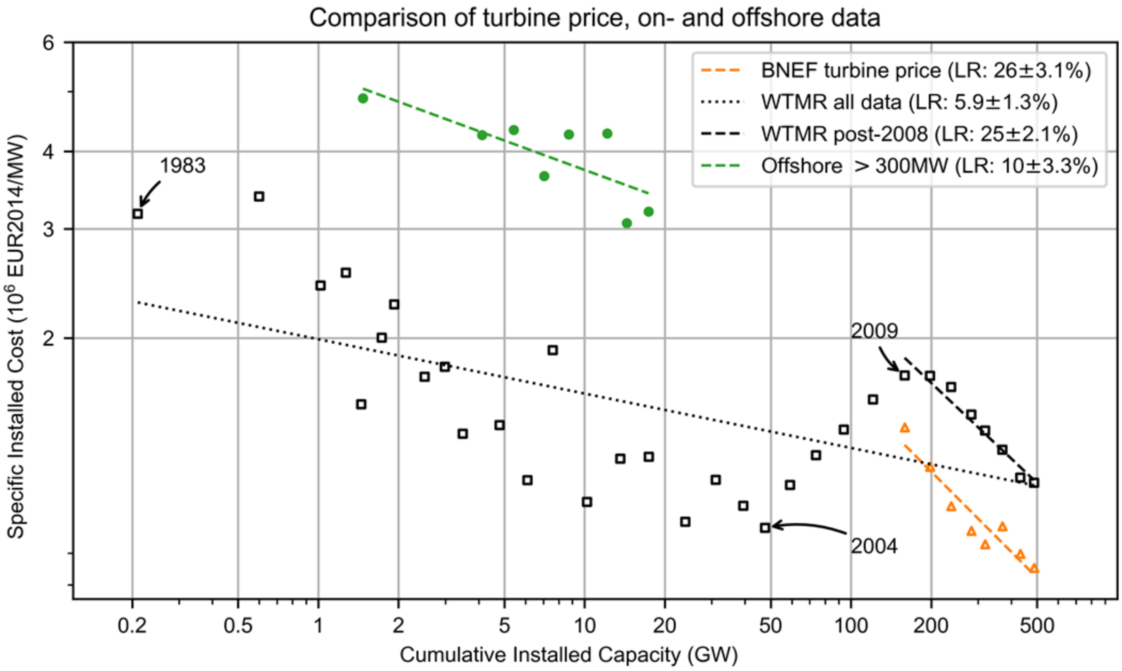

Figure 10: Comparison of experience curve data for wind energy: onshore systems, offshore systems and turbine price indices. Data sources: Own data collection (offshore), WTMR (Wyser & Bolinger, 2016; Wyser & Bolinger, 2017), BNEF turbine price (Wyser & Bolinger, 2017; BNEF, 2017).

3.2.4 *DATA COLLECTION AND METHODOLOGICAL ISSUES*

An overview of the general data collection issues applicable to wind energy is given in Table 4. As discussed above, for both on- and offshore wind, a clear price trend that can be used to determine experience curve parameters is lacking, even though a large dataset is available.

Market dynamics, changes in wind turbine pricing, and raw material prices have influenced the price developments of wind turbines (Wyser & Bolinger, 2017). By taking into account these factors in a multi-factor experience curve, a more accurate model to project future wind turbine, and on- and offshore wind farm prices could possibly be established. Since multi-factor curves require input data that is not produced by the models within REFLEX, this analysis was not yet performed. Further research should focus on this, and other aspects that characterise wind price developments.. Also, the prices for onshore wind and turbine price indices should continue to be tracked to establish whether prices will return to the trend that was present up to 2005, or that wind turbine and system prices are permanently altered. We aim to analyse these aspects for publication in the book from REFLEX WP3

For many recent offshore tenders, only the complete, estimated costs for the wind farms as a whole are often available. These costs lack a level of detail and are sometimes not complete. For instance, some costs reported for recent Dutch tendered wind farms do not include the grid connection to shore. Furthermore, most of these recent tenders at very low prices are for wind farms that will only be completed after several years, which leaves open the possibility of these projects' final budgets deviating significantly from the currently estimated budgets.

Another issue with the datasets of the figures above is the unit for which costs are specified, EUR/kW. Over time, the operation of wind farms has improved, in terms of O&M costs and capacity factors, thus, for a given wind farm capacity, the electricity generated has increased, and the operating costs have decreased relatively, resulting in lowered costs of electricity produced (LCOE). Furthermore, offshore wind farms are characterised by higher capital costs but have much higher capacity factors compared to most onshore wind farms. The increase of capacity factors is also the result of other improvements that might increase the costs in EUR/kW, like the application of higher towers.

As shown in previous research (Junginger et al, 2010), there can be large country-specific differences between wind system prices, due to e.g. differences between local government support schemes. While recent offshore wind farm data (see Figure 8) indicates that recent prices are becoming similar for four major European markets, further research should establish whether these price differences are still occurring for e.g. onshore wind farms.

Table 4: General data collection issues for on- and offshore wind power.

Issue	Resolution	Applicability
Data is not for cost	Price data is used	☑
Data not available for desired cost unit	Converted data to specific capacity costs	☑
Data is valid for limited geographical scope	Different datasets combined and compared	☑
Cumulative production figures not available		
Data is in incorrect currency or currency year	Convert currency and correct for inflation	☑
Early cumulative production figures are not clear or available		

Supply/demand affecting costs significantly	Use long term trends or suggest using expert estimates	☑
Lack of empirical (commercial scale) data		

3.3 Fuel cell Micro-CHP

3.3.1 Description of technology

Fuel cell micro combined heat and power production (fuel cell micro CHP) units, also called residential fuel cell units, concern a technology that gains interest for electricity and heat production at residential- or small-scale commercial buildings. The fuel cell micro CHP is visualised in Figure 11. Within the fuel cell system, a reformer converts natural gas to syngas, a mixture of hydrogen (H_2), carbon monoxide (CO) and carbon dioxide (CO_2). The produced hydrogen and outside air react in the fuel cell stack, producing heat and direct current (DC), which is converted by an inverter to alternating current (AC). When used in residential housing, usually a back-up boiler for peak heat demand and a grid connection are included. The grid connection enables to export electricity to the grid when electricity demand is low, or use additional electricity when demand is too high to be met by the fuel cell micro CHP. Fuel cell micro CHP systems can be designed for producing maximal heat, or maximal electricity (Nielsen & Prag, 2017).

The most common fuel cells used are polymer electrolyte membrane (PEM) fuel cells and solid oxide (SO) fuel cells. The PEM fuel cell uses polymer materials and operates at low temperatures of 60-160 °C, whereas the SO fuel cell, made of ceramic materials, operates at higher temperatures of 600-850 °C (Riddoch et al., 2017).

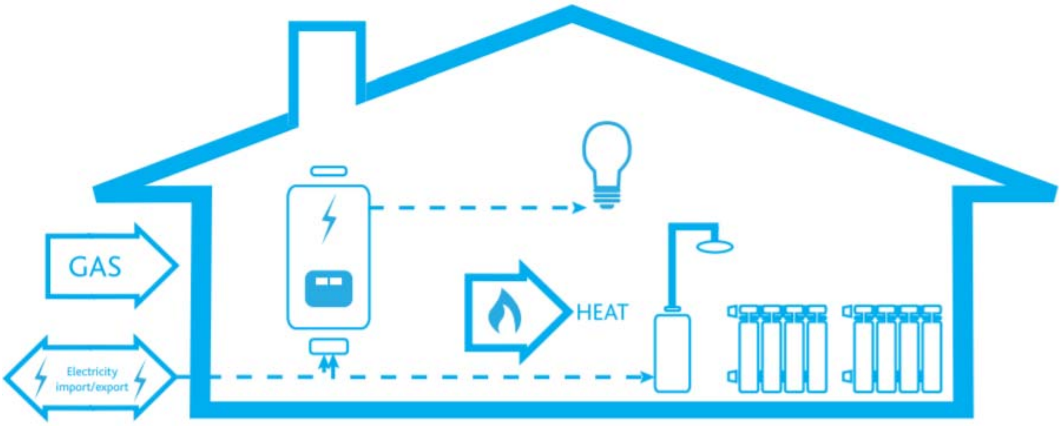

Figure 11: Overview of fuel cell micro CHP system in residential building. Source: Nielsen & Prag (2017).

Micro fuel cells CHP have efficiencies similar to large scale CHP plants and higher efficiencies than gas turbines, eliminating the need to convert gas to steam, and reducing transmission losses as they are placed at the end-use. Another advantage of the on-site installation is that they reduce the load on electricity grids. Total energy conversion efficiencies can reach 95%, and electrical efficiencies are in the range of 38-60% (Nielsen & Prag, 2017). However, as micro fuel cell CHPs still use natural gas, there are subject to debate. Opponents argue that no efforts should be put into the technology, as natural gas will be phased out when the technology matures. Contrary, proponents consider the micro fuel cell CHP as a viable alternative to high polluting gas turbines. In the long-term, renewable hydrogen or biogas could be a sustainable alternative to natural gas use in micro fuel cell CHPs (Pudjianto et al., 2017).

3.3.2 MARKET DEVELOPMENT

The global market for fuel cell micro CHPs to date is small. Japan is by far the country with the largest deployment, due to a large-scale demonstration and commercialisation programme called ENE-FARM. Between 2009 and October 2017, this programme resulted in the installation of 223,000 units, of which as much as 40,000 were sold in the last year (E4Tech, 2017). In Europe, a demonstration project for fuel cell micro CHPs has been carried out from 2012-2017, called ene.field.[2] During the project over 1000 units were installed, bringing the EU total to an estimated 3000 units. The majority of the units, about 75%, has been installed in Germany. Furthermore, two similar demonstration projects are currently active in Germany: Callux and KFW433 (Nielsen & Prag, 2017). Therefore, Germany is currently considered the main market in the EU for fuel cell micro CHP units.

Reported prices in Japan for residential micro CHPs were $12,600 for a PEM fuel cell unit and $16,200 for a SO fuel cell unit in 2016. As these prices would mean that the investment can be paid back in 18 years, governmental support is vital for the deployment of fuel cell micro CHPs. In Japan, the government has set the target of 1.4 million installations by 2020 and 5.3 million by 2030. Significant cost reductions are essential to reach such deployment (E4Tech, 2016).

The European ene.field project concluded that the technology is ready for large scale market penetration, and expects that the technology will reach mass commercialisation by 2020 with over 10,000 sales per year. Until 2020, the project PACE[3], also funded by the EU, aims to pave the way to large scale market uptake by preparing the supply chain (Riddoch et al., 2017, Nielsen & Prag, 2017). The ene.field project modelled scenarios for market uptake of fuel cell micro CHP units, ranging between 9 GW installed capacity by 2050 with no policy incentives, and 52 GW by 2050 with high policy incentives. It is expected that most fuel cell micro CHPs will be installed in Germany, Spain, the United Kingdom, Italy, Belgium and the Netherlands. The capacity in Germany will by far be the largest (Pudjianto et al., 2017).

3.3.3 EXPERIENCE CURVE

The experience curve and data for fuel-cell based micro-CHP systems is shown in Figure 12. The dataset was taken from the ENE-FARM programme, a Japanese programme aimed at commercialisation of residential fuel-cell systems (Maruta, 2016). Between 2009, and 2017 almost 200,000 units of this PEFC based micro-CHP were sold, while prices declined from almost 22,000 EUR2014/kW to under 9000 EUR2014/kW. The resulting experience curve has a learning rate of 19.3% with a relatively small error of 1.6%. Since the curve is based on cumulative sales within the ENE-FARM programme, the learning rate might be an overestimation of the actual global learning rate. However, as mentioned in the previous section, in e.g. Europe, only about 3000 micro-CHP units have been installed. Including these

[2] http://enefield.eu
[3] http://pace-energy.eu

units in the cumulative data shown in Figure 12 would hardly affect the established learning rate.

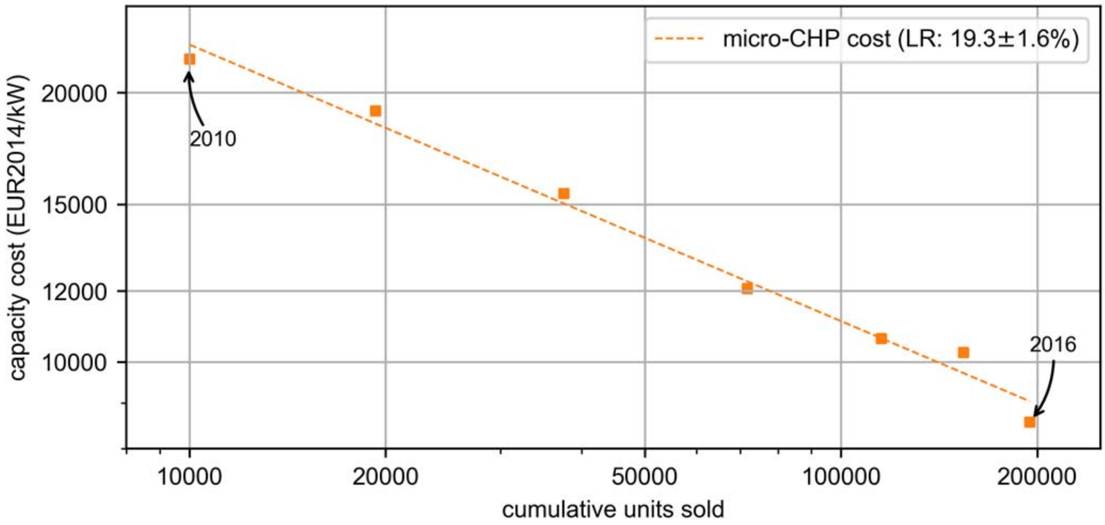

Figure 12: Experience curve for fuel cell based micro-CHP systems. Data: Maruta (2016).

3.3.4 *DATA COLLECTION AND METHODOLOGICAL ISSUES*

An overview of the general data collection issues applicable to fuel-cell micro-CHP systems is given in Table 5. Due to the limited penetration of fuel-cell based micro-CHP systems, the dataset that we present here is based on the ENE-FARM fuel-cell programme in Japan, and thus reflects prices of two very similar PEM based fuel-cell systems from two Japanese manufacturers. Hence, it is difficult to ascertain whether the price trends observed in this dataset, and the price levels in this dataset, can be generalised to be applied for global fuel-cell micro-CHP prices and price trends. However, since sales of fuel-cell systems outside of Japan are much more limited (see above), it is not possible to produce a dataset without these geographical limitations. Further research on fuel-cell system prices and further developments in the fuel-cell sector should indicate whether the price levels and trends described here are accurate for other markets.

Table 5: General data collection issues for fuel-cell micro-CHP systems.

Issue	Resolution	Applicability
Data is not for cost	Price data is used	☑
Data not available for desired cost unit	Converted data to specific capacity costs	☑
Data is valid for limited geographical scope	Data used as is, limited developments elsewhere	☑
Cumulative production figures not available		
Data is in incorrect currency or currency year	Convert currency and correct for inflation	☑
Early cumulative production figures are not clear or available		

Supply/demand affecting costs significantly
Lack of empirical (commercial scale) data

3.4 Electricity storage: Lithium and Redox-Flow batteries

3.4.1 *Description of technology*

Energy storage technologies are generally divided into four types: mechanical, electrical, chemical and electrochemical (Dunn et al., 2011). Batteries are a form of electrochemical energy storage. Batteries are built upon two or more electrochemical cells that can be combined in series to reach very high voltages. Series of cells can be configured parallel to realize required power. Because of this modular set-up, batteries are highly scalable (EASE/EERA, 2017).

