Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Current and future energy performance of power generation technologies in Switzerland

Study commissioned by the Swiss Academy of Engineering Sciences (SATW)

April 2018

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Preface

The Swiss Academy of Engineering Sciences (Schweizerische Akademie der Technischen Wissenschaften, SATW) aims at contributing to a fact-based discussion on the future of power generation. To this end, this study has been commissioned to Prof. Dr. Tobias Schmidt, head of the Energy Politics Group at ETH Zurich. The study aims at comparing the energy performance of different power generation technologies in Switzerland, and at pointing towards possible future developments concerning their energy performance.

The study has been prepared by the ETH Zurich author team in collaboration with the SATW. While the ETH Zurich team has been solely responsible for the methodology, data collection, and analysis, results and implications have been discussed continuously with Willy R. Gehrer (President of the SATW), Dr. Rolf Hügli (Secretary General of the SATW), and Prof. emeritus Ulrich W. Suter (Former President of the SATW), and their input as well as continuous support in the study is greatly acknowledged.

Finally, we like to thank the following experts that shared their view on the study methodology and results during an expert workshop on October 23rd, 2017 at ETH Zurich for their valuable input: Christian Bauer, Nils Epprecht, Daniel Favrat, Markus Friedl, Rolf Frischknecht, Toni Gunzinger, Tony Kaiser, Silvan Rosser, Rolf Schmitz, Andreas Ulbig, Christian Zeyer. The opinions expressed and arguments employed in this report do not necessarily reflect the views of the individuals involved in the expert workshop.

Note: This version (Nov 2018) includes two editorial changes: (1) Updated the reference for the academic article introducing the dynamic energy performance (upcoming in Energy & Environmental Sciences http://dx.doi.org/10.1039/C8EE01231H), (2) Correction of misprint in figure 20 (nr-CED of hard coal).

Abstract

With greenhouse gas emissions of fossil fuel-based energy systems posing a substantial threat to climate stability, societies worldwide recognise the need to transform their electricity generation portfolios fundamentally. In Switzerland, the ratification of the Paris Agreement and the decision to phase out nuclear power laid the foundation for realizing a new energy strategy with renewable energy technologies at its heart.

Assessing which power generation technologies are suitable to maintain security of supply while keeping carbon emissions low and electricity prices affordable, is, however, not trivial. Besides economic performance indicators and environmental indicators (both of which have been studied before), also energy performance indicators such as the non-renewable Cumulative Energy Demand (nr-CED) or the energy return on energy investment (EROI) can assist policy makers in comparing technological options. These indicators compare a technology's ability to make primary energy resources useful for society, and thus offer a complementary perspective independent from current price levels.

This study provides a consistent comparison of the present-day energy performance of power generation technologies, which can be considered relevant for the Swiss context. The analysis covers both renewable power generation technologies such as hydro power, wind power and photovoltaics, which are at the core of Switzerland's Energy Strategy 2050, and nuclear and fossil-fuel based technologies that are heavily used in neighbouring countries and are relevant given Switzerland's integration in the European electricity market. Furthermore, it provides a forward-looking assessment based on a novel dynamic energy performance indicator, taking into account possible learning effects with respect to material and energy efficiency.

Our results highlight the strong energy performance of hydropower. The study also shows a significant energetic improvement of solar PV and wind power over the last decades, making them a viable option in Switzerland from an energy performance perspective today. Consequently, concerns that the nuclear phase out and extension of renewables jeopardizes net energy efficiency and prosperity in Switzerland seem unfounded.

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Abbreviations

CF	Capacity factor
EROI	Energy Return on Energy Investment
IEA	International Energy Agency
kWh	Kilowatt hour
LCA	Life Cycle Assessment
LCOE	Levelized Cost of Electricity
LR	Learning rate
MJ_{el}	Megajoule of electrical energy
MJ_{pe}	Megajoule of primary energy
NDC	Nationally Determined Contributions (under the Paris Agreement)
nr-CED	Non-renewable Cumulative Energy Demand
O&M	Operation and Maintenance
PR	Performance ratio
W	Watt
WEO	World Energy Outlook
$	US dollar

1 Introduction

1.1 Motivation

With greenhouse gas emissions of fossil fuel-based energy systems posing a substantial threat to climate stability, societies increasingly recognise the need to transform their electricity generation portfolios fundamentally. The Paris Agreement, a landmark to combat climate change, has so far been ratified by 160 state parties (UNFCCC, 2015), with many of the commitments in the so-called ‘Nationally Determined Contributions’ (NDC) aiming at a decarbonisation of electricity systems (IEA, 2015; UNFCCC, 2016a).

In Switzerland, the majority of the electricity supply is currently provided by low carbon energy sources. However, in 2011, Switzerland has taken the long-term decision to phase out its five nuclear power reactors, which at present play a significant role in domestic power production (UVEK, 2011). This decision has laid the foundation for a new Energy Strategy, in which Switzerland commits to a sustainable and safe energy supply in the long term and places renewable energy technologies at the heart of its future electricity mix. Yet, with an expected increasing electrification of the transport and heating sector and the void left by the nuclear phase-out, Switzerland has to consider the full range of options for expanding its power generation capacities. Assessing which power generation technologies are suitable to maintain Switzerland’s current high level of security of supply while keeping carbon emissions low and electricity prices affordable, is, however, not trivial. Furthermore, as the public debates in the run-up to the referendum on the new Energy Law have shown, perceptions differ with regards to the relative merits of different technological options (NZZ, 2017). Thus, such complex decisions require a consideration of social, economic and environmental factors, a delicate balancing of competing interests and goals, and a careful analysis of all available technological options.

To complement domestic efforts, Switzerland also plans to use carbon credits from international mechanisms to reach its emission reduction commitments under the Paris Agreement (average reduction of greenhouse gas emissions by 35 percent over the period 2021-2030) (UNFCCC, 2016b). Credits from carbon mitigation abroad – e.g. by additional deployment of renewables in developing countries with a carbon-intense electricity mix – will be particularly crucial for Switzerland, as the comparably low-carbon Swiss electricity mix provides only limited potential for emission reductions, and other sectors such as industry and transport are often more difficult to de-carbonise. As determined in its NDC, Switzerland plans to only accept credits that meet high environmental standards, and will need to define which technologies qualify (UNFCCC, 2016b).

In this context, analytical tools can assist policy makers in assessment of technologies, and also Swiss policy makers increasingly turn to indicators providing information on the economic, environmental and energy performance of power generation technologies. For example, *economic performance indicators* such as the levelized cost of electricity (LCOE) measure the financial cost of generating one unit of electricity with a certain technology in CHF per kWh. *Environmental performance indicators* can, for example, assess the global warming potential in kg CO_2 equivalents per kWh generated by technology. Finally, *energy performance indicators* can, for example, quantify the the non-renewable Cumulative Energy Demand (nr-CED), or the Energy Returned on Energy Invested. For the Swiss context, the electricity generation costs and environmental performance of a wide range of power generation technology have been evaluated in several comprehensive studies (e.g. Bauer et al., 2017; Dones et al., 2007; Messmer and Frischknecht, 2016).

Energy performance indicators are also used in public debates (including in Switzerland), but have been less in the focus of academic research in Switzerland. Energy performance indicators compare a technology's ability to make primary energy resources useful for society (Carbajales-Dale et al., 2014). For the generation of electricity in any fossil-fuel based or nuclear power plant, energy must be invested to extract and process the fuel, to deliver it to the power plant, and to build, maintain and decommission the power plant. For the generation of electricity using renewable energy sources, significant amounts of energy need to be invested in the manufacturing of the renewable energy conversion technology, e.g. wind turbines and solar panels.