Electrochemical cells consist of two electrodes, the anode and the cathode, surrounded by liquid or solid electrolyte. The electrolyte avoids contact between the electrodes and allows only ionic transfer. When the battery is charged by connecting the anode and cathode with a potential, oxidation reactions take place at the anode and reduction reactions at the cathode, leading to the transfer of electrons between the electrodes. When the potential is disconnected, the electrons are stored. By connecting a load, the process is reversed leading to discharge of the battery. The charging and discharging of batteries is relatively efficient compared to other energy storage technologies: electrical energy out over electrical energy in is in the range of 70-95%, depending on battery type. Different chemical systems are used, depending on application. Lead based batteries are currently dominating the general battery market, but grid-connected electrochemical storage of electricity is dominated by lithium-based batteries. Also, redox-flow batteries are increasingly gaining attention (EASE/EERA, 2017).

Lithium-based batteries represent conventional battery configuration (see Figure 13a). The electrodes and electrolyte are combined in a single system. Besides the main battery used for energy storage, lithium-based batteries are also the most popular battery type used in portable electronics and electric vehicles (OECD/IEA, 2016b). Flow batteries, shown in Figure 13b, differ from conventional battery configuration, mainly because electricity storage occurs in electrolyte material that is kept outside of the cell instead of at the electrodes. Because the electrolytes are kept in external reservoirs and not inside the cell around the electrodes, power and capacity of the battery are decoupled. Scaling of capacity (by increasing reservoir size or electrolyte concentration) and scaling of power (changing the size or type of cells and electrodes) can thus be done separately (Dunn et al., 2011). This makes the flow battery configuration more flexible than conventional battery configuration.

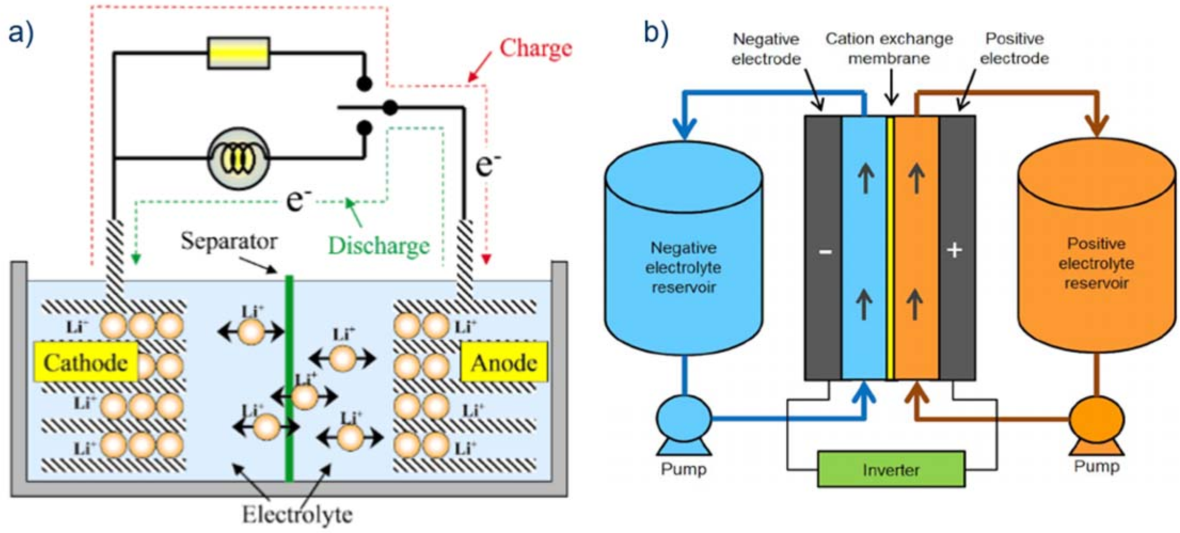

Figure 13: Graphical representation of lithium batteries (a) and redox-flow batteries (b). Source: Nishi, 2001; Arenas et al., 2015).

3.4.2 *MARKET DEVELOPMENT*

With 1,719 MW installed capacity in 2016, electrochemical storage represented only 1% of total global grid connected energy storage (96% of energy storage is pumped-hydro storage). As can be seen in Figure 14, the electrochemical storage market is led by the United States, followed by the Republic of Korea, Japan, Germany, Italy and Chile (REN21, 2017).

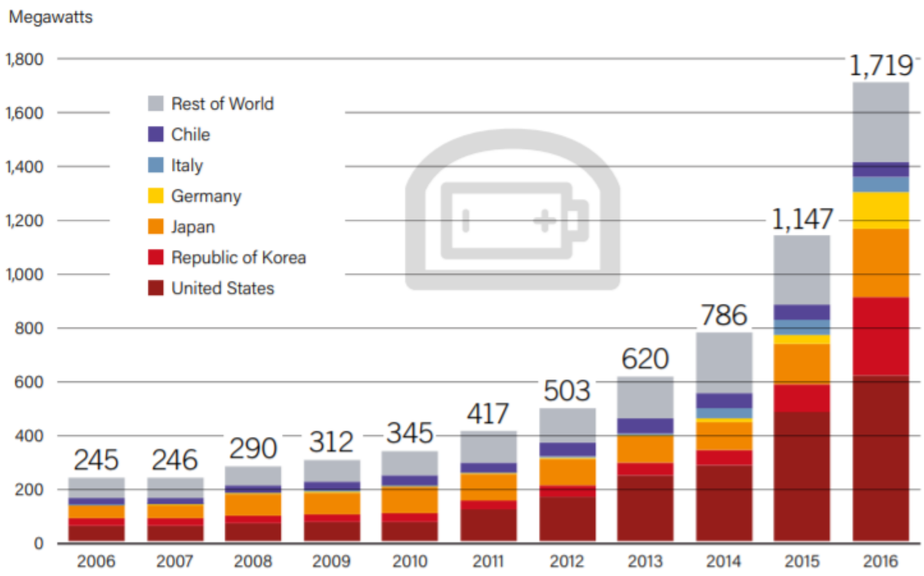

Figure 14: Global grid-connected stationary battery storage capacity, by country, 2006-2016. Source: REN21 (2017).

The electrochemical storage market is dominated by lithium batteries. In 2016, lithium-based batteries accounted for 69% of the total electrochemical capacity installed, followed by sodium- based batteries (13%), lead-based batteries (7%), flow batteries (5%) and nickel-based batteries (2%) (EASE/EERA, 2017). Redox-flow batteries represent a small percentage of global electrochemical storage capacity but are highly promising. In order to increase shares of these batteries, focus need to be on resolving issues with long-term performance and reliability (OECD/IEA, 2017a).

Even though the current electrochemical storage market is small, capacity growth was strong in 2016, with an increase of 55% compared to 2015 (REN21, 2017). This expansion is due to declining battery costs and favourable policies (OECD/IEA, 2017a). Costs of advanced batteries have declined significantly in the past years, mostly due to lower component costs and longer lifetimes (REN21, 2017). The electrochemical storage market profits from advancements in the electric vehicle market (see section 3.7), where lithium-based batteries are also dominating (OECD/IEA, 2016b; EASE/EERA, 2017).

Costs of grid-connected battery storage have decreased significantly in the last years. In 2015, costs have decreased by almost 70% compared to 2008 values. In certain small-scale markets with off-grid systems, battery storage is already cost-effective. In larger markets and grid-connected applications, batteries were still expensive in 2016. For example, lithium-ion batteries were four times more expensive than pumped hydro storage and even eight times more expensive than gas installations used for peak demand. It is expected that costs of lithium-ion grid-connected storage will achieve parity with pumped hydro before 2035 and with gas turbines by 2040 (OECD/IEA, 2016b). Furthermore, competing conventional lead-based batteries have also seen dramatic cost reductions (REN21, 2017), and costs of integrating batteries within systems are still rather high. Integration costs can reach 60% of total costs in some markets (OECD/IEA, 2017a).

It is expected that due to increases in renewable energy generation and consequent needs for grid flexibility the scale-up of the energy storage market will continue (EASE/EERA, 2017). Battery manufactures are planning to increase their annual manufacturing volume four-fold by 2020 compared to 2016. In order to meet the two degrees target of the Paris Agreement, battery storage capacity need to increase to 380 GW by 2040 (OECD/IEA, 2016b). Storage technologies are on track of meeting long-term targets of limiting global temperature increase to two degrees by 2100 as specified under the 2015 Paris Agreement. Nonetheless, to reach intermediate projected levels, further policy support is needed. Additionally, improvements need to be made in reducing material requirements, increasing energy densities of batteries and behind-the-meter storage for decentralised use (OECD/IEA, 2017a).

3.4.3 EXPERIENCE CURVES

The experience curves and data for three electricity storage technologies considered in REFLEX are shown in Figure 15. Considered here are residential- and utility-scale lithium-ion storage systems and redox-flow storage systems. Data was taken from Schmidt et al. (2017) and own data collection. The data shows learning rates of 12.5% and 15.2% for residential and utility scale lithium-based electricity storage systems, and 15.5% for redox-flow based systems, respectively. Especially for redox-flow, the limited number of data points and large variations from the fitted curve result in a high parameter error. In general, the available historical data for these upcoming technologies is limited. Since markets are currently developing rapidly, it is recommended to update these datasets frequently.

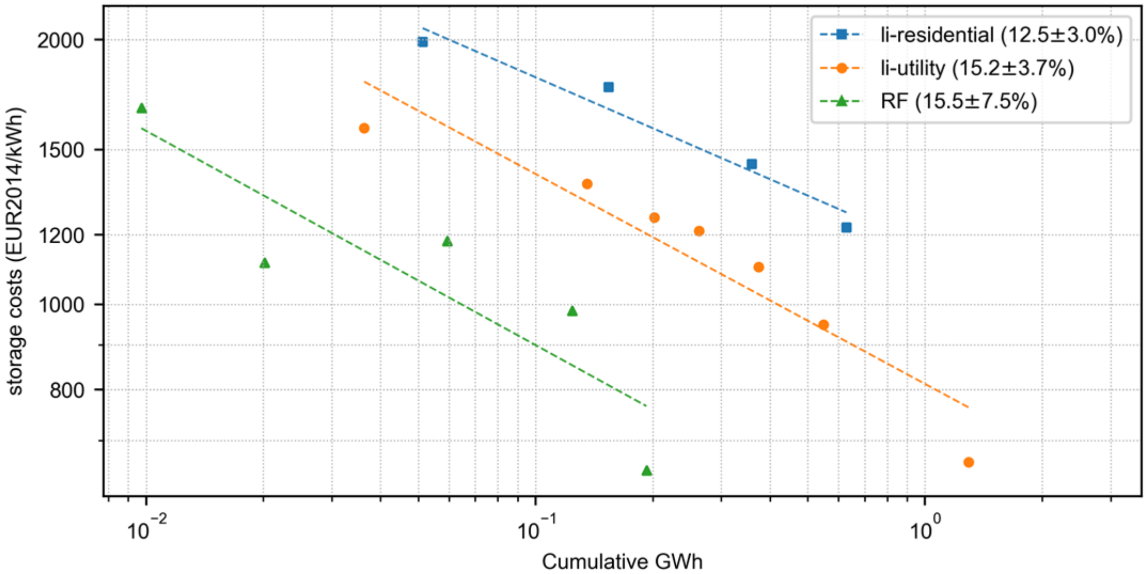

Figure 15: Experience Curves for energy storage technologies. Data source: Schmidt et al, 2017, [RF]. Split figure per technology? Leave out non-used data?

3.4.4 Data collection and methodological issues

An overview of the general data collection issues applicable to selected electricity storage technologies is given in Table 6. A main issue with the current experience curve datasets for the electricity storage technologies presented here is that the number of datapoints, as well as the number of doublings of cumulative capacities is still very limited. Especially for residential lithium-based systems the number of datapoints is low, but still these do stay close to the fitted experience curve, resulting in a low error in the established learning rate. For Redox Flow battery systems however, the five datapoints represent only about 3 doublings of cumulative capacity, and the technology is still very much an emerging technology (Schmidt et al, 2017). Variations in reported prices away from the fitted experience curve result in a high error of the established learning rate. The data for utility-scale lithium battery systems seem to reflect the exceptionally fast price declines of lithium batteries in general that was observed in 2017, highlighting another issue with the dataset, e.g. spill over effects. Spill over effects between different storage types are not considered here as this would induce complexity in modelling activities. It is however likely that there are spill over effects between e.g. the residential and utility scale lithium batteries, in terms of lithium battery cells and power electronics, between these sectors but also including other sectors like electric vehicle and electronics batteries.

Table 6: General data collection issues for electricity storage technologies

Issue	Resolution	Applicability
Data is not for cost but for price	Use price data as indicator for costs	☑
Data not available for desired cost unit	Convert data to desired unit if possible Use available data as a proxy	☑
Data is valid for limited geographical scope		
Cumulative production figures not available		
Data is in incorrect currency or currency year	Convert currency and correct for inflation and PPP	☑
Early cumulative production figures are not clear or available		
Supply/demand affecting costs significantly	Us data as is but recommend tracking and updating	☑
Lack of empirical (commercial scale) data		

3.5 HEAT PUMPS

3.5.1 DESCRIPTION OF TECHNOLOGY

A heat pump is a device that transfers heat from a lower temperature level (source) to a higher temperature level (sink) by adding work to the system. The mechanism is described as an inverse Carnot cycle or refrigeration cycle, shown in Figure 16a (Çengel & Boles, 2015). Work ($W_{net,in}$) can be added in the form of electric or thermal energy (REN21, 2017). Figure 16b shows the inverse Carnot cycle for cooling purposes (left) and heating purposes (right). Heat pumps are able to deliver more energy than is required to operate them. In standard conditions, they can deliver three to five times more energy than consumed (REN21, 2017).

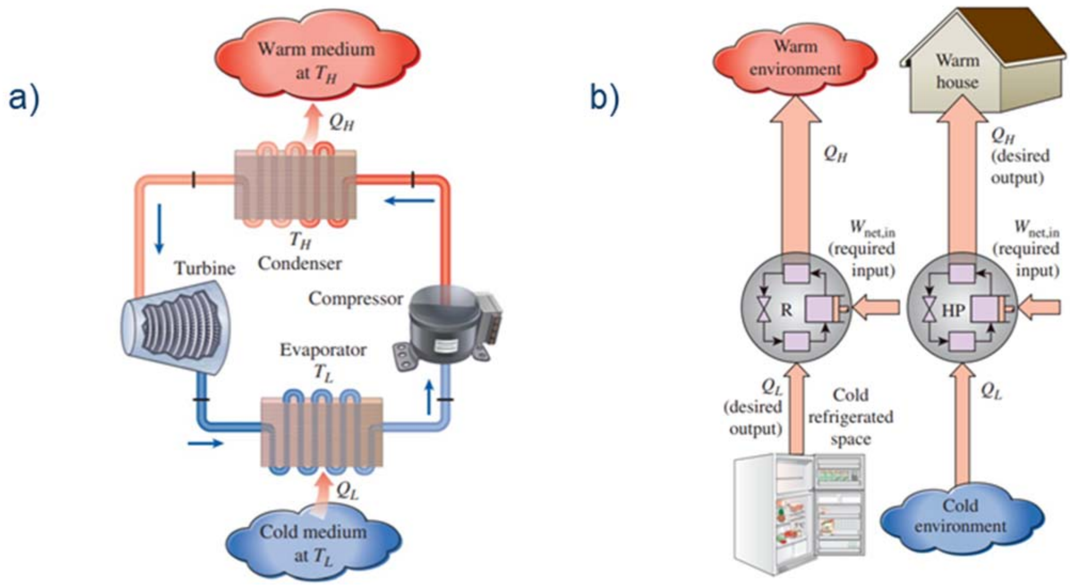

Figure 16: Schematic overviews of (a) the inverse Carnot cycle and (b) applications of the inverse Carnot cycle for cooling and heating. Source: Adapted from Çengel & Boles (2015).

Two types of heat pumps are most often distinguished: air source heat pumps (ASHPs) and ground source heat pumps (GSHPs). For ASHPs, the heat pump unit is normally fitted to the side of the building and this type is commonly used in densely populated, urban areas. There are two main types of ASHPs. Air-to-air systems directly heat the air of the rooms, and can also function as air-conditioning units. Air-to-water systems are connected to the (water-based) central heating system of a house, and can provide both space heating/cooling and hot water. For GSHPs, a heat exchanger unit is installed underground. This enables the system to reach a higher quality source of heat, but also leads to higher costs (Staffell et al., 2012). Because of the stability of the underground temperature, GHSPs are very efficient year-round. ASHPs however, have much lower efficiency when the outside air temperature is lower. In many cases, ASHPs commonly require an additional boiler (electrical or condensing gas) as back-up for winter months.

Other types of heat pumps include water source heat pumps (extracting heat from water such as groundwater layers, lakes, rivers or the sea), systems that utilise waste heat from industrial processes, sewage water or buildings, and hybrid systems that combine different heat sources (REN21, 2017).

Heat pumps are mainly used for space heating, cooling, and providing hot tap water in buildings in the residential or commercial sector (REN21, 2017). Also in the industrial sector heat pump applications are found, to increase the temperature of industrial waste heat so it can be re-used in the process. Industrial heat pumps are more advanced than heat pumps in the building sector, because they should be able to deliver higher temperature heat at 100-250 °C, with a difference of up to 100 °C between source and sink (Kleefkens & Spoelstra, 2014).

3.5.2 *MARKET DEVELOPMENTS*

The scale of the current heat pump market is difficult to assess, due to a lack of data and dataset inconsistency. The latter is caused by classification issues in different countries, as the main function of heat pumps differs per climate type: heating in cold climates or cooling in moderate climates. Therefore, global data for heat pumps is limited (REN21, 2017).

In the EU, the total stock of heat pumps is estimated to have reached almost 8 million units in 2014, see Figure 17 (EHPA, 2015).

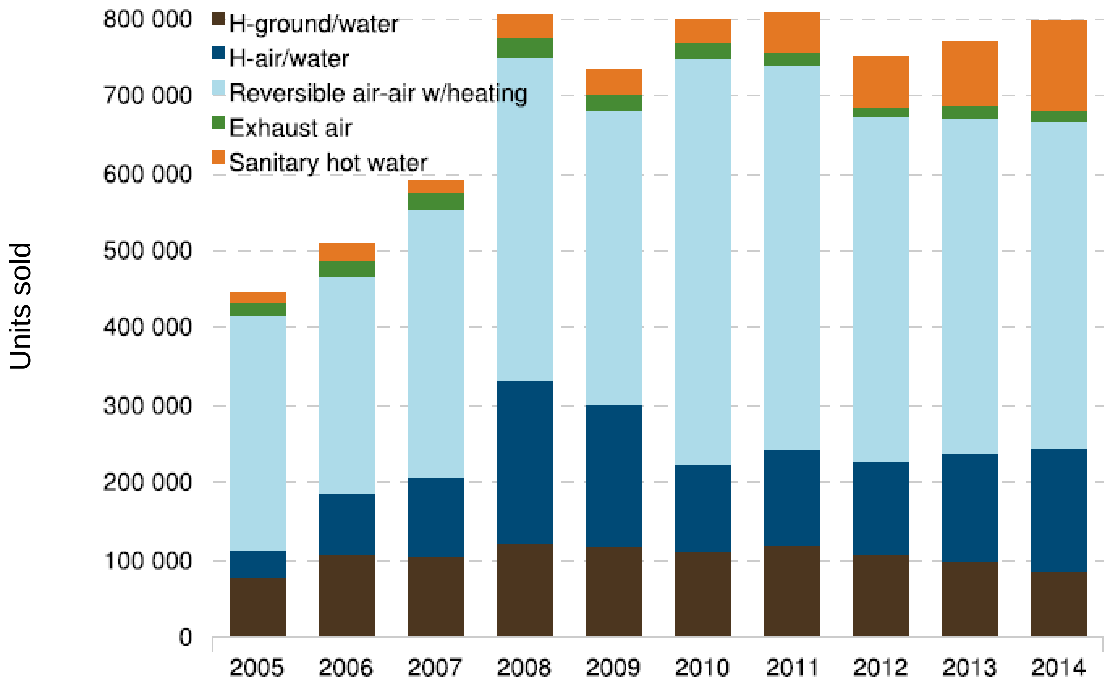

Figure 17: Development of heat pump sales in Europe 2005-2014, by category. Cooling-only units are not included. Source: EHPA (2015).

Figure 17 shows that the EU market is dominated by air-source heat pumps, representing more than 80% of the market. The largest growth is seen in the sanitary hot water type, that combine a heat pump with a hot water storage tank (air-to-water system). Another trend observed by the European Heat Pump Association is that larger heat pumps for industrial applications are gaining popularity (EHPA, 2015). In 2014, the strongest growth in heat pump sales was seen in Ireland and Lithuania, followed by France and Poland (EHPA, 2015). For 2015, numbers on heat pumps in the EU show a growth of about 12% for air- and ground source heat pumps. An estimated 73.6 GW_{th} was installed by the end of 2016. The market is led by Sweden, accounting for a total capacity of 5.6 GW_{th} (REN21, 2017). Even though the market is expanding, heat pumps delivered less than 1% of total final heating and cooling demand in Europe in 2015. For the residential sector, this share was a little higher, but remained lower than 2% (Fleiter et al., 2017).

Numbers for heat pump markets outside of Europe are uncertain. The global amount of heat pumps installed in 2015 is estimated at 20 million units in buildings, and 0.2 million units in the industrial sector (IRENA, 2018a). Heat consumption from heat pumps is estimated to have grown by 7% in 2017 compared to 2010, with the largest growth of 50% in China (OECD/IEA, 2017a). For ground-source heat pumps only, the United States and China had a capacity of 16.8 GW_{th} and 11.8 GW_{th} at the end of 2014, respectively. Other important markets in Asia are Japan and the Republic of Korea (REN21, 2017). For 2017, IRENA reported a record increase in installed heat pumps globally (IRENA, 2018a).

Current investment costs for ground source heat pumps are still significantly higher than natural gas boilers. At higher levels of space heating demand, ground source heat pumps are expected to become a cost-effective option in the EU around 2020, because of the relatively low operation costs. Air source heat pumps are already competitive with condensing gas boilers, but are hampered by the fact that they are most suited for very well insulated buildings only, and require back-up in colder climates, among other issues. For low temperature industry heat, it is expected that costs of heat pumps will be similar to costs of natural gas boilers around 2040. This expectation is driven by increasing operational costs of gas boiler costs due to increasing CO_2 taxes and fuel costs, and maintaining similar costs for heat pumps due to higher electricity costs opposing technological learning (OECD/IEA, 2016b).

The future market size of heat pumps remains uncertain, but heat pumps play a critical role as source of renewable heat in scenarios of both the IEA and IRENA for keeping global temperature rise under two degrees. The IEA scenario shows an increasing trend of heat pump units installed towards approximately 25% of heating (space and water) equipment in buildings by 2060 (OECD/IEA, 2017a). The IRENA scenario expects the stock of heat pumps to increase to 253 million units in buildings, accounting for a share of 27% of the heat demand, and 80 million units in the industrial sector by 2050 (IRENA, 2018a). With the current growth rate, heat pump technology is not on track of meeting the two degrees scenario (OECD/IEA, 2017a).

3.5.3 Experience Curves

Figure 18 shows two experience curves for a 7.6 kW residential heat pump sold in Switzerland and the Netherlands. The country's specific selling prices were plotted against cumulative EU heat pump sales. The experience curve for the Swiss heat pumps derived from the dataset of Weiss et al., shows a learning rate of 26.0% for a time series of 24 years (1980 - 2004), which seems rather high. In their publication, Weiss et al. also discuss their concerns with this particular dataset (Weiss et al., 2008). ***The observed cost reductions can be attributed to technological learning in the manufacturing and installation of both heat pumps and related system components (Weiss et al., 2008). In the past decades, heat exchangers became both smaller and cheaper. The main components of a heat pump (e.g., the vapour compression cycle, heat exchangers) are used in the cooling industry and therefore the major driver for cost reductions in heat pumps can be attributed to technological learning in heat pump assembling and***

system integration. Cost reductions were also achieved by economies of scale, including manufacturing costs, purchasing costs, sales costs, and possibly other cost items (**Weiss et al.**, 2008). Further learning potential could be expected from other optimisations in the design and production processes when heat pumps are produced in larger numbers.

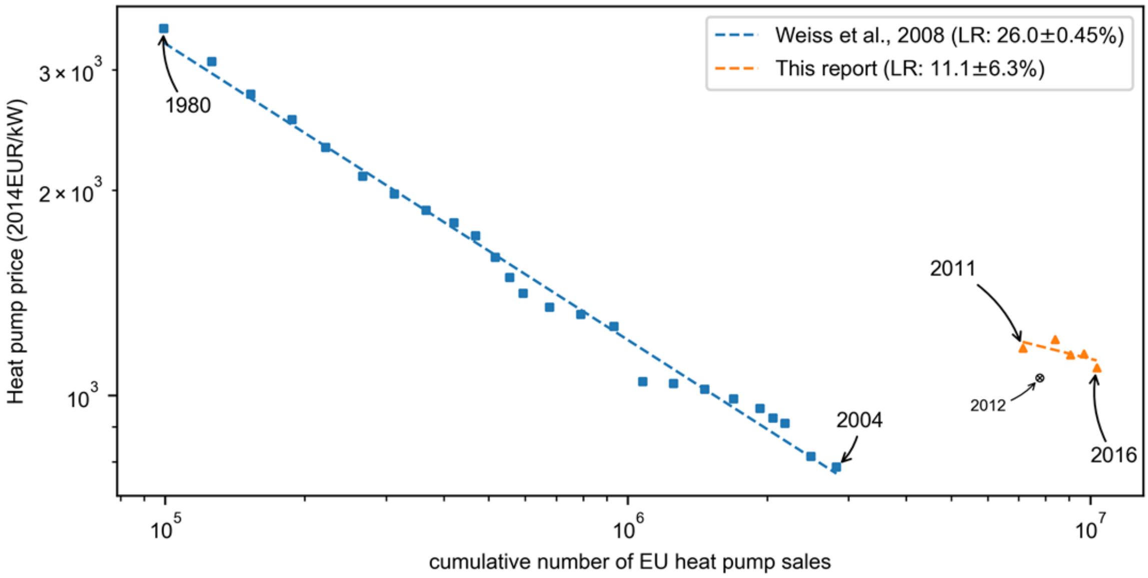

Figure 18: Experience curves for heat pumps. Blue data points were taken from Weiss et al. (2008), orange data points were gathered for this report, and were scaled to costs for heat pump with a thermal capacity of 7.6 kW.

A second experience curve for Dutch heat pump prices is also shown in Figure 18***, based on own data collection. The curve for the Dutch heat pumps shows a learning rate of 11% for a time series of 5 years (2011 – 2016).*** We used price lists for different heat pump capacities from the year 2011 to 2016. This price data was harmonised with the 7.6 kW heat pump capacity selected for the Swiss heat pump learning curve by Weiss et al. For all years together (2011-2016), price data was plotted against their respective capacity on a linear axis and a power curve was fitted to the graph to estimate a scale factor for the heat pump cost. The equation of the power curve was then used to calculate the price per kW for a 7.6 kW heat pump. For each year, the average price was taken and plotted above. From this dataset, the data for the year 2012 was omitted since it was determined to be an outlier.

The heat pump price in the Netherlands for the year 2011 is higher by a factor of 1.2 than the Swiss heat pump price in the year 2004. The high prices and low learning rates in the Netherlands could be attributed to the fact that heat pumps have to compete with high efficiency condensing gas boilers which are cheap and have considerably lower spatial requirements. Condensing gas boilers and the potential follow-up technology of micro-CHP systems are supported by a powerful gas lobby (Weiss et al., ***2008***). Air source heat pumps are economically competitive, if there is demand for both space heating and cooling, but so far there is hardly any market for residential space cooling in the Netherlands (Weiss et al., ***2008***). Therefore, these differences in prices and learning rates for heat pumps between Switzerland and the Netherlands is probably due to a demand driven heat pump market that allows producers to increase their profit margins.

3.5.4 DATA COLLECTION AND METHODOLOGICAL ISSUES

An overview of the general data collection issues applicable to heat pumps is given in Table 7. The major issue in heat pump learning rates is the short time series (2011-2016) for Dutch heat pump market and the time series gap between the year 2004 and 2011 between the Swiss and Dutch heat pump market. The short time series for Dutch heat pump prices could have a major effect on the low learning rates shown in Figure 18 while the time series gap inhibits from providing a concrete and accurate reason for price differences between Dutch and Swiss heat pump prices. The price data gathered for the Dutch market was harmonised to analyse in conjunction with the data from Weiss et al. (2008). The method of harmonisation and/or the inclusion of different heat pump capacities could have affected the learning rates that were derived.

Table 7: General data collection issues for heat pumps.

Issue	Resolution	Applicability
Data is not for cost but for price	Use price data as indicator for costs	☑
Data not available for desired cost unit		
Data is valid for limited geographical scope	Convert currency Combine with other datasets from various geographical scopes	☑
Cumulative production figures not available	Calculate from annual production figures Calculate from annual sales figures	☑
Data is in incorrect currency or currency year	Convert currency and correct for inflation	☑
Early cumulative production figures are not clear or available	Restrict the dataset to time horizon for which reasonable cumulative production figures are available	☑
Supply/demand affecting costs significantly	Data discarded for final recommended learning rate	☑
Lack of empirical (commercial scale) data		

3.6 CARBON CAPTURE AND STORAGE

Carbon capture and storage (CCS) is a concept that involves the capturing of CO_2 produced by burning fossil fuels to store it in such a way that it will not reach the atmosphere. CCS can play an important part in the power sector, where fossil fuels are burnt to generate electricity, and the industrial sector, that involves the burning of fossil fuels to provide process energy. This chapter looks into these two sources of CO_2 in CCS: the industrial sector and the power generation sector.

3.6.1 *DESCRIPTION OF TECHNOLOGY*

The three main distinctive technological varieties of carbon capture technology in the power sector are post-combustion capture, pre-combustion capture and oxy-fuel combustion capture. An overview of the CCS technologies is shown in Figure 19.