Simply put, energy must be invested to produce energy, and energy that is spent in the process of generating electricity is not available to fuel the economic activities of our societies anymore. It is therefore crucial to consider how much of these energy investments a power generation technology requires, to provide a unit of electricity ready for society to use. Clearly, a power generation technology should return substantially more energy over its life-time than it "consumed" in the form of energy investments. It also matters whether the energy extracted from the environment in order to produce one unit of electricity is renewable or non-renewable. Thus, energy performance indicators examine the "energy viability" of power generation technologies, and can therefore offer a complementary perspective in performance assessments of power generation technologies.

Recently, energy performance indicators have been used by some authors to question the energy viability of renewable energy technologies, in particular solar PV, claiming that manufacturing requires more energy than the technology can return over its lifetime. So far, academic contributions have struggled to provide a consistent picture with respect to the energy performance of power generation technologies, as a wide range of studies applying diverging modelling approaches and assumptions exist, which lead to scattering results. Some progress has been made in standardizing approaches, however, depending on the region the availability of studies with "apples-to-apples" comparisons is limited. For the Swiss context, such comparative studies are lacking altogether. Also, assessments of energy performance from the past are not necessarily appropriate to inform forward-looking decisions, especially for emerging technologies such as many renewables. The Swiss Academy of Engineering Sciences (SATW) therefore commissioned this study, to provide a meaningful and forward-looking basis for a debate on the energy performance of power generation technologies for the Swiss context. Additionally, given the importance of power storage technologies in future energy systems with high shares of intermittent generation, the energy performance of selected power storage technologies is analysed in an excursus.

1.2 Background and previous research

The domain of studying the net output of energy producing technologies and activities is referred to as Net Energy Analysis (Carbajales-Dale et al., 2014). The principal metric of Net Energy analysis, the EROI, has its origin in the 1980s, when it was predominantly applied to the extraction of fossil fuels (Hall, 2017; Hall and Cleveland, 1981). At that time, a number of studies showed that the oil extracted from American oilfields, as compared to the energy spent in the drilling and extraction efforts, was constantly declining, meaning that the EROI of American oil extraction was decreasing (e.g. Hall & Cleveland 1981). Thus, in addition to concerns at the time about the *availability* of fossil fuels (e.g. depletion of fossil fuels and peak oil; Hubbert (1966)), scientists also worried about the *accessibility* of the remaining fossil fuels (IAEA 1994). It was feared that an ever increasing portion of the available energy output would have to be re-invested to exploit less easily accessible fuels, leaving society with less energy available to power economic activities and growth (Hall et al., 2014; International Atomic Energy Agency and International Atomic Energy Agency IAEA, 1994). The worst possible scenario in this context, was that someday, the energy input required to extract a barrel of oil would be the same as the output of the extraction activity, rendering oil an unusable energy source for society.

However, with fears of fossil fuel shortages proving unfounded and fuel prices declining, the interest in the EROI waned in the following decades (Gupta and Hall, 2011). In recent years, there has been a renewed interest in Net Energy analysis and metrics like the EROI (or alternative indicators, such as the nr-CED) (e.g. Kittner et al. (2016); Raugei et al. (2012); Arvesen & Hertwich (2015a); Bhandari et al. (2015); Hall et al. (2009); Raugei & Leccisi (2016); Weissbach et al. (2013). Unlike in the beginnings where the EROI debate focussed on fuels, the metric is now increasingly applied to assess and compare the energy performance of *power generation technologies*: A controversy has arisen about the energy performance of new renewable energy technologies such as photovoltaics and wind energy, with questions coming up what the shift to renewable energies for climate protection reasons means for today's energy systems, and whether the abundance of energy which powers the wealth and growth of societies is at stake (Ferroni and Hopkirk, 2016; Weißbach et al., 2013).

While to date, no studies exist which specifically refer to Swiss conditions, several contributions analysing technologies for the European context have recently been published. These studies arrive at very different results when it comes to the energy performance of renewable energy technologies as compared with the performance of more conventional technologies.

For example, Weissbach et al. (2013) evaluated the EROI for wind energy, photovoltaics, solar thermal, hydro, natural gas, biogas, coal and nuclear power for the German context. They found significantly lower EROI for renewable technologies as compared with conventional fossil and nuclear options, and claim that the EROI of solar PV in Germany falls below a critical economical threshold. A recent paper by Ferroni & Hopkirk (2016) claimed that EROI of photovoltaic systems is even so low that they actually act as net energy sinks, rather than delivering a net energy surplus. However, this paper has not been received well in the academic literature, and both the methodical procedure as well as the used data basis of this contribution have been rejected in a broadly supported response by leading Net Energy Analysis an LCA exponents (Raugei, Sgouridis, et al. 2016).[1]

In contrast, in a study comparing the energy performance of the full range of employed power generation technologies in the United Kingdom, Raugei & Leccisi (2016) found much lower net energy returns for conventional power generation technologies such as coal-fired electricity than in previous literature, and found wind power and PV to be viable alternatives from an energy performance perspective. Bhandari et al. (2015) conducted a meta-analysis of literature data on EROI (and other energy performance metrics) of PV systems, harmonising various literature estimates for Southern European insolation conditions, in an attempt to produce more accurate evaluations. They found mean harmonized EROI values for the PV crystalline silicon sub technologies mono-Si and poly-Si to be around 9 and 12, respectively. For thin film CdTe PV systems, the mean harmonized EROI was found to be 34.

These contributions reveal large differences in the reported EROI values for one and the same power generation technology, and in particular for new technologies (e.g., solar PV ranging from below 1 (Ferroni and Hopkirk, 2016) to over 34 (Bhandari et al., 2015)). The differences stem from the adoption of diverging system boundaries, methodical procedures and assumptions, which makes a direct comparison of calculated EROI values in literature very difficult. In recent years, efforts to standardise procedures have increased, and a number of methodological papers and shared protocols have been published with the clear aim to increase the comparability of results in energy performance literature (cr. Raugei, Frischknecht, et al. (2016); Murphy et al. (2011)). Another important methodological contribution came from Arvesen & Hertwich (2015a), which highlighted some caveats when calculating EROI values from readily available LCA data, and proposed a procedure consistent with the definition of the EROI.

For the Swiss context, studies which compare the full range of power generation technologies, based on a consistent “apples-to-apples” methodology and in line with the recent harmonization efforts, have so far not been conducted.

Independently from the regional context under study, the lion’s share of contemporary energy performance research is concerned with establishing what the present-day energy performance of technologies is. Only few scholars have recently begun to consider a phenomenon which has already had a dramatic influence on the financial performance of some power generation technologies: *Technological learning* results in increasing technology performance and decreasing technology cost, enabled by experience with the technology from the manufacturing and use phases (Rosenberg,

[1] A major critique has been the fact that extended system boundaries were chosen for the analysis of renewable energy systems, but not for the analysis of conventional power generation technologies used for comparison (Raugei, Sgouridis, et al., 2016). (In general, the wider the boundaries of the analysis, the lower are the resulting EROI values.) There was further criticism that outdated data has been used for the calculations (e.g. an outdated 10 year average for the performance per m^2 PV panel, even though more recent data is readily available, which demonstrates that the efficiency of PV panels has been improving steadily) and that in several cases the calculation method was flawed, with energy contributions being counted double (Raugei, Sgouridis, et al., 2016).