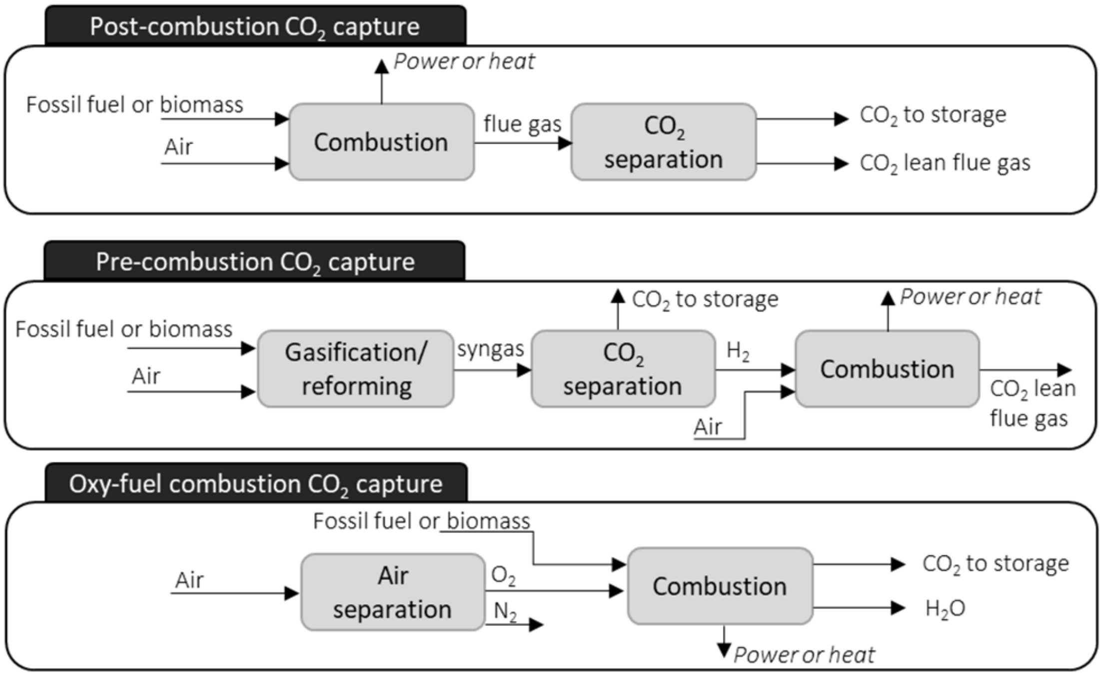

Figure 19: Overview of CCS technologies. Adapted from OECD/IEA (2016a).

- In post-combustion capture, CO_2 is removed from the flue gas of a power plant or industry activity after combustion has taken place. The removal is usually done by chemical or physical sorbents. After attachment of the CO_2 to the sorbent, both can be separated by increasing temperature (Gibbins & Chalmers, 2010). Sorbent technology has been applied at a large scale for post-combustion capture. Other approaches, such as membranes or adsorbents are at different levels of development (OECD/IEA, 2016a). Post-combustion capture is assumed to be suitable for the majority of pulverised coal boilers in power generation (Kenarsari et al., 2013).
- In pre-combustion capture, the primary fossil fuel or biomass type is not combusted in its original form. Gasification or reforming processes are used to produce hydrogen (H_2). The by-product carbon monoxide is converted to carbon dioxide by water gas shit reactions. The CO_2 is captured for storage and the hydrogen is used as fuel for combustion (Kenarsari et al., 2013). This process is performed when there is an

application for hydrogen, for example for energy purposes (Gibbins & Chalmers, 2010).

- The last CCS technology is oxy-fuel combustion capture. This is a form of post-combustion capturing but differs in that the combustion of the fuel takes place in pure oxygen rather than air. This process ensures an almost pure stream of CO_2 after combustion, making the capturing process easier, as simpler condensation processes can be used instead of energy-intensive chemical separation processes. However, the separation of oxygen from air (composed of mainly nitrogen and oxygen) imposes an energy penalty (Gibbins & Chalmers, 2010; Kenarsari et al., 2013).

Capturing CO_2 from streams with a high concentration or purity faces less technological challenge than capture from diluted streams (IEA/UNIDO, 2011). After capturing CO_2 from the flue gas, CO_2 is compressed and transported to a suitable site. The CO_2 is stored by injecting it deeply underground in rock formations, usually more than two kilometres deep (Global CCS Institute, 2016).

1.1.1 *MARKET DEVELOPMENTS*

CCS took its first steps in the 1970s, when waste CO_2 was utilised for the first time in the southern United States. By mid-2016, fifteen large-scale[4] CCS projects were operating globally, accounting for an annual capture of 30 $MtCO_2$. Most of the projects are located in the United States, with some projects in Canada, Norway, Brazil, Saudi Arabia and the United Arab Emirates. The vast majority (80%) of the projects use carbon storage for enhanced oil recovery. The rest of the projects have a dedicated use for the CO_2. In 2014, the first project capturing CO_2 from diluted flue gas instead of high concentrated streams commenced, demonstrating advancements in technology (OECD/IEA, 2016a). In 2017, the number of operating CCS projects increased to a total of seventeen. Also, the first large-scale bio-energy CCS project started operation in 2017 (Global CCS Institute, 2017).

CCS from industrial processes, mainly natural gas processing, is currently dominating. Industrial CCS has historically offered chances for early development, since within this sector several processes exist that remove CO_2 as part of the process itself. Furthermore, it represented a niche market were CCS demonstration was possible (IEA/UNIDO, 2011; Romano et al., 2013). CCS in the power generation sector is less developed. Only two out of seventeen projects in 2017 applied CCS on power generation. Four new projects for industrial CCS are planned to start operation in 2018 accounting for an additional capture of six $MtCO_2$/year, compared to zero power generation CCS projects (Global CCS Institute, 2017).

Costs of CCS differ greatly depending on the sector. In processes that already produce a highly concentrated vent of CO_2, such as natural gas processing, biomass-to-ethanol, and fertilizer production, costs are between 20-33 USD/tCO_2 avoided. Costs are significantly higher in other sectors, starting with supercritical pulverised coal and oxy-fuel combustion in the power sector (60-121 USD/tCO_2), followed by iron and steel production (67-119 USD/tCO_2), natural gas power production (80-160 USD/tCO_2) and the cement industry (104-194 USD/tCO_2) (Global CCS Institute, 2017).

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[4] Large scale projects denote a size of at least 800,000 tCO_2/year for coal-based power plants, and 400,000 tCO_2/year for all other industrial and power facilities (OECD/IEA, 2016a).

In general, it is considered that CCS deployment is going too slow. This is a result from lower policy and financial support than anticipated in the last years (OECD/IEA 2016a). In order to meet the two degrees target from the 2015 Paris Agreement, CCS deployment should increase to 400 $MtCO_2$ per year stored by 2025, meaning a tenfold increase from current practice. By 2050, 6.8 $GtCO_2$ should be stored annually. In this scenario, CCS accounts for 14% of emission reductions by 2060, compared to 35% renewables, 40% efficiency, 6% nuclear and 5% fuel switching. Therefore, the International Energy Agency urges governments to re-evaluate their support for CCS (OECD/IEA, 2017a). Figure 20 shows the CCS deployment in non-OECD and OECD countries for this scenario (Global CCS Institute, 2017).

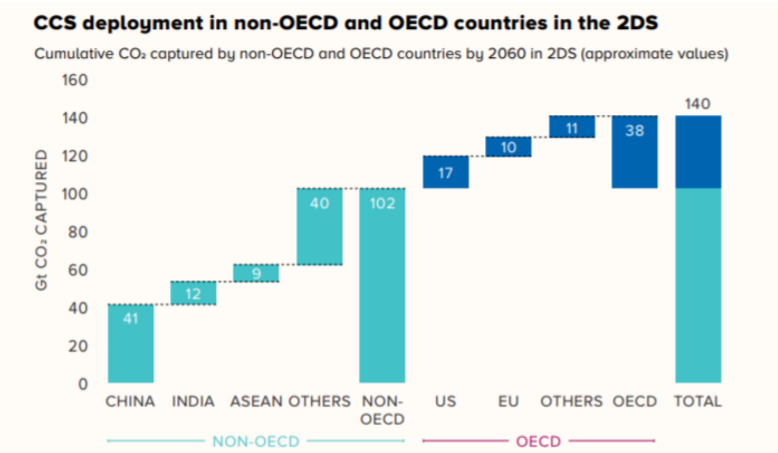

Figure 20: Cumulative CO_2 captured in the two degrees scenario per region. Source: Global CCS Institute (2017) based on data from the International Energy Agency's Energy Technology Perspectives 2017.

The figure shows that CCS is expected to be mainly important in non-OECD countries. China offers an especially high potential for CCS, due to a large number of coal-fired power plants that are relatively new and could be adapted to suit CCS (Global CCS Institute, 2017). It is estimated that 310 GW of Chinese coal-fired capacity is suitable for a retrofit to CCS (OECD/IEA, 2017a). Figure 21 shows an overview of the deployment per sector corresponding to the two degrees target.

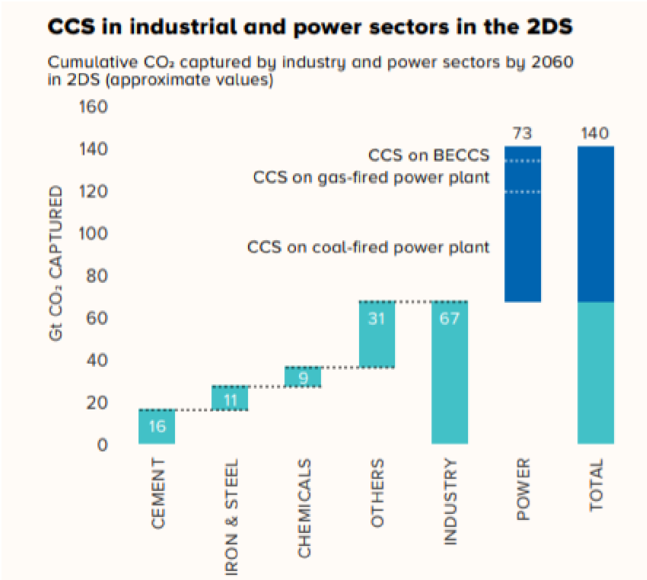

Figure 21: Cumulative CO_2 captured in the two degrees scenario per industry. Source: Global CCS Institute (2017) based on data from the International Energy Agency's Energy Technology Perspectives 2017.

Even though current deployment of CCS in the power industry is minimal, it is expected that the technology will take off in the next years. Due to increased shares of intermittent renewables in power generation, fossil fuels are assumed to remain important providing base load, balancing, and reserve capacity. Coal, being the fossil fuel in power production associated with most emissions, has the highest need to decarbonise. It is expected that total coal capacity decreases, while remaining capacity will be almost completely retrofitted to suit CCS by 2045 (OECD/IEA, 2017). In order to reach high deployment, the building rate of CCS installations at coal plants needs to be similar to historic growth rates of coal capacity (IEAGHG, 2012). Natural gas capacity is expected to increase until 2045, and decrease towards 2060 while the share of CCS in natural gas capacity increases to 50% in 2045 and 90% in 2060. For natural gas, the growth rate of CCS installations is lower than historical rates of natural gas capacity (IEAGHG, 2012). Bioenergy capacity is expected to increase, combined with CCS from 2045 onwards (OECD/IEA, 2017a).

For the industrial sector, CCS remains important as there are not many other options for decarbonisation in this sector (OECD/IEA 2016b). In order to meet the two degrees target, CCS use in the industry has to increase to sequestering 1.8 $GtCO_2$ per year, corresponding to capturing 26% of CO_2 produced in the sector and reaching a cumulative capture of 67 $GtCO_2$. Most important are the cement industry, the iron and steel industry, and the chemical industry (see **Fehler! Verweisquelle konnte nicht gefunden werden.**). When looking at scenarios aiming to keep global temperature increase significantly lower than two degrees (so-called beyond two degrees scenarios), CCS in industry becomes more important than CCS in the power sector (OECD/IEA, 2017a).

3.6.2 Experience curves

Figure 22 shows the experience curves for a range of technologies related to or used as a proxy to derive learning rates for CO_2 capture at natural gas and coal fired power plants. These experience curves were used by Rubin et al. (2006) to estimate future cost reductions that might be achieved by power plants employing CO_2 capture based on the rate of cost reductions achieved by other process technologies in the past analogous with capture plant components.

The analogous technologies assessed in the report are Flue gas desulfurization (FGD), Selective catalytic reduction (SCR) Gas turbine combined cycle (GTCC), Pulverized coal boilers, LNG production, oxygen production and hydrogen production (SMR).

The learning rates provided from Rubin et al. for NGCC plant and PC plant with CO_2 capture are a nominal value of 2.2% with a range of 1.2 - 3.6% and nominal value of 2.1% with a range of 1.1 - 3.5% respectively. These low learning rates can be attributed to the fact that NGCC and PC (without CO_2 capture) plants are one of the most developed and widely used technologies and therefore leave a small potential for learning. Low learning rates for the mature sub systems are a major reason for seeing slow cost decline in NGCC and PC plants with CO_2 capture (Rubin et al. 2006).

Table 8 provides the learning rates for the sub systems of NGCC and PC plants with CO_2 capture. A similar approach was used to provide learning rates for CCS in the industrial sector since they have similar sub systems and due to arguable absence of actual developments in the sector and thus lack of empirical data.

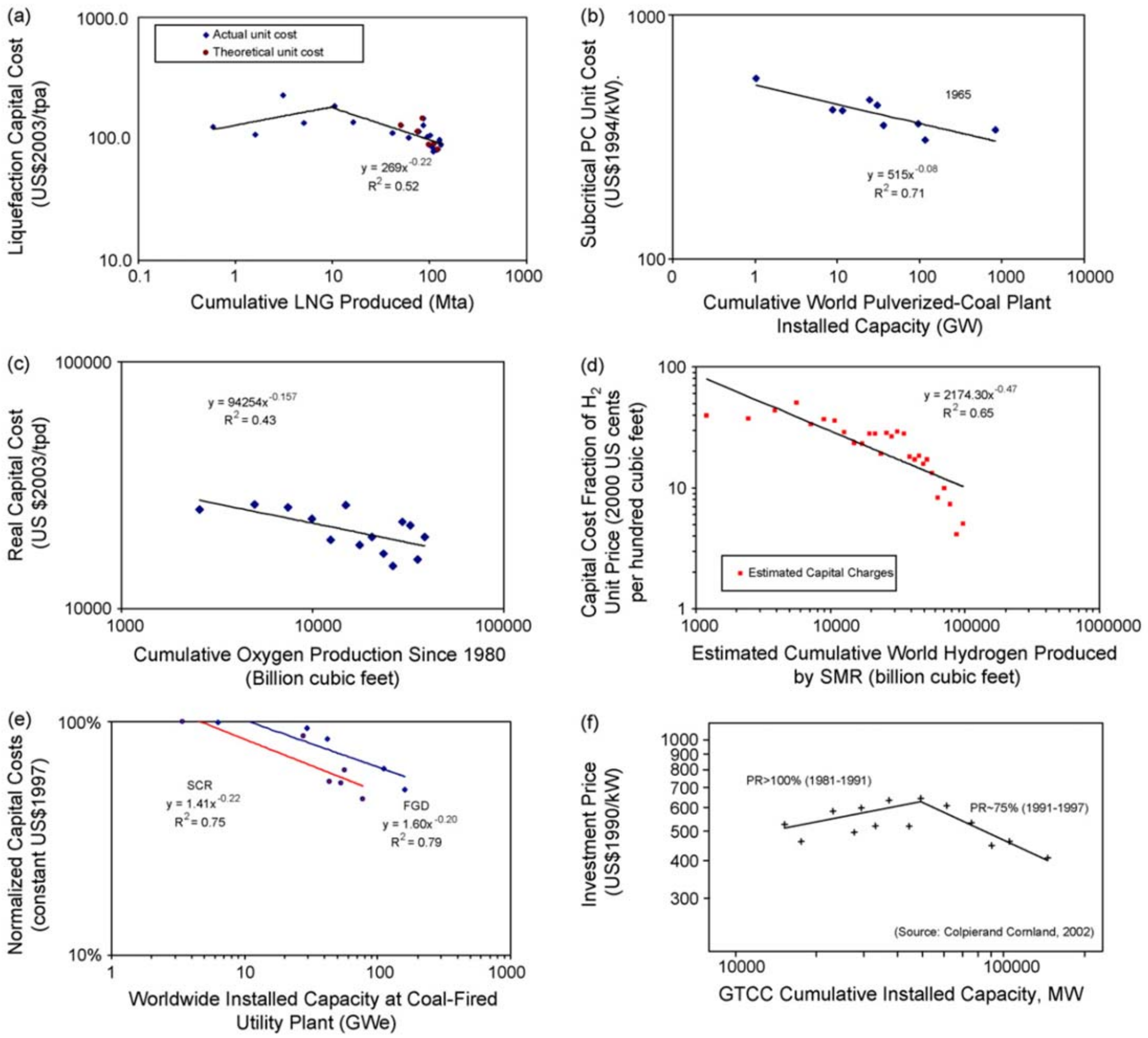

Figure 22: Experience curves derived for proxy technologies and other related technologies used to estimate technological learning in CO2 capture costs by Rubin et al, 2007. Capital cost experience curves for (a) LNG production, (b) pulverised coal boilers, (c) oxygen production, (d) SMR hydrogen production,(e) FGD and SCR systems at coal-fired power plants and (f) CCGT power plants. Figure from Rubin et al, 2007.

There are currently 18 industry related CCS sites around the world out of which natural gas processing (9 sites) holding the major share (Global CCS Institute). A dataset was collected and an experience curve was developed for natural gas processing plants with CCS and the resulting curve is shown in Figure 23. It shows a learning rate of 32% but that value cannot be considered due to the poor fit (R^2 = 0.18) of the curve. It may therefore be concluded that the rate of implementation is in its infancy stages and more installations need to me made before the technology can achieve true learning.

Table 8: Overview of learning rates of subsystems of NGCC and PC plants with CO_2 capture Source: Rubin E., Yeh S., Antes M., Berkenpas M., Davison J. (2006). Estimating Future Costs of CO_2 Capture Systems Using Historical Experience Curves. Proceedings of GHGT-8, International Conference on Greenhouse Gas Control Technologies, Trondheim, Norway

Plant type and technology	Analogous technology	Learning rate	
		Nominal	Range
<u>Natural Gas Combined Cycle</u>			
GTCC (power block)	GTCC	0.10	0.05 – 0.15
CO2 capture (amine system)	FGD	0.11	0.06 – 0.17
<u>Pulverised Coal</u>			
PC Boiler/turbine-generation area	PC boiler	0.06	0.03 – 0.09
AP controls (SCR, FGD)	FGD/SCR	0.12	0.06 – 0.18
CO2 capture (amine system)	FGD	0.11	0.06 – 0.17

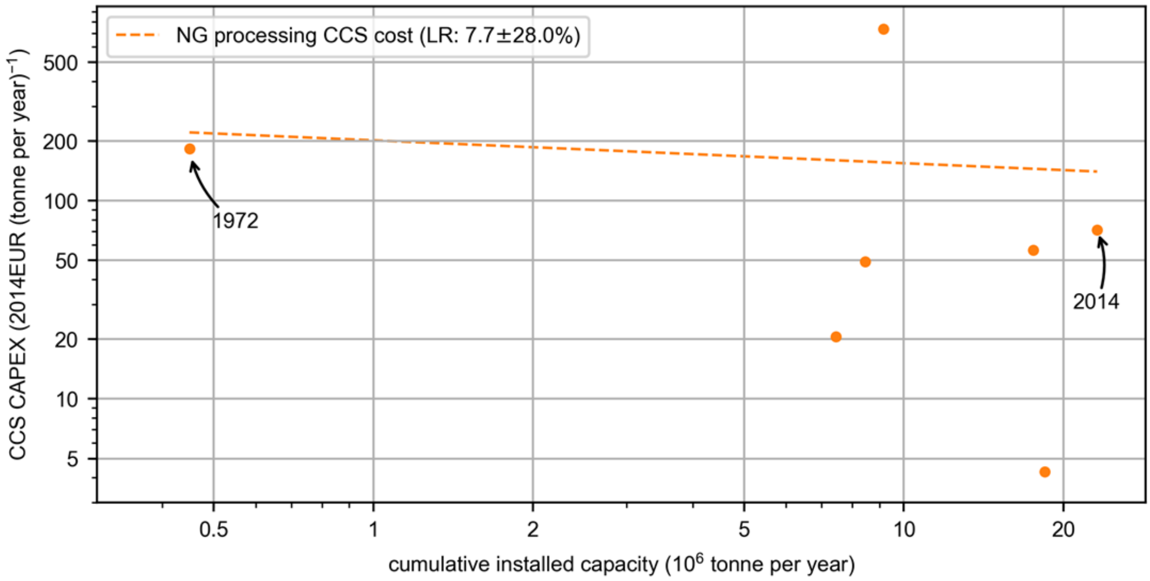

Figure 23: Experience curve for industrial CCS (from natural gas processing).

3.6.3 DATA COLLECTION AND METHODOLOGICAL ISSUES

An overview of the general data collection issues applicable to carbon capture and storage is given in Table 9. Due to lack of available data, learning rates for CCS in the power sector were derived on a component basis of analogous technologies (Rubin et al., 2006). This method can lead to uncertainties and can provide skewed results as opposed to learning rates derived from actual power plant with CCS. This method calculates learning rates based on incremental improvements to existing technologies and therefore does not consider technological breakthroughs like radically new CO_2 capture technologies that would result in further cost reductions and therefore higher learning rates. The initial capacities estimated for power plants with CCS were based on assumptions made by Rubin et al. A different assumption of initial installed capacity would provide different learning rates.

The issues mentioned above and in Table 9 are also applicable for learning rates generated for CCS in the industrial sector since a similar methodology was used due to arguable absence of actual developments and thus lack of consistent empirical data. Hence, until sufficient CCS projects are developed and a reasonable basis of empirical data is generated, modelling activities still rely on the results of the study by Rubin et al.

Table 9: General data collection issues for carbon capture and storage

Issue	Resolution	Applicability
Data is not for cost but for price	Use price data as indicator for costs	
Data not available for desired cost unit	Convert data to desired unit if possible Use available data as a proxy	☑
Data is valid for limited geographical scope		
Cumulative production figures not available		
Data is in incorrect currency or currency year	Convert currency and correct for inflation and PPP	☑
Early cumulative production figures are not clear or available		
Supply/demand affecting costs significantly		
Lack of empirical (commercial scale) data	Use data available for analogous technologies	☑

3.7 ELECTRIC VEHICLES

3.7.1 DESCRIPTION OF TECHNOLOGY

Electric vehicles include every road-, rail-, sea-, or air-based vehicle that is at least partially powered by electricity. Recent advancements in battery technology led to an expansion of the road-based electric vehicle market. Electric road transport is generally categorized in three main types:

- Battery Electric Vehicles (BEVs) are fully powered by electricity. They make use of an electric propulsion system and rely on energy delivered by a battery pack. The battery is charged externally at charging stations and by recovered braking energy, called regenerative braking (Yong et al., 2015). The type of battery varies across different BEV models, but lithium-based batteries are currently dominating (EASE/EERA, 2017). BEVs have several advantages over the currently dominating fossil fuel combustion engines. Besides having no tailpipe emissions and no reliance on fossil fuels, BEVs have higher vehicle efficiencies and better acceleration (Pollet et al., 2012; Mahmoudzadeh Andwari, 2017). Disadvantages of BEVs are related to the low energy density of batteries available, leading to low driving ranges, high costs, low lifetime and safety concerns.
- Hybrid Electric Vehicles (HEVs) combine an electricity power source with any other power source. Usually, an electric motor with battery storage is combined with a conventional internal combustion engine and fuel tank. The electric motor and combustion engine can be coupled in series, parallel, or series-parallel (Yong et al., 2015). Lithium-based battery packs are common for HEVs, as with BEVs, but also nickel metal hydrate (Ni-MH) batteries are used (EASE/EERA, 2017). Plug-in Hybrid Electric Vehicles (PHEVs) are supplemented with an external charging system for the battery and can be plugged into a power outlet, whereas general HEV batteries are only charged by regenerative braking and the internal combustion engine (Biresselioglu et al., 2018). As PHEVs and HEVs both contain an internal combustion engine, they usually have smaller battery packs than BEVs (IRENA, 2017).
- Fuel cell electric vehicles (FCEVs) rely, just like BEVs, solely on an electric propulsion system, but with the main source of energy being a fuel cell. FCEVs also contain a battery, and are therefore hybrid vehicles, but the battery in FCEVs are much smaller than in BEVs and mainly used for the application of regenerative braking (OECD/IEA, 2015). The electrochemical process in fuel cells converts the chemical energy of a fuel and an oxidative substance. The most common combination is hydrogen with air. By-products of this process are heat and water, leading to zero tail-pipe emissions. Fuel cells are lighter and smaller than batteries and the vehicle can be recharged quickly, because a fuel is used. However, FCEVs are currently more expensive than battery electric vehicles and several components need to reduce in price before they are competitive (Cano et al., 2018). The most common type of fuel cell in FCEVs is the polymer electrolyte membrane (PEM) type (Pollet et al., 2012).

Figure 24 shows examples of power train configurations for BEVs, HEVs, PHEVs and FCEVs. Note that not all possible configurations (series, parallel, series-parallel) are shown.

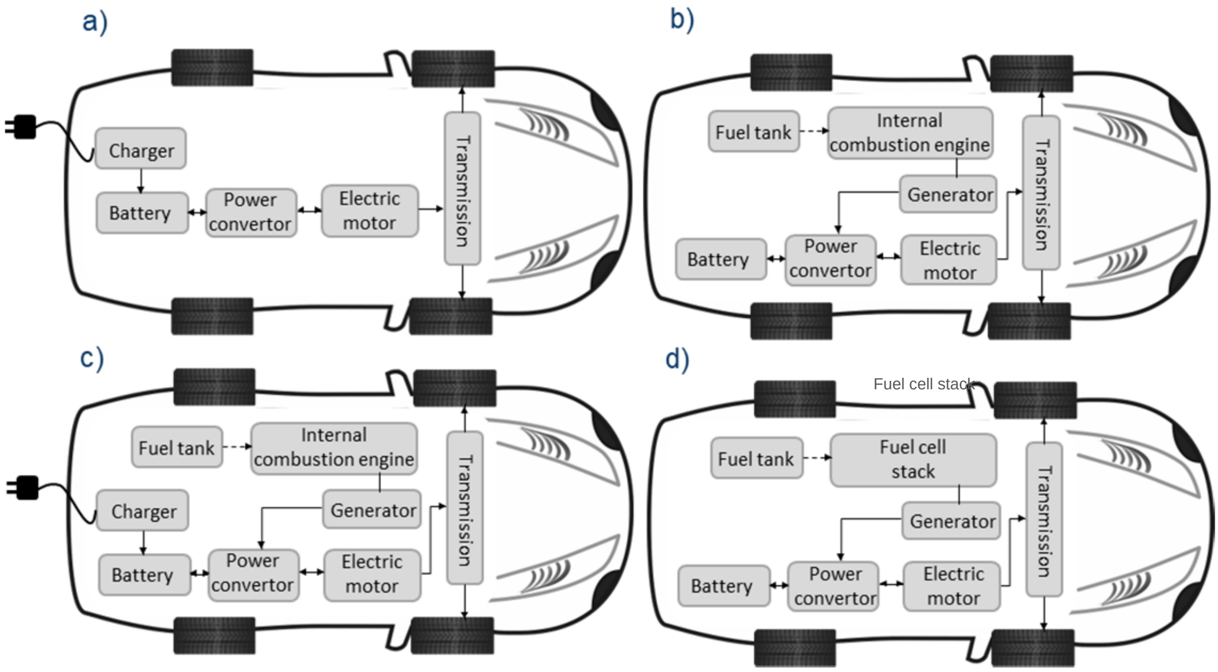

Figure 24: Overview typical power train configurations of (a) BEV, (b) series HEV, (c) series PHEV, and (d) series FCEV. Based on Yong et al. (2015) and Das et al. (2017).

3.7.2 MARKET DEVELOPMENT

The first electric vehicle was developed in 1834, prior to the first internal combustion engine. However, due to limited storage capacity in batteries and improvements in the internal combustion engines, attention for electric vehicles decreased. In the 1970s, the oil crisis lead to renewed interest into battery-electric vehicles (Pollet et al., 2012). From then on, electric vehicles have reappeared periodically and since the 2000s, the most recent and strongest growth is taking place (OECD/IEA, 2017c). The first FCEVs were developed in the 1960s, but only recently the technology has developed sufficiently for car manufacturers to announce FCEV models (OECD/IEA, 2015). By 2016, Hyundai, Toyota, Daimler and Honda had FCEV passenger models available. Several other car manufacturers have announced the development of FCEVs in the future (Curtin & Gangi, 2017; Cano et al., 2018).

The global market of electric vehicles has grown rapidly in recent years. In 2016, 775 thousand electric passenger vehicles were sold globally, corresponding to a 80% market growth and resulting in a total of 2 million passenger vehicles worldwide (see Figure 25). Growth was mainly driven by China, whose fleet increased from 11,600 vehicles in 2012 to 350,000 in 2016. China is also home to the world market leader for electric vehicle manufacturing, BYD, followed by Renault-Nissan (France-Japan), Tesla (US) and BMW (Germany) (REN21, 2017). Concerning global fuel cell shipment, largest volumes are shipped for application in transport both in 2016 and 2017. This is because the size of fuel cells in FCEVs is significantly larger than for application in portable electronics or stationary storage (E4Tech, 2017).

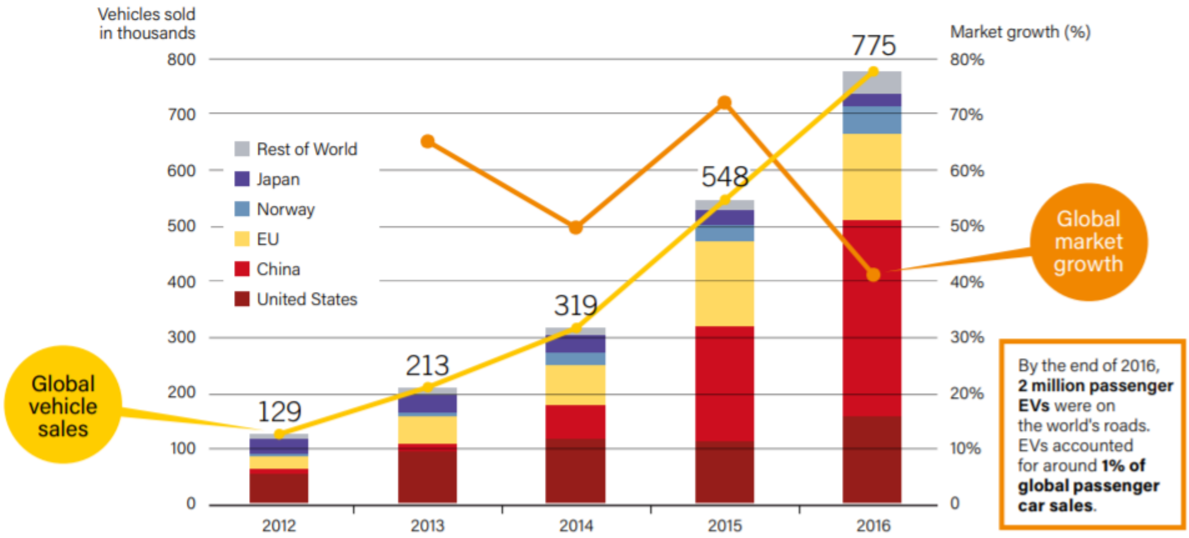

Figure 25: Global sales of passenger electric vehicles, by country, 2012-2016 (includes BEV, HEV, PHEV and FCEV). Source: REN21 (2017).