1982). This empirical phenomenon is often measured and represented with learning curves, and for solar PV and wind power, very steep cost learning curves have been observed (Trancik et al., 2015). Many of the drivers behind these learning curves also affect the energy balance. For instance, with increasing experience, also the material and energy efficiency of power generation technologies improves, which would not only mean that energy performance assessments are time-dependent, but also that they could be subject to changes in the future. These forward looking dynamics have, however, hardly been analysed in literature. To assess these dynamics, the present study takes a forward-looking, dynamic perspective on the energy performance of power generation technologies, using the novel concept of “energy learning curves” (Steffen et al., 2018).

1.3 Objectives of study

To contribute to an informed decision-making by all stakeholders concerned with future portfolios of power generation technologies, the goal of this study is two-fold:

The first objective, to be addressed in the *static* part of the analysis, is to **provide a meaningful, apple-to-apple comparison of the present-day energy performance of power generation technologies, which can be considered relevant for the Swiss context**. The analysis covers both renewable power generation technologies such as hydro power, wind power and photovoltaics, which are at the core of Switzerland’s Energy Strategy 2050, and nuclear and fossil-fuel based technologies that are heavily used in neighbouring countries and are relevant given Switzerland’s integration in the European electricity market. An “apple-to-apple” comparison requires the analysis to be based on a set of suitable energy performance indicators, to apply a consistent methodology with transparent disclosure of methodological assumptions, to use the same system boundaries across technologies, and to base calculations on a trustworthy data source. More specifically, the ecoinvent database, founded in Switzerland and currently the world’s most used life cycle impact database, is used for this part of the study. Additionally, the energy performance of selected power storage technologies is to be analysed in an excursus, drawing on additional data sources for reasons of data availability.

The second objective in the *dynamic* part of the analysis is to **provide a forward-looking assessment of the energy performance of technologies**. If stakeholders are to use energy performance assessments as an ingredient to guide them in decisions on the future electricity supply, it is crucial that these considerations are based on the future performance of technologies, taking into account possible learning effects with respect to material and energy efficiency. To this end, a dynamic energy performance indicator is employed, which takes into account energy learning curves.

This remainder of the report is structured as follows: Chapter 2 introduces two static indicators for power generation technologies, and a related indicator for storage technologies, which are used as a basis for the assessments of energy performance. Chapter 3 presents the static energy performance analysis for the Swiss context, highlighting key methodical assumptions, detailing the methodology and data used and presenting the results. Next, Chapter 4 describes a dynamic concept of energy performance. The approach of deriving historical energy learning curve for each technology, which are then extrapolated, is detailed and the resulting energy performance for the time period up to 2040 is shown, including an uncertainty analysis. Finally, Chapter 5 discusses the results and implications for policy makers in Switzerland and beyond.

2 Indicators for energy performance of power generation and storage technologies

For meaningful energy performance assessments, indicators need to be well-chosen. Also, a clear and transparent definition and description of what the indicators include is indispensable. Much of the confusion in the history of energy performance literature stemmed from an inconsistent naming of indicators: In some cases, indicators applied in literature were identical in their definition, but named slightly different. Similarly, it has happened that the same indicator was applied, but interpretations of what the indicator includes drifted apart, resulting in incomparable results (Modahl et al., 2013). This chapter therefore discusses in detail the two indicators which are used to assess power generation technologies in this study, as a basis for the definition of key assumptions in chapter 3.

2.1 Framework for analysis

Energy indicators based on Life Cycle Assessments (LCA) quantify the total environmental impact in terms of energy use of a system: the Cumulative Energy Demand, or Embodied Energy (alternatively named Embedded Energy) metrics express all primary energy requirements throughout the life cycle of a system or product. An alternative important metric, the non-renewable Cumulative Energy Demand, the nr-CED, refers to the non-renewable part of energy requirements only. The most frequently used metric in Net Energy Analysis is the Energy Return on Energy Investment (EROI), which quantifies the net energy return of a technology.

While the EROI is the principal indicator in Net Energy Analysis, in the LCA literature the nr-CED is the predominant energy indicator used. To date, there are relatively few studies which analyse the energy performance for power generation technologies based on both of these indicators. However, as will be presented later in this chapter, there are compelling reasons for looking at *both* these indicators in parallel. In order to define these indicators and point out their differences, it is useful to introduce an abstract representation of power generation systems, which will be discussed in the following sections.

Two basic types of power generation systems can be distinguished: fuel based systems and renewable energy based systems. The following section first sets out the basic components and transformation processes, which are associated with power generation in the two systems.

Fuel based power generation systems rely on a fuel (e.g. coal, natural gas, uranium, or biomass), whose chemical or physical energy content is converted to electrical energy in a power plant. Figure 1 depicts the energy flows of such a fuel based power generation system.

In order to transform the primary energy extracted from the environment to a useful form of energy – electricity – it must first be processed to a feedstock convertible in a power plant (compare upper section of Figure 1). The first subsystem (represented by the left grey box in Figure 1) therefore represents the delivery of feedstock to the power plant.

For example, when extracting natural gas from underground natural gas deposits, it comprises a mixture of gases, as well as water and oil. Only after processing does it become “marketable” natural gas, which mainly consists of methane, and which meets the purity specifications for the feed-in into pipelines. The natural gas is then transported from the well to the point of use via pipelines (International Energy Agency 2005). The numerals T.1 – T.3 show the transformation steps in the graph. Each of these transformation steps is inevitably associated with losses, for example in the form of fugitive methane emissions during the extraction phase or leakage from pipelines during transport (L.1 – L.3 in the graph).

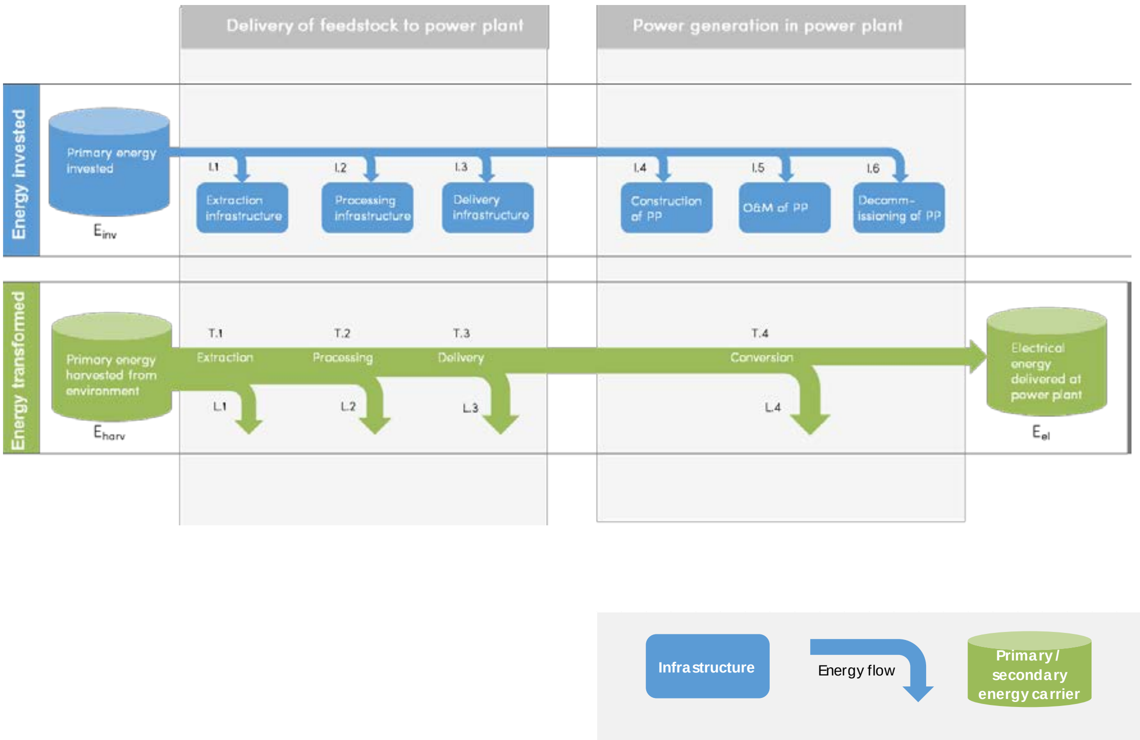

Figure 1: Energy flows of fuel based power generation system.

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In order to realise this energy transformation chain, energy investments need to be made (compare lower section in Figure 1), as energy is required to implement and operate the infrastructure used to extract, process and deliver the feedstock – for example the drilling machinery, the processing infrastructure and the pipeline network in the case of natural gas. Those energy investments associated with the delivery of the feedstock to the power plant are labelled with I.1 - I.3 in the graph.

The second subsystem compromises the power plant, in which the transformation of the fuel to electrical energy occurs (T.4). Here, energy needs to be invested in the power plant – not only for the construction, but also for the operation and maintenance, and eventually the decommissioning of the plant (I. 4- I.6).

The system could be considered complete at this point, with the final output being the electrical energy delivered by the power plant, at the exit of the power plant. However, the system could be also be complemented with a further subsystem which represents the integration of the electrical energy into the electrical grid, and which ends with the electrical energy arriving at the end-user (see Figure 2). This subsystem comprises further energy investments into the transmission and distribution systems, and entails further transformation steps. Between the generating station and the consumer, electric power flows through several substations and is transformed to the required voltage levels for transportation at different grid levels.

However, when extending the system, it has to be kept in mind that the perspective on a single power generation technology is abandoned, since the transmission and distribution system is shared between all power generation technologies. Therefore, it is necessary to allocate the energy investments to the different power generation technologies, which makes a comparison of the EROI more difficult.

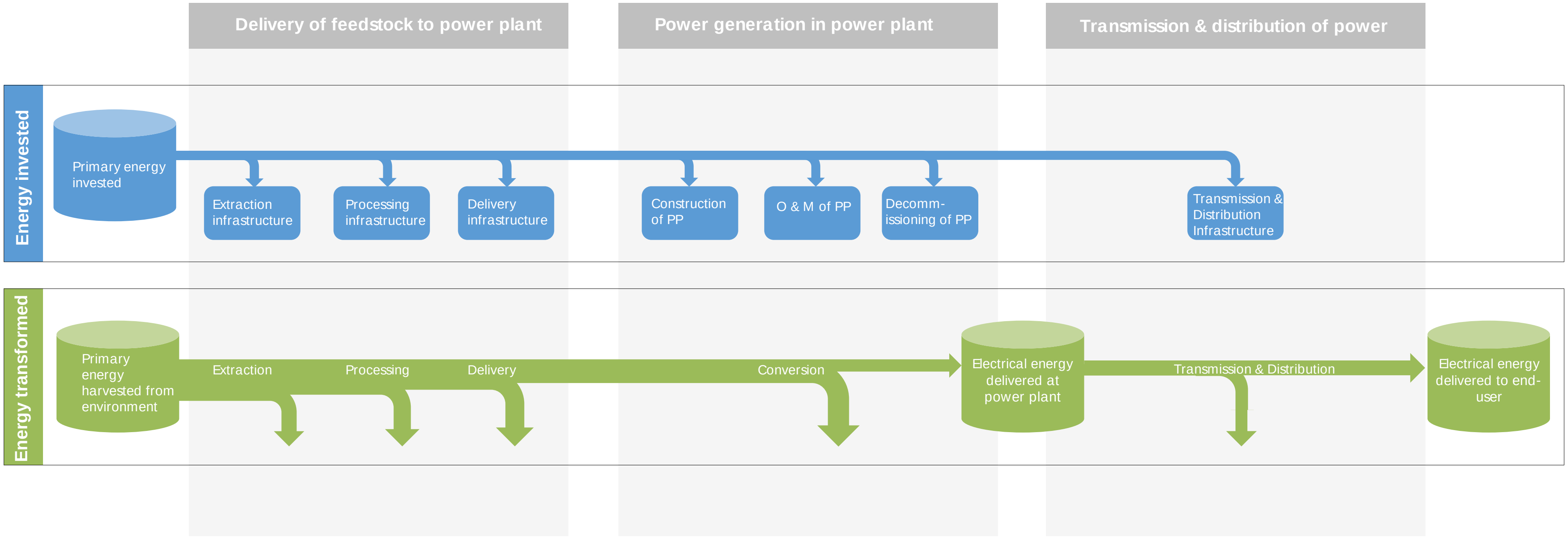

Figure 2: Extended energy flows of fuel based power generation system including transmission and distribution.

Figure 3 shows the schematics of a (non-biomass) renewable energy based power generation system. Since (non-biomass) renewable energy based power generation systems directly convert the primary energy extracted from the environment into electrical energy, there is no feedstock that needs processing and delivering to the power plant, and no energy needs to be invested into the corresponding infrastructure. There is only one subsystem, which comprises the power generation unit (for example a wind turbine or a solar panel). The energy investment therefore only includes the construction, the operation and the decommissioning of the plant (I.1 – I.3).

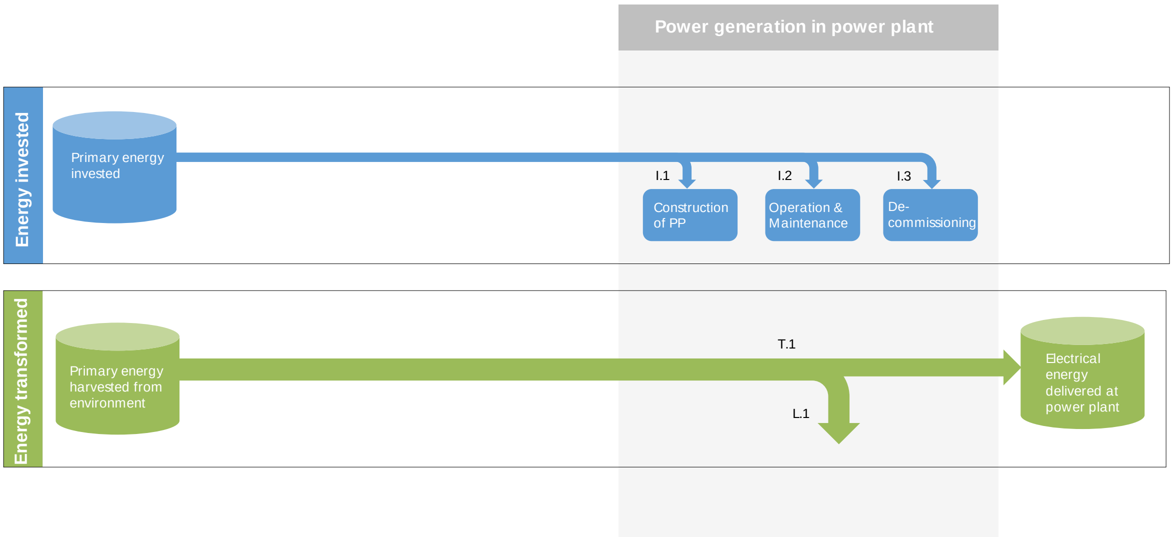

Figure 3: Energy flows of renewable energy based power generation system.