The growth of the electric vehicle market is mainly due to the diffusion of BEVs and PHEVs (OECD/IEA, 2017b). However, despite rapid growth, the market share of these vehicles in terms of sales remains low in most countries. Exceptions are non-EU countries Norway and Iceland. In Norway, electric vehicles have obtained a market share of 39.2% in 2017, followed by Iceland with a market share of 14.1% (EAFO, 2018). Even though China's and the US's market are largest in absolute terms, market shares in 2017 remained small with 4% for China (EV Volumes, 2018), and a little over 1% for the US, mainly due to growth in California (EV Adoption, 2018). Within the European Union, the countries with the largest market shares in 2017 were Sweden (5.3%), Belgium (2.7%), Finland (2.6%), the Netherlands (2.2%) and Austria (2.1%). In Sweden, Belgium and Finland the majority of the vehicles are PHEVs, whereas in the Netherlands and Austria BEVs are dominating. For the European Union as a whole, the market share of electric vehicles was 1.4% in 2017 with similar shares of PHEVs and BEVs (EAFO, 2018).

The market for FCEVs remains small and public numbers are not widely available. Global sales of FCEVs represent only a small percentage of total EV sales: 0.5% in 2016 (Cano et al., 2018). The European Alternative Fuels Observatory reported in the first quarter of 2018 a FCEV fleet of 640 passenger cars, 85 buses, and 239 light commercial vehicles. The EU countries with the most FCEV deployment are Germany, Norway, and Denmark. France has a remarkable high share of light commercial FCEVs (EAFO, 2018).

Deployment of BEVs, HEVs and FCEVs are mainly dependent on advancements in battery or fuel stack technology (Cano et al., 2018). Prices for batteries have declined rapidly in the last years. Average costs for battery packs in 2015 were less than \$270/kWh for PHEVs and estimated \$210/kWh for BEVs (OECD/IEA, 2016b). It is generally assumed that in order to compete with internal combustion engines, battery costs should decrease further to around \$150/kWh (Nykvist & Nilsson, 2015; IRENA, 2017). A study by Nykvist & Nilsson (2015) combining results from different publications shows that this level is expected to be reached by 2025. For FCEVs total vehicle costs are estimated at \$60,000 (OECD/IEA, 2015).

In the World Energy Outlook 2017, the growth of electric vehicles is expected to continue. When including announced policy plans, decreasing battery costs, increased charging infrastructure and predicted trends in the oil industry, it is expected that the global electric vehicle market will reach 106 million and 277 million vehicles by 2030 and 2040, respectively. China remains the main actor in the market, accounting for 40% of global investments in electric vehicles. However, the global market share of electric vehicles by 2040 is expected to be only 14%. For larger market shares and for keeping global temperature increase under two degrees, stronger policy support is needed. In a two degrees scenario the global amount of electric vehicles increases to 243 million in 2030 and 873 million in 2040, with a 40% share of car stock in 2040 (OECD/IEA, 2017c). The IRENA two degrees roadmap shows a lower total electric vehicle stock projection of 160 million by 2030 (IRENA, 2017). With the current growth rate, electric vehicles are on track for the two degrees scenario (OECD/IEA, 2017a). According to IRENA, a two degrees scenario shows over 1 billion of electric vehicles on the road by 2050, of which 965 million are passenger cars. In order to achieve this number, most of the passenger vehicles sales from 2040 onwards need to be electric (IRENA, 2018a). Projections for electric vehicles are mainly based on BEV and PHEV deployment, because these are much wider diffused than FCEVs (OECD/IEA, 2017b).

3.7.3 EXPERIENCE CURVES

The experience curves and datasets for the three vehicle types considered (BEVs, HEVs and FCEVs) are shown below in

Figure 26. The data represent battery pack (or fuel cell stack) costs per kWh as a function of cumulative GWh sold of each technology. Thus, these curves represent only the electricity storage component of the respective vehicles. Other components of electric vehicles likely

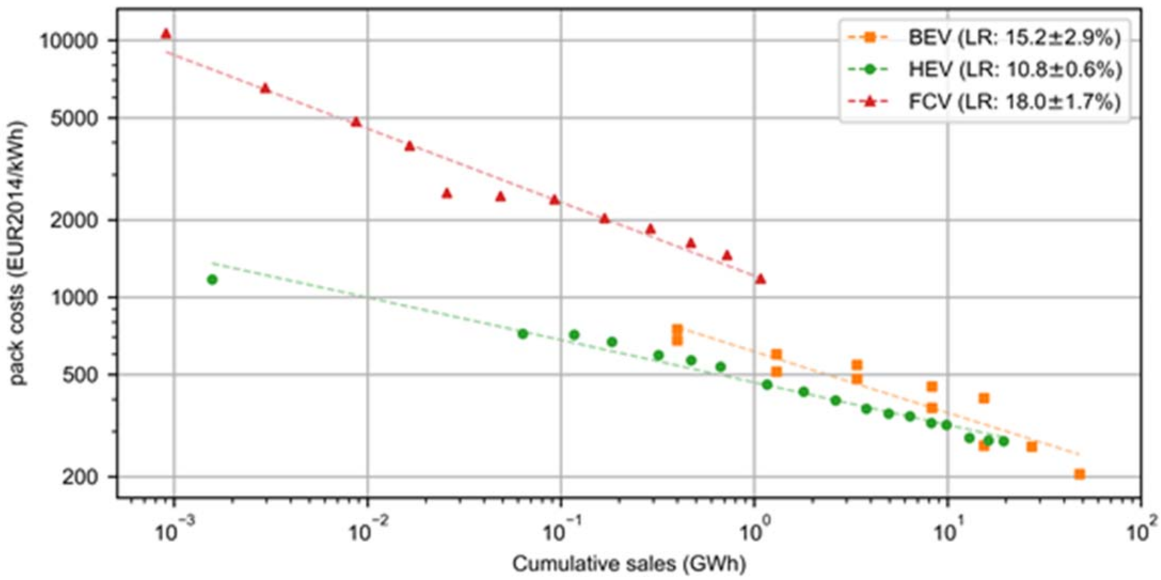

Figure 26: Experience curve for vehicle battery packs and fuel cell stacks. Data sources: Schmidt et al (2017), Nykvist & Nilsson (2015), own data collection.

also show learning effects, but since the energy storage packs account for the majority of the cost difference between electric and conventional vehicles, we have examined only this component. The results indicate varying learning rates for the different vehicle types. The highest learning rate is observed for fuel cell stacks (18%), while hybrid EV batteries only have a learning rate of 10%. The data for BEV batteries is taken together from two data sources with varying differences between the costs, resulting in a learning rate of 15.2±2.9%.

3.7.4 DATA COLLECTION AND METHODOLOGICAL ISSUES

An overview of the general data collection issues applicable to electric vehicle battery/fuel-cell packs is given in Table 10. The main issues related to the collected datasets for electric vehicles is that they do not refer to electric vehicles as a whole, but rather describe the costs for just the battery packs or fuel cell stacks of electric vehicles. Although these costs for the electricity storage components currently represent the majority of the price differential between EVs and conventional vehicles, it would be beneficial to gain insight into the price developments of other components specific to EVs such as the power train and battery management system, to analyse in more detail the historical and prospective price trends of these vehicles, and to have insight in the development of costs of complete electric vehicles.

The battery pack costs shown here are given in EUR/kWh, as a function of cumulative GWh of battery packs sold. Both units do not directly relate to electric vehicles, hence, to estimate future costs of electric vehicles, assumptions need to be made on the battery pack size per electric vehicle. Assuming larger battery packs would result in faster price declines of the battery packs for the same number of electric vehicles sold. Thus, the time dependent decline in battery pack prices depends strongly on the assumption of battery pack size in future electric vehicles.

As with the energy storage datasets, spill over effects from other applications in the electricity storage industry could likely affect BEV battery pack prices but are not taken into account due to the complexity of this in regards to modelling. Ideally, in a more complex experience curve modelling environment, separate experience curves should be used for lithium-ion cells, battery management and power electronics, and other components.

Table 10: General data collection issues for electric vehicle battery and fuel cell packs

Issue	Resolution	Applicability
Data is not for cost but for price		
Data not available for desired cost unit		
Data is valid for limited geographical scope		
Cumulative production figures not available		
Data is in incorrect currency or currency year	Convert currency and correct for inflation	☑
Early cumulative production figures are not clear or available		
Supply/demand affecting costs significantly	Us data as is but recommend tracking and updating	☑

Lack of empirical (commercial scale) data

3.8 Power to Hydrogen (Electrolysis)

3.8.1 Description of technology

Producing hydrogen is based on the scientific principle of dissociation of water, where two molecules of water (H_2O) are separated into two molecules of hydrogen (H_2) and one molecule of oxygen (O_2). The dissociation of water is an endothermic reaction, so it requires energy to take place. The use of electricity for producing hydrogen is called electrolysis (Abbasi & Abbasi, 2011; Twidell & Weir, 2015). Electrolysis is performed by applying a voltage to two electrodes that are submerged in water, to which an electrolyte is added. For electrolytes, high conductivity is important to reduce transport losses. This can be achieved by using strong acidic or strong alkaline electrolytes (Schalenbach et al., 2016). Electrolysis technologies are usually categorized in low temperature systems with alkaline cells or proton exchange membrane (PEM) cells, and high temperature systems with solid oxide (SO) cells. From these types, the alkaline electrolyser is most mature and economically attractive (Reiter, 2016). Common alkaline electrolysers use potassium hydroxide (KOH) as electrolyte. These electrolysers do not require valuable or rare metals. Typically they use electrodes made of nickel (NREL, 2009).

An overview of hydrogen production by electrolysis at the cell level is shown in Figure 27a and at the system level in Figure 27b. Besides the electrolysis module, typical systems include cooling water for the hydrogen generation unit, pre-pressurization gas, and inert gas (NREL, 2009).

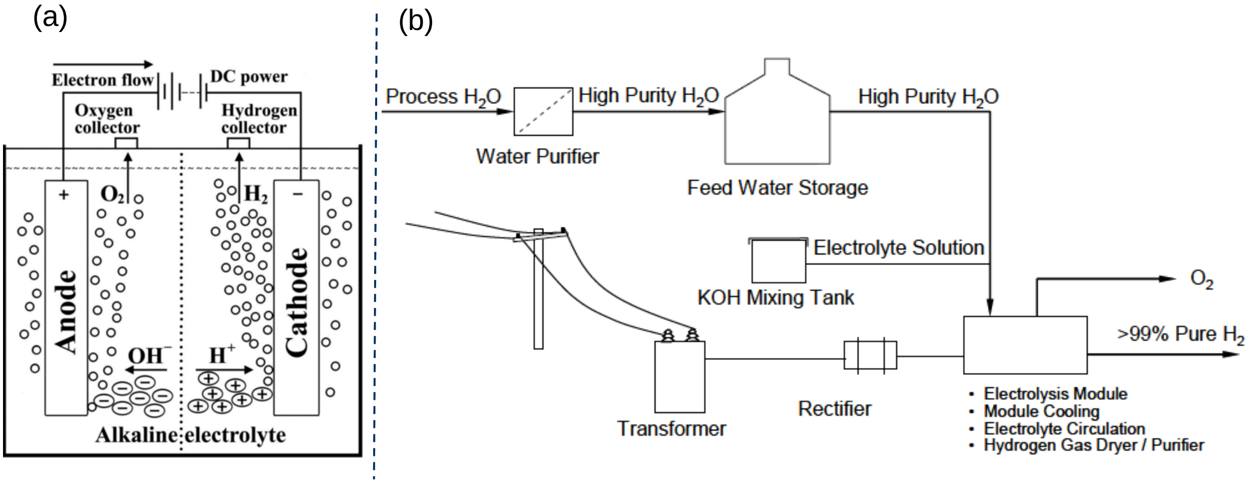

Figure 27: Schematic overview of alkaline electrolysis (a) and typical process for hydrogen production via electrolysis (b). Sources: Santos et al. (2013) & NREL (2009).

The electrolyser unit comes in different sizes and can be applied both to small-scale distributed production as well as large-scale central facilities for connection to the electricity grid (US DRIVE, 2017).

3.8.2 Market developments

Today, hydrogen is used as a feedstock in many industries. It is used in the refining industry for hydrocracking and desulphurization, in the chemical industry for ammonia and fertilizer production, for metal and methanol production, and in the food and electronics industries (IEA Hydrogen, 2017). Required hydrogen for these applications is mainly produced from fossil resources, representing 95% of global production and 60 Mt/year (Philibert, 2017). Hydrogen from fossil resources is produced by means of mature technologies operating on a large scale (OECD/IEA, 2015).

Because of the need for decarbonisation of emission-intensive hydrogen production from fossil fuels, producing renewable hydrogen via electrolysis is gaining interest. The technology of water electrolysis is about 200 years old. The first experiments took place around 1800 and the first applications around 1890. The alkaline electrolyser has been developed around 1930, and the PEM electrolyser in the 1970s (Rashid et al., 2015). SO electrolysers gained interest from 1980 onwards and are the least developed technology (Laguna-Bercero, 2011).

Besides current uses, (renewable) hydrogen is believed to have opportunities as fuel for transportation (see fuel cell electric vehicles in section 3.7), as energy carrier for storage applications, and as substitute for fossil fuel in various industry applications (IEA Hydrogen, 2017). Table 11 shows the performance of renewable hydrogen production technologies compared to conventional hydrogen production by fossil fuels, called steam methane reforming (OECD/IEA, 2015).

Table 11: Overview of hydrogen production methods. Source: OECD/IEA (2015).

Application	Power or capacity	Efficiency	Initial investment	Lifetime	Maturity
Steam methane reformer (large scale)	150-300 MW	70-85% (LHV)	400-600 USD/kW	30 years	Mature
Steam methane reformer (small scale)	0.15-15 MW	51% (LHV)	3,000-5,000 USD/kW	15 years	Demonstration
Alkaline electrolyser	Up to 150 MW	65-82% (HHV)	850-1,500 USD/kW	60,000-90,000 hours	Mature
PEM electrolyser	Up to 150 kW (stacks) Up to 1 MW (systems)	65-78% (HHV)	1,500-3,800 USD/kW	20,000-60,000 hours	Early market
SO electrolyser	Lab scale	85-90% (HHV)	-	~1,000 hours	R&D

It can be seen that alkaline electrolyser is considered the most mature and economically attractive electrolyser technology. However, it remains more expensive than large scale steam methane reforming. As PEM and SO electrolyser technologies are less developed, they are considered to have greater potential for cost-reductions and technology improvements (OECD/IEA, 2015). Furthermore, PEM and SO electrolysers are better suitable for electrolysis with intermittent electricity sources such as wind or solar (OECD/IEA, 2015; Götz et al., 2016). Such electrolysis units are currently reaching demonstration scale and have not yet seen large deployments (REN21, 2017). Technology advancements are needed before being ready for widespread commercialisation (IRENA, 2018a).

The uptake of renewable hydrogen by electrolysis is facing difficulties because of low conversion efficiencies and high costs in transportation and distribution. Furthermore, the uptake of electrolysis is dependent on developments in other sectors as well. Future wide availability of (excess) electricity and high fuel costs will favour electrolysis (OECD/IEA, 2017a). A roadmap by the organisation US Drive, a partnership of various actors in the US, considers distributed hydrogen production via electrolysis a near- to midterm pathway, and centralised hydrogen production a longer-term pathway (US DRIVE, 2017).

3.8.3 EXPERIENCE CURVE

Figure 28 shows an experience curve for alkaline electrolysis. The experience curve is derived from the dataset of Schmidt et al (2017) and from literature by Caprioglio et al. (1974), Bogers (1975), Kelley et al. (1976), Cox & Williamson (1977), Hammerli (1984), Hoffman et al. (2001), Gløckner & Aalberg (2005) and Kuckshinrichs et al. (2017). Data on electrolyser capacity and prices gathered from Schmidt et al., were provided in GWh and price per energy ($/kWh) respectively. The power-to-energy ratio (C-rate) provided by Schmidt et al. (C= 1/10h) was used to calculate capacity and price data in terms of power. The curve fitted to the dataset provides a learning rate of 17.8% with a relatively high parameter error, resulting from the spread of data around the fitted curve, and the relatively low number of data points. Especially the first data point strongly determines the slope of the curve (and as such the learning rate).