The following two sections cover both aforementioned energy performance metrics, the non-renewable Cumulative Energy Demand (nr-CED) and the Energy Return on Energy Investment, in greater detail. Both the capabilities and limitations of applying those concepts to power generation technologies are analysed. In the last section, an indicator related to the EROI, but applied to power storage technologies, the Energy Stored on Energy Investment ESOI, is introduced.

2.2 The nr-CED concept

2.2.1 Purpose and definition

The Cumulative Energy Demand (CED) is one of the key indicators addressed in Life Cycle Assessment (LCA). While it is often used to determine the total energy consumption over the lifecycle of a product, it can also be applied to energy carriers and energy systems. In this context, the CED describes the primary energy that must be harvested from the environment in order to produce a given amount of usable energy carrier (Frischknecht, Wyss, et al., 2015). Hence, the CED accounts for the total primary energy withdrawn from nature: all use of energy is traced back to the natural resource origin, taking into account losses along the way (Arvesen & Hertwich 2015). This includes not only direct uses of energy, but also indirect consumption of energy due to the use of materials (Hischier et al., 2010).

This means, that the CED takes all primary energy flows into account: the primary energy extracted from the environment (which is “exploited” and eventually transformed to useful energy), and the primary energy invested required to make this transformation possible. The CED is therefore a reliable metric for the total efficiency of the system, indicating the total amount of energy input required – the energy content of the exploited and transformed resource, including all losses along the transformation, plus the additional energy investment - per unit of electricity output.

Since in LCA a clear distinction between renewable and non-renewable energy sources and flows is made, the non-renewable Cumulative Energy Demand (nr-CED) can be calculated, which corresponds to the non-renewable share of the CED. For the long-term sustainability of a power generation system, the demand for non-renewable energy can be considered as decisive. For example, Huijbregts et al. (2006) conducted a comprehensive regression analysis and investigated the correlation between fossil CED of energy carriers and environmental impact categories such as global warming, resource depletion, ozone formation, eutrophication etc. They found high correlations for most environmental impact categories, and particularly high correlations for global warming and resource depletion, pointing to use of fossil fuels as an important driver for many environmental problems.

2.2.2 The nr-CED for power generation technologies

Applied to a power generation technology, the following formula quantifies the nr-CED:

$$\text{nr-CED} = \frac{\text{non-renewable energy invested} + \text{non-renewable energy harvested from env.}}{\text{energy delivered}}$$

$$= \frac{E_{\text{inv, non-renewable}} + E_{\text{harv,non-renewable}}}{E_{\text{el}}} \left[\frac{MJ_{pel}}{MJ_{el}}\right] \tag{1}$$

Figure 4 illustrates the energy flows for the calculation of the nr-CED. The blue and green circular cylinders on the left hand side of the figures represent the parameters $E_{\text{inv, non-renewable}}$ and $E_{\text{harv,non-renewable}}$, while the cylinder on the right hand side represents E_{el}.

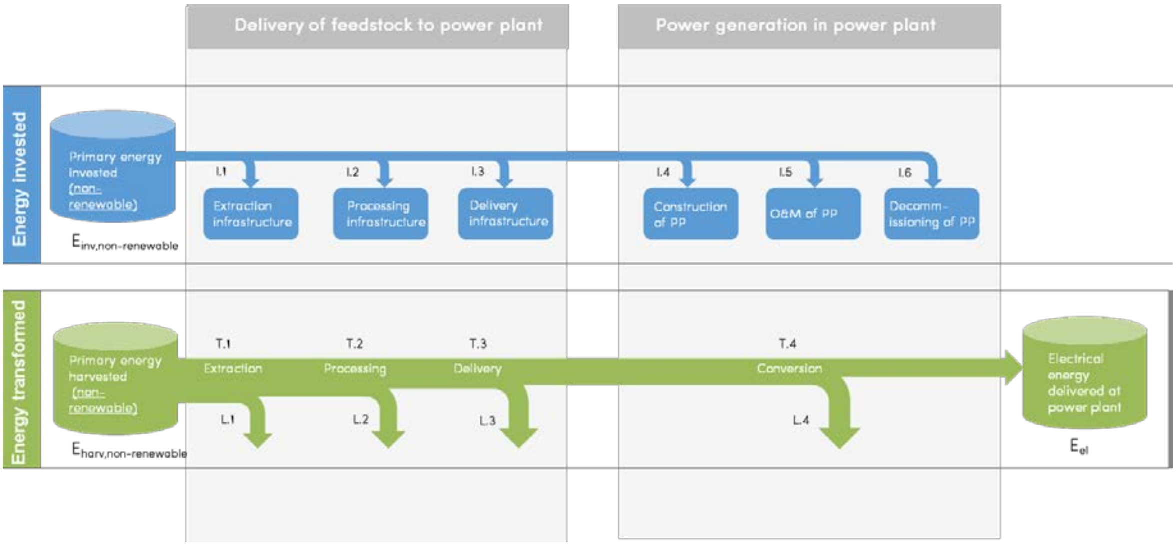

Figure 4: Energy flows for calculation of the nr-CED for a fuel based power generation system.

2.2.3 Limitations of the nr-CED

The concept of cumulative energy demand is very popular and is often quantified in LCAs. However, despite its popularity, there are diverging concepts on how to compute the indicator. The main focus of the debates are the primary energy equivalents, i.e. which primary energy content is attributed to energy sources. Particularly controversial is the primary energy content of nuclear energy and renewable energy sources like solar and wind power. Also, various terminologies and definitions exist for the non-renewable share of the CED. Variations include the fossil CED, the non-renewable fossil CED or the non-renewable CED, and it is often not clear which energy sources are included.

A second limitation is that, for conventional power generation technologies, which require a feedstock or fuel for electricity generation, the nr-CED is dominated by the primary energy extracted from the environment, thus, the energy which is contained in the fuel. The additional energy investments, which enable the subsequent conversion of primary energy to electricity vanish next to the large energetic fuel inputs. Thus, changes in the amount of energy invested are not well visible with this indicator.

Another limitation is that the interpretation of the nr-CED indicator is less intuitive than for net energy analysis indicators such as the EROI (see following sections for further explanations) and does not offer a threshold, which energy technologies need to surpass in order to be energetically viable.

2.3 The EROI concept

2.3.1 Purpose and definition

While LCA literature aims at quantifying environmental impacts, with the consumption of primary energy resources being a subset of these, the Net Energy Analysis literature is concerned with energy consumption only. Net Energy Analysis aims at quantifying the extent to which an energy production system is able to provide a net energy gain – or energy surplus – to society, by contrasting the energy society has to divert to make energy available to the energy returned by the system (Arvesen and Hertwich, 2015). Hence, it characterizes the system's long-term ability to power societal activities and drive economic growth (Hall et al., 2014).

A widely used metric in Net Energy Analysis is the Energy Return on (Energy) Investment (EROI). It is defined as the ratio of the amount of energy that is delivered to society by converting a primary energy source into a useful form, compared to the amount of energy invested in the capture and delivery of this energy (Hall et al. 2014).

$$\text{EROI} = \frac{\text{Energy delivered to society}}{\text{Energy invested in the capture and delivery of energy}} \tag{2}$$

If both numerator and denominator are measured in the same units, the EROI becomes a dimensionless ratio which allows the following interpretation: If the EROI of a given technology (or a mix of technologies) is smaller than 1, it describes in fact an energy sink (a negative net energy return), since the energy investment is larger than the obtained energy output. Likewise, an EROI larger than 1 describes an energy source (positive net energy return), for which the required energy investment is smaller than the obtained energy output. A high positive EROI is evidently socially desirable for any energy system since it returns significantly more energy than previously invested in it, with a large remaining surplus available to the economy for the production of goods and services (Raugei, Sgouridis, et al., 2016). Hall et al. (2009) even claim that, for any energy source or technology, the minimum EROI required to maintain economic activity in our societies lies around 3:1.

Historically, the EROI indicator has been very useful to show energy trends in agriculture or in oil extraction (Modahl et al. 2013). For instance, a number of studies have impressively shown that the EROIs of oil and gas exploitation have decreased over time, and are likely to continue declining (e.g. Hall & Cleveland 1981). With time, it has become more widespread to use the EROI indicator not only for identifying time trends for a particular fuel or resource, but also for the purpose of comparing the net energy gain of different power generation technologies for society (Modahl et al. 2013). Against the backdrop of highly energy dependent societies, and with new power generation and storage technologies emerging, it is of great interest whether the net energy gains provided by technologies will continue to cover societal energy demands well, or whether the energy abundance powering the wealth and growth of societies is at stake

2.3.2 The EROI for power generation technologies

The established formula for calculating the EROI of a power generation system is (Raugei et al. 2012):

$$EROI_{el} = \frac{E_{delivered}}{E_{invested}} = \frac{E_{el}}{E_{Inv,\ Feedstock} + E_{Inv,\ PP}} \left[\frac{MJ_{el}}{MJ_{pe}}\right] \tag{3}$$

With

E_{el} = electrical energy delivered [MJ_{el}]

$E_{Inv,\ Feedstock}$ = energy invested in extraction, processing and delivery of feedstock [MJ_{PE}]

$E_{Inv,\ PP}$ = energy invested in construction, operation & maintenance and decommissioning of PP [MJ_{PE}]

For a renewable energy based generation system, this reduces to:

$$EROI_{el} = \frac{E_{el}}{E_{INV,\ PP}} \tag{4}$$

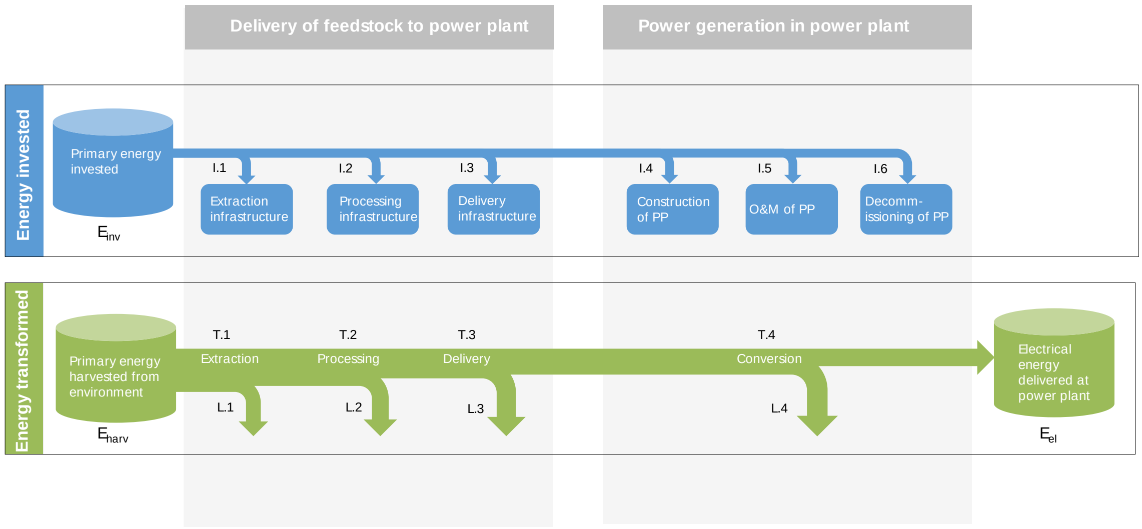

Figure 5: Energy flows for calculation of the EROI for a fuel based power generation system.

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2.3.3 Limitations of EROI

When using the EROI indicator for the purpose of comparing various power generation technologies, it is necessary to highlight limitations of such comparisons.

The EROI gives an indication of the benefits that one receives from an energy system. It compares how much energy the system delivers to how much of society's energy carriers, which are already available and ready to use, must be spent to produce this energy. It therefore provides reliable information on the effective use of available energy carriers in the mid-term. However, it is important to note that the primary energy harvested (i.e. extracted from the environment in its natural state) does not form part of the EROI calculation. The EROI only accounts for the additional energy investments that are required to implement and operate the chain of processes required to convert a primary energy source (e.g. coal, gas, uranium etc.) to a useful energy carrier (e.g. electricity), without considering the energy flow itself that is being exploited (Raugei et al. 2016).

This has important consequences for the interpretation of the EROI indicator. Firstly, the EROI is *not* concerned with measuring the overall amount of primary energy consumed per energy delivered (i.e. the life cycle efficiency, as calculated in Life Cycle Analysis), since the largest primary energy input - the fossil fuel feedstock or the renewable energy input - is not accounted for. It therefore does not track how efficient the system is in converting the primary energy source to a useful energy carrier. Secondly, the EROI is blind to whether the primary energy harvested is of renewable or of fossil nature. No distinction is made between a system which delivers energy by mainly depleting exhaustible non-renewable primary energy stocks and one that is harvesting renewable energy flows. Raugei et al. therefore argue that "taken in isolation, EROI is arguably a rather poor indicator of the long-term sustainability of an energy exploitation system", and suggest complementing the EROI indicator with other indicators, which can make statements on the amount of (non-renewable) resources depleted.

2.4 The ESOI concept

2.4.1 Purpose and definition

Energy storage is seen as a key component for integrating an increasing share of intermittent generation into the electric grid. Among the technologies, that could absorb, for example, surplus energy from renewables in times of low demand, are large-scale technologies like pumped hydro storage, compressed air energy storage and power-to-gas-to-power set-ups. For small-scale applications, a wide range of battery technologies are available, with different characteristics in terms of energy density, round-trip efficiency, and lifecycle cost.

Building on the EROI concept, recent work has introduced a related metric for net energy analysis of energy storage technologies, the energy stored on energy invested (ESOI) (Barnhart & Benson 2013). As this study uses the ESOI in an excursus on storage technologies, the following subsections illustrate this novel concept in greater detail.

2.4.2 The ESOI for power storage technologies

For a given energy storage capacity, the ESOI compares the amount of stored energy returned over its lifetime, to the energy required to manufacture the storage device.

$$\text{ESOI} = \frac{\text{Stored energy returned over lifetime}}{\text{Energy required for manufacturing}} \qquad (5)$$

Both the nominator and denominator refer to the same energy storage capacity, with the storage capacity eventually cancelling out. The resulting ESOI value can therefore be interpreted as electrical energy returned over primary energy required per unit of electrical energy storage, allowing for the comparison of large-scale and small-scale storage technologies.