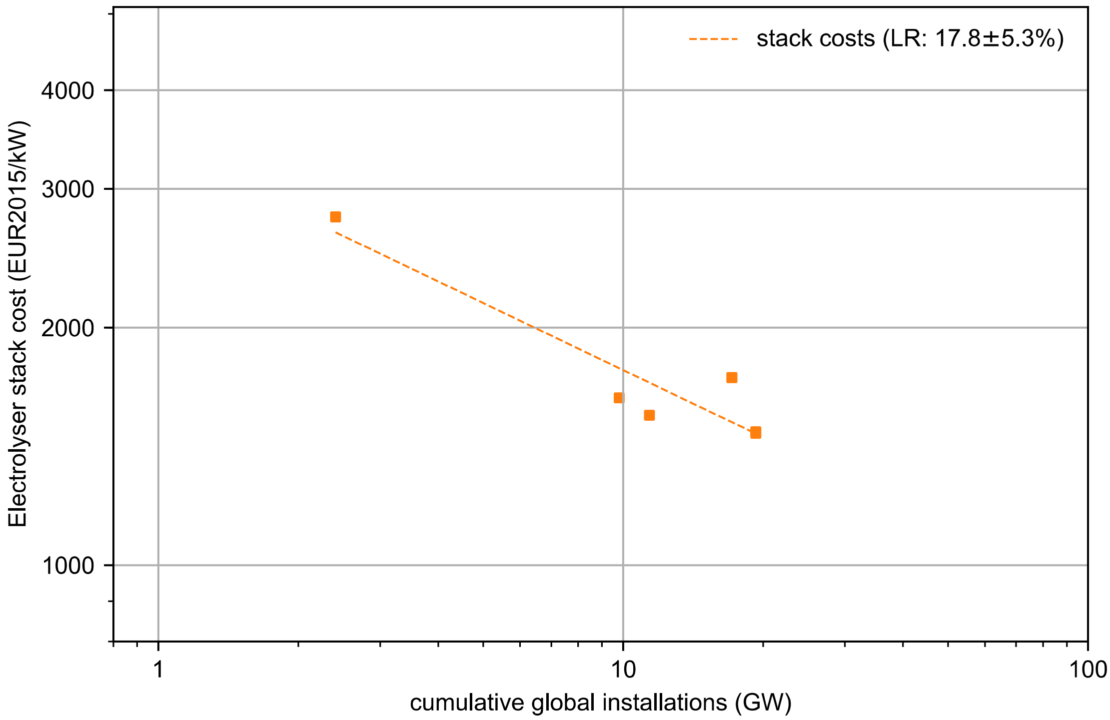

Figure 28: Experience Curve for Power-to-Hydrogen (alkaline electrolysis)

All electrolysers consist an electrolyser stack, comprising up to 100 cells, and the BOP. Stacks can be mounted in parallel using the same BOP infrastructure, which is why electrolysers are highly modular systems. Therefore, most price reductions can be attributed to technological improvements at a modular level. Some of these improvements are (Ursua, Gandia, Sachis; 2012):

- Minimizing the space between the electrodes in order to reduce the ohmic losses thus making it possible to work with higher current densities. Currently, distances among the electrodes below 1 mm are typical, what is referred to as zero-gap configuration.
- Development of new advanced materials to be used as diaphragms replacing the previous ones made of asbestos. In this regard, the use of ion exchange inorganic membranes has become widespread.
- Development of high-temperature alkaline water electrolysers: Working temperatures up to 150°C increase the electrolyte conductivity and promote the kinetics of the electrochemical reactions on the electrodes surface.
- Development of advanced electro-catalytic materials to reduce the electrode over voltages.

3.8.4 DATA COLLECTION AND METHODOLOGICAL ISSUES

An overview of the general data collection issues applicable to power-to-hydrogen is given in Table 12. Other than the standard issues detailed in this table, few other issues were encountered during data gathering and analysis. Some of the data gathered from literature sources had no clear distinction between centralized and decentralized hydrogen production and were derived from interviews with manufacturers and experts and may not mirror true prices of electrolysers. There was a lack of reliable capacity and price data between the year 1956 and 1970, probably due to the low deployment rate which can be attributed to alkaline electrolysers being in its infancy stage. This results in the learning rate being significantly affected or determined by the first datapoint in the graph of Figure 28. Cumulative installed capacity data derived from Schmidt et al. was provided in kWh (storage). This data was reproduced as kW using a C-rate (power to energy ratio) defined by Schmidt et al. A different C-rate (or a C-rate changing over time) would affect the cumulative installed capacity thereby affecting the learning rate.

Table 12: General data collection issues for power-to-hydrogen.

Issue	Resolution	Applicability
Data is not for cost but for price	Use price data as indicator for costs	☑
Data not available for desired cost unit	Convert data to desired unit if possible	☑
Data is valid for limited geographical scope	Convert currency Combine with other datasets from various geographical scopes	☑
Cumulative production figures not available	Calculate from annual production figures Calculate from annual sales figures	☑
Data is in incorrect currency or currency year	Convert currency and correct for inflation	☑
Early cumulative production figures are not clear or available		
Supply/demand affecting costs significantly		
Lack of empirical (commercial scale) data		

4 OVERVIEW AND COMPARISON OF EXPERIENCE CURVES

4.1 OVERVIEW OF DEVISED LEARNING RATES

In Table 13 below, an overview is given of the learning rates found for the technologies presented in this report. A number of general observations are made:

With the exception of onshore wind[5], 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 (7.5% 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. 2008; chapter 19). The learning rates presented in Table 13 below show an average of 15% (the learning rates of 24.5 and 25.8% for onshore wind were excluded) from this average).

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

4.2 COMPARISON AND DISCUSSION OF FINDINGS BETWEEN TECHNOLOGIES AND SECTORS

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 has 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 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

[5] 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.

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 most 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, there are undisputedly the technology following most closely and consistently an experience curve. 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, it also become apparent that the balance-of system costs need to be modelled separately, as these learn with a different learning rate (about 13%).

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

Table 13: Overview of learning rates and learning rate errors presented in this report.

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, 2006
NGCC + CCS	2.2%		MW installed	kW	From Rubin et al, 2006
Coal + CCS	2.1%		MW installed	kW	From Rubin et al, 2006
Industrial CCS	11% 12%		Na.	Na.	From Rubin et al, 2006 for 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	15.5%	7.5%	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 – turbine price index	25.8%	3.1%	GW installed	MW	2009-2016 data only, not advised to use
Wind – offshore system	10.3%	3.3%	GW installed	MW	
Wind – onshore system	5.9%	1.3%	GW installed	MW	1982-2016 data
Wind – onshore system	24.5%	2.1%	GW installed	MW	2009-2016 data only
PEFC micro-CHP	19.3%	1.6%	Units sold	kW	

learning between about 10-18%, depending amongst others on the chosen system boundaries (Neij et al. 2003; Junginger 2005, PhD thesis). However, as discussed in section 0, 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 onshore wind shown for the 2009-2016 period are excluded from the range cited above, as this is only over a rather short period of time / few doublings of cumulative capacity. 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: 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 (Voormolen et al. 2016), 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.

Another energy-producing technology covered by this report is ***PEFC micro-CHP***. For this technology, only one study 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.

Last but not least, 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.

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 curves somewhat uncertain, an 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%). 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.

Last but not least, ***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. 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 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.

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.

5 MODEL IMPLEMENTATION

5.1 OVERVIEW

In the following, the implementation of learning rates into the energy system models used in the project Reflex is described. Figure 29 gives an overview on the models used and the methods they are based on. Depending on the methods, learning rate implementation is facing different challenges.

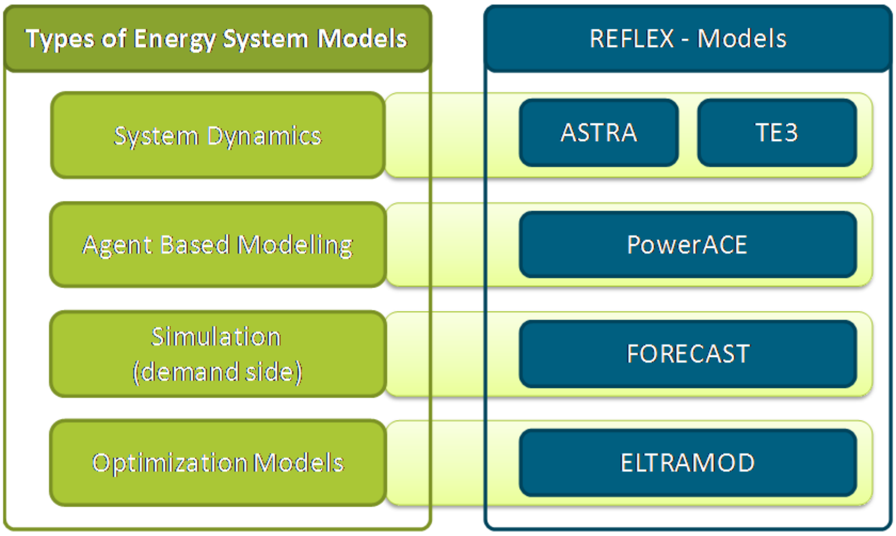

Figure 29: Overview of energy system models used in Reflex to implement learning rates

5.2 Implementation of Experience Curves in ELTRAMOD

5.2.1 General Model Information

ELTRAMOD (Electricity Trans-shipment Model) is a bottom-up electricity market model incorporating the electricity markets of the EU-28 states, Norway, Switzerland and the Balkan region (Albania, Bosnia-Herzegovina, Macedonia, Montenegro, Serbia) as well as the Net Transfer Capacities (NTC) between these countries while the electricity grid within one country is neglected. Each country is treated as one node with country specific hourly time series of electricity demand and renewable feed-in. ELTRAMOD is a linear optimisation model which calculates the cost-minimal generation investments and dispatch in additional transmission lines and storage facilities. The set of conventional power plants consists of fossil fired, nuclear and hydro plants where different technological characteristics are implemented, such as efficiency, emission factors and availability. Daily prices for CO_2-allowances, as well as daily wholesale fuel prices supplemented by country specific mark-ups are implemented in ELTRAMOD. The country and technology specific parameters and the high temporal resolution of 8760 hours allows detailed analyses of various research questions concerning the challenges of the future European electricity system. For example, the trade-off between network extension and storage investment as well as import and export flows of electricity in Europe can be analysed. Furthermore, the integration of intermittent renewable feed-in, such as the interaction between RES-curtailment and storage or transmission expansion can be explained. Additionally, flexibility requirements or changes in the price structure can be identified and analysed. An overview of the technologies which are considered in endogenous investment decisions in ELTRAMOD are shown in Table 14.

Table 14: Technologies considered in endogenous investment decisions in ELTRAMOD

Technology List		Learning Curves
Combined Cycle Gas Turbine	CCGT	
Open Cycle Gas Turbine	OCGT	
Gas-Steam-Turbine	GasSteam	
Combustion-Gas-Turbine with CCS	Gas_CCS	x
Combined Cycle Oil Turbine	CCOT	
Open Cycle Oil Turbine	OCOT	
Oil-Steam-Turbine	OilSteam	
Hard Coal Power Plant	Coal	
Hard Coal Power Plant with CCS	Coal_CCS	x
Lignite Power Plant	Lignite	
Lignite Power Plant with CCS	Lignite_CCS	x
Nuclear Power Plant	Nuclear	
Lithium-Ion Battery	Battery_Li	x

Redox-Flow Battery	Battery_RF	x
Adiabat Compressed Air Energy Storage	A-CAES	
Power-to-Gas (Electrolyzer)	P2G	x
Power-to-Heat (Electric Boiler)	P2H	

5.2.2 *Challenges of Implementing Learning Curves in ELTRAMOD*

Within the REFLEX-project, ELTRAMOD is used to analyse interdependencies between different flexibility options in the European electricity system, taking existing regulatory frameworks into account. For this purpose, endogenous investments, based on learning curves, as well as the dispatch of each technology will be modelled and investigated. The implementation of learning curves in ELTRAMOD is challenging due to the fact that ELTRAMOD is an optimization model. To find a global optimal solution, the problem has to be convex. The characteristics of learning curves lead to a non-linear and non-convex optimization problem, where the global optimal solution cannot be guaranteed. A solution would be the linearization of the non-linear and non-convex problem by step-wise approximation of the cost-curve (see Figure 30, approach presented by Barretto (2001)).

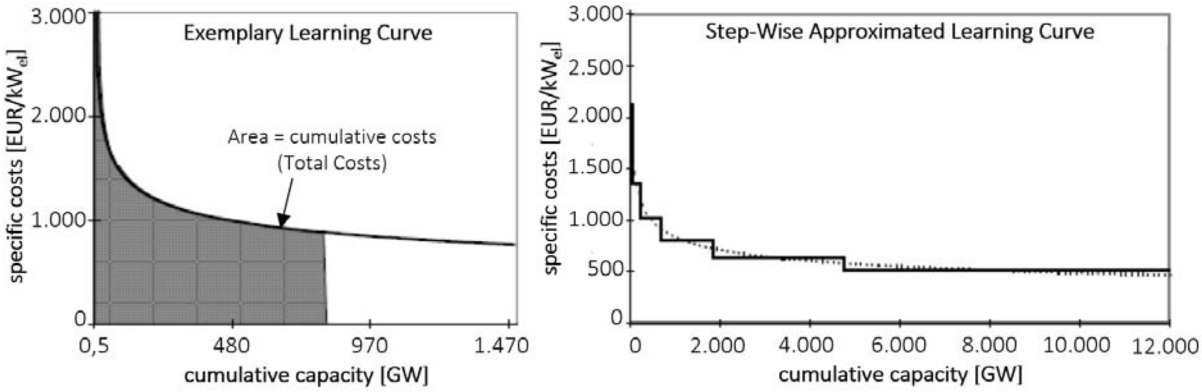

Figure 30: Exemplary experience curve (left) and its step-wise approximation (right). From Barretto (2001).

The implementation of the step-wise approximated learning curve into ELTRAMOD is complex and leads to very high computation times. A more simplified solution is the direct implementation of the specific investment costs [EUR/MW_{el}] per technology, year (2014-2050 in ten-year-steps) and scenario (Mod-RES, High-RES Decentralized, High-RES Centralized) in the target function, which is presented in the next section. However, this simplified approach cannot clearly be defined as implementation of learning curves because the learning is not calculated endogenously in ELTRAMOD. The approach, that implements the specific investment costs exogenously, consider the worldwide technological progress under perfect foresight and the respective years, but the capacity expansion in ELTRAMOD is not considered in the learning progress. Nevertheless, due to the fact that ELTRAMOD only calculates the capacity expansion in EU-28, Norway, Switzerland and the Balkan countries the approach can be chosen. The technological learning is considered by worldwide capacity expansion of the specific technologies. The influence of the added capacity in Europe on the experience curves is marginal.

5.2.3 MATHEMATICAL MODEL FORMULATION

The table below presents all conventional power plants and storages that are considered in the endogenous investment decisions within ELTRAMOD. For several technologies learning curves are implemented as for Gas CCS, Coal CCS, Lignite CCS, Lithium-Ion and Redox-Flow batteries as well as Power-to-Gas technologies (marked with x). For other conventional power plants learning curves are not formulated due to the scarcity of data or because of the fact that the technology learning is already saturated and no significant cost improvements are assumed. Hydro power plants as pump storage plants, reservoirs, run-of-river power plants and biomass as well as other renewable energy sources (RES) are not expanded endogenously within ELTRAMOD INVEST. The expansion of wind onshore, offshore and photovoltaic is calculated by another REFLEX-partner KIT-IIP. Their results are implemented exogenously into the model ELTRAMOD.

The specific investment costs [$co\_inv_{p,t}$ in EUR/MW_{el}], which results from the learning curves for some technologies, are directly implemented due to the annuity of total investment costs in the target function of the model. In the target function the total system costs are minimized under the assumption of perfect competition. The model is formulated as linear program (LP) in the General Algebraic Modeling System (GAMS). It uses the commercially solver CPLEX.

5.2.4 TARGET FUNCTION

The target function is minimized under the fulfilment of various equations (not mentioned here) as e.g. the energy balance or technical constraints of power plants and storages. For more information, please see the selected references (ESA[2], 2013; Gunkel et al., 2012; Müller et al., 2013; Barreto, 2001). An overview of ELTRAMOD's target function is shown in Figure 32

$$MIN \left(\begin{aligned} &\sum_{p \in P} \sum_{t \in T} (OC_{exist_{p,t}} + OC_{new_{p,t}} + CO\_LC_{UP_{p,t}} + CO\_LC_{DOWN_{p,t}}) \\ &+ \sum_{p \in P} (INV_p + (C_{INST_p} + C_{ADD_p}) \cdot co_{fuel}) \\ &+ \sum_{t \in T} \sum_{app \in APP} \sum_{c \in C} (DSM_{UP_{t,app,c}} \cdot co_{dsm_{t,app}}) \\ &+ \sum_{t \in T} \sum_{c \in C} (CURT_{RES_{t,c}} \cdot co_{curt_{t,c}} + DUMP_{DEM_{t,c}} \cdot co_{voll_{t,c}}) \end{aligned} \right)$$

$$\forall p \in P;\ \forall t \in T;\ \forall c \in C;\ \forall app \in APP$$

$$INV_p = C\_ADD_p \cdot an_p$$

$$an_p = \sum_{p \in P} \sum_{t \in T} co\_inv_{p,t} \cdot \left(\frac{(1+i)^n \cdot i}{(1+i)^n - 1} \right)$$

$OC_{exist_{p,t}}$	Operational costs of existing power plants
$OC_{new_{p,t}}$	Operational costs of new installed power plants
$CO\_LC_{UP_{p,t}}$	Costs of upward load changes
$CO\_LC_{DOWN_{p,t}}$	Costs of downward load changes
INV_p	Investment costs for new power plants
C_{INST_p}	Installed capacity
C_{ADD_p}	Added capacity
co_{fuel}	Fuel costs
$DSM_{UP_{t,app,c}}$	Load increase by P2X − technologies
$co_{dsm_{t,app}}$	Costs of load increase by P2X − technologies
$CURT_{RES_{t,c}}$	Curtailed generation of wind and pv
$co_{curt_{t,c}}$	Costs for curtailment
$DUMP_{DEM_{t,c}}$	Dumping surpluses of demand
$co_{voll_{t,c}}$	Costs of value of lost load
an_p	Annuity
n	Economical lifetime
i	Interest Rate
$co\_inv_{p,t}$	Specific investment costs $[EUR/MW_{el}]$

Figure 32: Overview of target function and parameters for ELTRAMOD

5.3 Experience Curve implementation in ASTRA

In ASTRA, the technology share of new vehicle purchases is modelled based on an adapted total cost of ownership (TCO) approach that considers consumer prices for vehicles, cost for energy consumption, maintenance costs, taxes, insurance, road charges and fuel procurement costs. Learning curves are implemented for the development of the consumer prices for battery electric vehicles (BEV), plug-in hybrid electric vehicles (PHEV) and fuel cell electric vehicles (FCEV).

The total vehicle price is calculated as the sum of the following three parts:

- a technology-independent vehicle base price with a development of prices over time due to increasing safety, efficiency and convenience of the vehicles,
- a price for major technology-dependent components of new powertrain vehicles, in particular batteries and fuel cell stacks that are implemented via learning curves, and
- a technology-dependent part representing diverse components related to the specific technology that either do not show additional learning effects anymore like for internal combustion engines or that are assumed to decrease slightly over time.

ASTRA is a System Dynamics model. Learning curves can be implemented endogenously using the stock and flow concept. Cumulative production of batteries and fuel cell stacks as basis for the learning curves is implemented by a stock in the model. Battery and fuel cell capacities related to the new vehicle purchases flow into this stock. As technological learning does not only relate to prices but also to the ranges of vehicles, an increase of battery capacity per vehicle is assumed over time.

Within the model, battery capacities of BEVs and PHEVs are summed up across all road modes - cars, light duty vehicles, trucks and buses. The same approach was used for the fuel cell stacks of FCEVs.

ASTRA covers the EU28 countries plus Norway and Switzerland. For these countries, cumulative production is simulated endogenously. As learning parameters refer to global learning, capacities of non-European vehicle purchases were added to the cumulative production by using external data.

For cars, ASTRA exchanges purchase numbers with the TE3 model in several rounds to simulate global learning. TE3 covers sales for the USA, China, India and Japan. In order to scale up to the cumulative production of global car purchases, the numbers of these four countries were multiplied with a factor based on global production statistics.

5.4 Implementation of experience curves in a system dynamics model using the example of the TE3 Model

The purpose of the TE3 (Transport, Energy, Economics, Environment) model is to support policy-making in the context of oil demand reduction and GHG mitigation from car travel (Gomez Vilchez, 2016). This tool explores key impacts of future car technology market developments and provides an international perspective by covering six major car markets. The modelling approach is a mixed method combining econometrics and system dynamics (SD).

For the implementation of the experience curve of electric vehicle battery (EVB) in the TE3 model the SD method is used, which means feedback loops as well as stock and flow variables are included. Especially the following equation (1) is used.

$$Y = a \cdot X^{b} \qquad (1)$$

$$Y = 797.48 \cdot X^{-0.2097} \qquad (2)$$

Equation (2) represents the equation (1) with provided data for the parameter a and b by the University Utrecht and this is implemented in the TE3 model. The variable *Y* represents the costs as function of cumulative kWh of battery in USD/kWh and the variable *X* includes the cumulative production for the batteries. The EVB cost is affected by the learning rate and the cumulative production of EVs. By endogenizing the latter, the EVB cost can be altered. There is a partial endogenization of the EVB costs. This means that, after a certain simulation year, the experience curve no longer relies on historical data on cumulative EV production but is instead based on the cumulative EV production simulated in the model. The EVB cost is determined using data for the period 2000-2015 and the simulated cumulative EV production for the period 2016-2050. Moreover, there is a linkage with another transport model, ASTRA, to include simulated EU sales of EV and PHEV. In this way, key non-European countries and the EU countries are jointly connected, thereby determining their future EV market evolution. This linkage represents the global development of the EVB with the respective experience curves included.

5.5 FORECAST

The FORECAST model is designed as a tool that can be used to support strategic decisions. Its main objective is to develop scenarios for the long-term development of energy demand and greenhouse gas emissions for the industry, residential and tertiary sectors of entire countries. FORECAST considers a broad range of mitigation options combined with a high level of technological detail (see Table 15). It is based on a bottom-up modelling approach considering the dynamics of technologies and socio-economic drivers. Technology stock turnover and adoption are explicitly simulated to allow insights into transition pathways and speed.

Table 15: Technology detail included in FORECAST

Industry	**Buildings** (services and residential)	**Appliances** Services and residential)
Energy intensive processes and products • oxygen steel, electric steel, aluminium, copper, cement, paper, pulp, flat glass, ethylene, ammonia, chlorine, etc. **Steam generation** • Boilers (electric, gas, etc.) • Steam turbines • Gas turbines • Fuel cells • Large heat pumps • Internal combustion engines **Electric motor systems** • Pumps, Fans, Compressed air, Machine tools, Process cooling, Other motors **Lighting** **Space heating** **Space cooling**	**Buildings** • Single family • Multi family • Commercial **Space heating** • Electric radiator • Coal boiler • Lignite boiler • Natural gas boiler • Oil boiler • Solar thermal plus others • Biomass boiler • District heating • Heat pump • CHP	**Residential appliances** • Lighting • Refrigerators, Freezers, • Washing machines, Dryers • Dishwashers • TV • Space cooling • Cooking • Circulation pumps • Others **Service sector appliances** • Lighting • Street lighting • ICT data centers • Ventilation and air-conditioning • Circulation pumps • Elevators • Cooking • Laundry • Refrigeration

The investment decision in new space and process heating equipment is modeled as a discrete choice process, where households or companies choose among alternative technologies to satisfy a certain energy service. It is implemented as a logit-approach considering the total cost of ownership (TCO) of an investment plus other intangible costs. This approach ensures that even if one technology choice is more cost-effective than the others, it will not gain a 100% market share. This effect reflects heterogeneity in the market, niche markets and non-rational behavior of companies and households, which is a central capability to model policies (see for example Elsland et al. 2014, Biere et al. 2015).

Principally, the FORECAST simulation approach is well suited to include technology learning, because:

- Technology is explicit: Level of detail allows consideration of technology parameters
- Total costs of ownership (TCO) are a central element in decision making
- Parameters like CAPEX or efficiencies are specifically considered for individual technologies
- Technology diffusion in year t is a function of the diffusion in year t-1 plus additional parameters
- Less mathematical challenges compared to optimisation models

However, there are also limitations and restrictions to model implementation. Among others, these are:

- Models are used for countries, while learning is (partly) driven by global developments
- Models are sectoral, while learning is cross-sectoral for many technologies
- Scarce empirical data for demand side technologies
- Complexity of models: Understanding the dynamics of technology choice is already very complex with exogenous consideration of technology cost
- For energy efficiency, costs and performance of technologies are compared to a reference

Having these challenges in mind and particularly the sectoral system boundaries of FORECAST in face of cross-sectoral technology learning, we have decided to choose an iterative approach to integrate learning rates into FORECAST, where the actual calculation of technology costs is done outside the core model. Figure 33 summaries the iterative approach finally used. Accordingly, it starts with an estimation of future installed capacities for the technologies in focus, which provides the basis for the calculation of future technology costs. This still takes place outside the core FORECAST model. Then, the costs time-series are fed into the model, the simulation is run and results on future installed capacity are extracted by sector. These results are summed up and compared to the initially assumed future cumulative capacity. In case of high deviations, the process begins from the beginning, taking the resulting capacity projection as input to the next iteration.

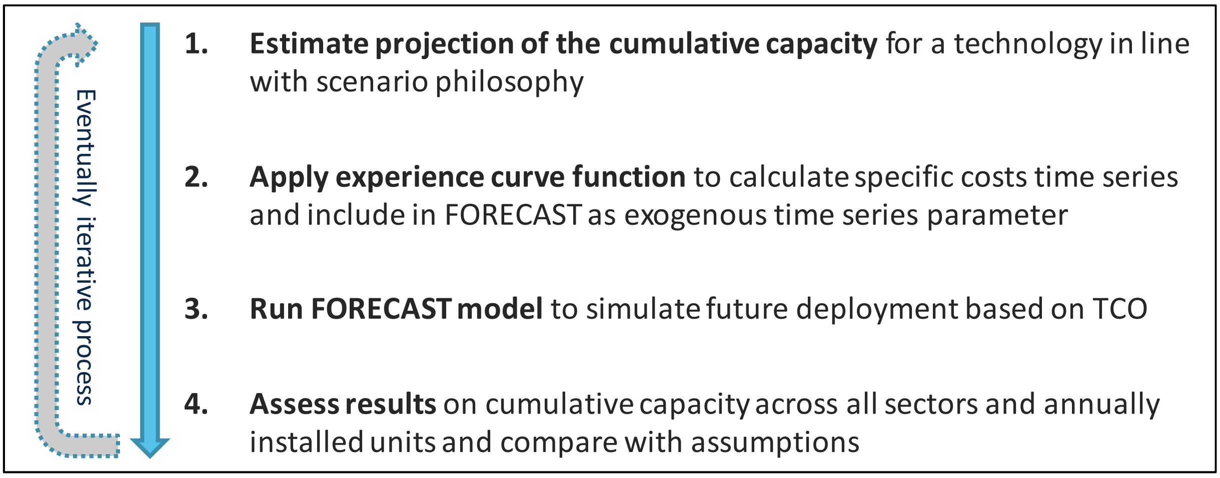

Figure 33: Experience curve implementation in FORECAST

With the modelling of technology learning, it was decided to focus on technologies with high demand response potentials. Consequently, technology learning has been decided to include for heat pumps used for space heating and process heating in industry. Other relevant technologies like electric boilers are already very saturated and future technology learning is expected to be very low, hence a learning approach was not applied here.

5.6 PowerACE

PowerACE is an agent-based simulation model developed for the analysis of European electricity markets. The model includes various agents representing, e.g., generation companies and regulatory authorities. The different supply agents determine the dispatch of their own power plants on the day-ahead market (short-term perspective) and evaluate capacity expansions through investments in new generation capacities (long-term perspective).

Each simulated year, the supply agents perform investment decisions by calculating the net present values (NPVs) for different investment options including various types of conventional power plants (e.g. nuclear, lignite, coal, open cycle gas turbine, combined cycle gas turbine) as well as storage options (lithium-ion batteries, redox-flow batteries, compressed air energy storage). The input parameters for the NPV calculation include the specific investment costs [EUR/MW], yearly fixed costs for operation and maintenance and variable costs consisting, e.g., of the costs for fuel or emission allowances. Further, the expected future electricity prices are a fundamental driver affecting the investment decisions.

Given the methodology of the investment module in PowerACE, an endogenous implementation of experience curves is feasible by calculating new specific investment costs for the following simulation year using the added capacity of a certain technology resulting from the model-endogenous investment decisions. However, with the geographical scope of PowerACE currently being limited to Germany and its neighboring countries, this approach would not account for the technological learning outside of the regarded markets.

As the countries modeled in PowerACE only represent a comparably small share of the global markets, an alternative solution, which has been chosen for the REFLEX project, is an exogenously given adjustment of the specific investment costs per technology depending on the respective simulation year. Although, using this approach, model-endogenous investment decisions no longer have an impact on the development of the specific investment costs, still, a more realistic future development is modeled as worldwide learning is now being considered. Experience curves are only implemented for recent technologies, i.e., primarily large-scale batteries or carbon capture and storage.

6 RECOMMENDATIONS FOR MODELLING AND POLICY IMPLICATIONS

Within the REFLEX project, historical cost data was collected for a number of energy technologies, shown in Table 1. From this data, where possible, experience curves were derived. This report presents the technologies and data collected for those technologies for which experience curves could be derived. These 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 are 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 within Work Package 3 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 from this report. 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 deployment developments.

Aside from this issue, endogenous modelling can also be hampered by the design of the models. As an example, some of the models investigated within REFLEX are optimisation models that have 'perfect foresight'. Thus, when presented with competing technologies with different learning rates, these models will never choose to invest in some of the technologies, even though these technologies may be cheaper on the short term. In real life, however, this perfect foresight is lacking and government incentives in a world without this perfect foresight could lead to lock-in effects, as is also modelled by myopic (short-sighted) models, which only optimize of one time step rather than over the entire modelling period. The specific value of learning rates for individual technologies will heavily determine such lock-in effects, as they determine the speed of cost reductions. Varying learning rates as part of sensitivity and uncertainty analysis and comparing outcomes of both myopic and perfect foresight models may provide insights in such mechanisms. Furthermore, some technical issues also remain, like the issues with non-linearity in optimisation models. A simplified or exogenous approach to implement technological learning is thus sometimes required and in many cases also justified.

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 timeseries 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 expected with this more detailed approach, and weigh this against the added data requirements and increase of modelling complexity.

Policy implications:

- As a prime and major conclusion, we can state that al 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 missing, 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 design 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.

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