For batteries and pumped hydro storage power plants, the electrical energy returned per unit of storage capacity can be expressed as the product of the total amount of cycles during the lifetime of the device and the round-trip efficiency and depth-of-discharge per cycle.

$$\text{ESOI} = \frac{e_{el}}{e_{battery}} = \frac{\lambda \eta D}{e_{battery}} \qquad \left[\frac{MJ_{el}}{MJ_{PE}}\right] \qquad (6)$$

e_{el}:Electrical energy returned over lifetime per unit of storage capacity $\left[{}^{MJ_{el}}/_{\text{MJ storage capacity}}\right]$

$e_{battery}$:Embodied primary energy per unit of storage capacity $\left[{}^{MJ_{PE}}\!/_{MJ\ storage\ capacity}\right]$

λ: Total cycle life [-]

η: Round-trip efficiency [-]

D: Depth-of-discharge (DOD)[-]

2.4.3 Limitations of ESOI

When applying the ESOI concept, it must be kept in mind that its purpose is to compare the energy and material requirements (the "energy costs") of energy storage technologies. The purpose of storage technologies is to enable a temporal shift in energy consumption, therefore adding flexibility to energy systems. Given their fundamentally different functions in the energy system, a direct comparison between the energy performance of power generation and storage technologies is not appropriate. The ESOI concept should therefore only be used to compare the "energy costs" across storage technologies.

Of course, the ESOI does also not provide any information on the capacity of the storage system to add flexibility to the system, thus, its value to the energy system. For example, it does not indicate whether it is a short-term or seasonal storage etc. For a comprehensive assessment of storage technologies, naturally additional factors would have to be taken into account; nevertheless the ESOI serves well as a handy metric allowing high-level insights on energy performance of different technological alternatives.

2.5 Summary of contribution of indicators

In this section, the relative contributions of these three indicators to energy performance assessments are jointly discussed. In this context, it is particularly important to highlight the differences in the interpretation of the nr-CED and the EROI indicators again, which often lead to confusion and misunderstandings.

The nr-CED quantifies the total amount of non-renewable resources depleted, thus, it offers a long-term sustainability perspective on a power generation system. The nr-CED indicator has been coined in LCA literature, and is closely related to environmental indicators such as greenhouse gas emission indicators, which are commonly reported on in LCA literature. However, in Net Energy Analysis literature, the EROI indicator is the dominant indicator, with the nr-CED indicator being hardly used in this domain. Thus, comparisons of the energy performance of power generation technologies in scientific literature are often made based on the EROI indicator, and claims of a low energy performance of new renewable energy technologies refer exclusively to low EROI values which have been published by some authors.

The EROI is based on the premise that the energy, which is expended during the production of electricity, is not available anymore to provide energy services powering economies and societal life (Carbajales-Dale et al., 2014). The indicator therefore accounts for all energy in direct form and in the form of materials, which is invested during the lifecycle of energy production. The feedstock to be converted to electricity (e.g. the coal, uranium ore or gas to be exploited from the environment) is not part of this accounting, as it is considered a form of energy which is not available (yet) for societal purposes. The EROI thus answers the following question: if one unit of energy is available for investing into the generation of further electricity units today, what would be the most productive energy investment for society? Put differently, the EROI is designed to compare a power generation system's ability to render primary energy useful for society.

Since the EROI indicator does not take into account all energy inputs, it can be seen as a subset of more comprehensive LCA indicators, such as the CED (Carbajales-Dale et al., 2015). On its own, it is hardly suited to deliver a complete assessment of energy performance of technologies. However, in combination with other indicators, such as the nr-CED, it can make highly relevant statements and can add a complementary perspective. The EROI sheds light on upstream and infrastructure energy requirements that are often overlooked, by systematically accounting for all energy invested, directly and indirectly in the form of materials, during the lifecycle of energy production (Carbajales-Dale et al., 2014). The fuel input, if it were to be considered in this accounting, would dominate in these considerations, and the energy investments in infrastructure and upstream activities would vanish in comparison. In addition, the EROI is clearly the better metric to show improvements or learnings in terms of material and energy efficiency during the energy production process, as such improvements are only well visible in the EROI indicator, while they would be hardly visible in the nr-CED indicator, which is dominated by the fuel input. The EROI is also the principal metric used in the net energy analysis literature, which allows for a comparison of results with other academic studies.

Thus, in order to provide the full picture of the energy performance of power generation technologies and to identify possible trade-offs, it is highly beneficial to take advantage of the complementarity of the two indicators, and complement the perspective on the energy effectiveness, as offered by the EROI indicator, with the perspective of long-term sustainability, as offered by the nr-CED indicator. Thus, this study bases the first part of the energy performance assessment – the static analysis for the Swiss context – on both the nr-CED and the EROI indicators. For the excursus on power storage technologies, the ESOI metric is used, a metric specifically introduced for the energy performance assessment of storage devices and technologies.

However, each attempt of assessing the energy performance of power generation technologies is inevitably time dependent, as technologies evolve over time as technological experience accumulates. The second part of this study therefore introduces a dynamic indicator, which allows to take into account technological learning of technologies.

3 Static energy performance indicators for Swiss context

3.1 Key assumptions

Although the previously presented indicators are straightforward in their basic idea, methodological challenges arise when applying them to power generation systems. There are a set of important methodical assumptions which can greatly affect the comparability of results from different sources. These assumptions give rise to much of the diversity in published literature values for the EROI for one and the same technology[2], as, if handled differently by scientist, they lead to very large numerical differences. For a transparent apple-to-apple comparison between power technologies, it is therefore crucial, on one hand, to clearly state what choices in terms of these methodical assumptions have been made, and on the other hand, to analyse all technologies on the same methodical basis.

Figure 6 illustrates the five most important methodical assumptions based on the previously introduced schematic representation of power generation technologies. Each of these assumptions are briefly discussed in the following sections, and a rationale for the choices made for this study is provided.

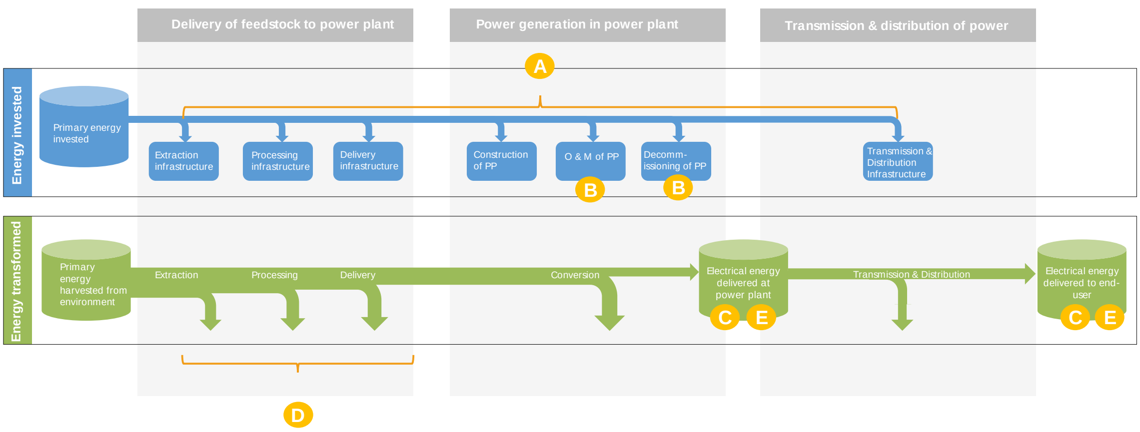

Figure 6: Key methodological assumptions in the modelling approach for EROI and nr-CED. (A: level of energy inputs; B: modelling of the life cycle of the power plant; C: location of energy output; D: handling of losses during fuel supply chain; E: conversion of electrical energy delivered in primary energy equivalents).

3.1.1 Level of energy inputs considered

Much variation in published EROI values for a specific technology results from the level of energy inputs that is considered, i.e. what is considered an energy investment (Murphy et al. 2011).

[2] The debates in the literature focus on the EROI, but some of the key assumptions are of equal importance for the nr-CED, because they determine the system boundaries i.e. the definition of what the system includes.

Energy inputs into a process may take a number of forms: as fuels directly used in the process (e.g. diesel fuel consumed on a drilling rig), in the form of electricity or heat, or in the form of material inputs, whose embodied energy reflect the energy required to produce those materials. Additionally, it can be argued that other, non-energy inputs (e.g. labour, capital, insurance) are also associated with a certain energy consumption (Murphy et al. 2011).

Accordingly, the system boundaries for the energy investment can be chosen arbitrarily narrow or wide. Raugei et al. (2016) define three levels of system boundaries for EROI and nr-CED calculations: narrow, intermediate and wide.

In the narrowest definition of energy inputs, only direct inputs of energy carriers to the process itself are accounted for – e.g. fuels, electricity or thermal energy. On the intermediate level, direct material and energy inputs to the process are included. The widest boundaries for the energy invested includes non-energy resources. Since data for energy consumption associated with those non-energy resources is often not available, typically a conversion of monetary costs to energy costs is required (Murphy & Hall 2010). Approaches in literature range from converting reported financial costs to energy units using regional energy intensity values from economic data (units of energy consumed per unit of GDP) to the use of Input-Output tables (Raugei et al. 2016). However, those methods are not without controversy, and most authors do not recommend their application (e.g. Fthenakis et al. (2011)), as they can lead to double counting of embodied material and direct energy costs.

In this study, intermediate system boundaries have been used, classifying only direct energy inputs and energy embodied in material inputs as energy investments. This is also in line with the majority of the literature (cr. Bhandari et al. (2015); Raugei & Leccisi (2016); Arvesen & Hertwich (2015a); Weissbach et al. (2013)). The ecoinvent data base, the life cycle inventory database which was used for the calculations, also uses these system boundaries. Furthermore, it can be argued that the energy investments associated with labour and capital inputs are rather small as compared to the investments associated with energy and material inputs.

3.1.2 Modelling of the life-cycle of the power plant

Another important choice concerns which phases of the life cycle of the power plant are considered. For a generalised power generation system, an energy investment is required for the power plant. Normally, the system boundaries include the whole life cycle of the power plant. However, some studies only include the construction of the power plant in the energy investments, pursuing a so-called “cradle-to-gate” approach - instead of applying the alternative “cradle-to-grave” approach, which models the whole life cycle of the power plant, from the initial construction phase over the operation phase to the final decommissioning stage. This is mainly done when data on the operation, maintenance and end of life of power plant systems is lacking (e.g. for PV systems).

In this study, a cradle-to-grave approach is pursued: the ecoinvent database, which forms the basis for this part of the study, also provides life cycle impact data on the maintenance and decommissioning phase of infrastructure units such as power plants. Therefore, not only for the power plants, but for all infrastructure components of power generation systems, the whole life cycle feeds into the calculations.

3.1.3 Location of energy output

The system boundaries are also determined by the stage of the energy supply chain at which the energy carrier is considered an output, i.e. what is considered to be the energy delivered.

There are two different possibilities as to where to locate the electrical energy delivered. It can either be considered at the power plant gate, just before it is fed into the grid, or it can be considered when it is delivered to the end-user (Raugei et al. 2016). Depending on the location of the energy output, additional energy investments have to be included in the analysis, since the same boundaries must be used for both the energy delivered and the energy invested (Murphy & Hall 2010). For example, if the energy delivered is defined to be the "electrical energy delivered to the end-user", then the associated investments into transmission and distribution networks need to be taken into account.

In this study, the energy delivered is considered to be located at the exit of the power plant, since the aim of the analysis is a comparative assessment of power generation technologies *at the technology level.* If the final energy output is considered upon arrival at the end-user, further components and services of the electricity system need to be considered (e.g. back-up and storage capacities, transmission and distribution networks), which are shared between all power generation technologies. In this case, the technology level is abandoned, and the corresponding energy investments are easiest addressed in an analysis at the power system level, thus avoiding a complicated allocation of these energy investments to single technologies.

This methodical issue has been the source of some controversy in the EROI literature, in particular regarding the assessment of new renewable energies with intermittent electricity production. Some authors have included comprehensive energy investments for the "buffering" and the integration of those energy sources into a flexible electricity supply in their energy accounting. For example, in their (highly criticised) study of the energy performance of PV in Switzerland, Ferroni and Hopkirk (2016) incorporate investments for the construction of back-up capacities (pump storage system, gas power plants) and for the operation of smart-grid infrastructure, and account for the losses due to the need to store the renewable energy until it is needed.

However, the general approach to include those additional investments only for renewable energy technologies and not for fossil fuel based technologies, has been clearly rejected by a multitude of EROI exponents (cf. Raugei, Sgouridis, et al. (2016)), who argue that none of the existing electricity generation technologies would be able to meet the patterns of energy demand exclusively on their own. They conclude that "if deployed on their own, they would all require some storage capacity (and/or complementary generation assets) in order to do so" (2016, p. 18). They recommend to address the issue of energy storage at a more aggregated level, for example in an analysis that investigates a country's grid mix, and not at the level of an individual power generation technology.

3.1.4 Handling of energy losses during fuel supply chain

Bringing up an important aspect, Arvesen and Hertwich (2015) point out that losses along the feedstock supply chain of fossil and nuclear systems (e.g. losses during extraction, such as methane released from coal seams during mining or during transport) are often not dealt with consistently when calculating the EROI. The authors argue in favour of not including those losses in the energy invested feeding into the EROI calculation. They specify that, since the amount of energy that is lost during the feedstock supply chain has never been at society's disposal in the first place, it cannot be considered as energy that has been diverted from other societal uses (and needs to be returned or paid back), and is therefore not to be considered an energy investment. This contribution is of particular importance, since many studies compute the EROI from CED data obtained from LCA studies, which, by definition, includes all energy losses (see also Chapter 4.3).

This study adopts a consistent approach for the handling of losses during the fuel supply chain, following the general logic of Arvesen and Hertwich (2015) (see chapter 3.2.3 for calculation details). Losses during the fuel supply chain of fossil and nuclear systems are therefore not considered energy investments in EROI calculations, but feed into the calculations for the nr-CED.

3.1.5 Conversion of electrical energy delivered in primary energy equivalents

Another controversial issue is in which energy units the energy delivered for determining the EROI (the amount of electricity generated by a system) should be accounted for. The energy delivered can either be expressed in units of electrical energy, or it can be expressed in terms of equivalent primary energy.

If the latter approach is followed, one needs to adopt a conversion factor to convert electrical energy units in primary energy units. Typically this is done based on the conversion efficiency of a country's electricity mix, i.e. the ratio of the yearly electricity output and the corresponding total yearly primary energy input required for electricity generation (e.g. Bhandari et al. 2015). As a result, the meaning of the EROI changes, since the energy delivered (measured in primary energy equivalents) is now to be interpreted as the hypothetical amount of primary energy input that the renewable power system replaces. Or, put differently, it is to be interpreted as the primary energy input needed to produce the same amount of electricity in a hypothetical, the grid mix representing power plant. However, a downside of this approach is that the resulting EROI is no longer an absolute indicator of the energy performance of a technology, but rather a relative indicator, which must be interpreted in the context of the technology mix that it is assumed to replace. If the energy delivered is calculated in terms of equivalent primary energy, the corresponding EROI value is often referred to as $EROI_{PE\text{-}eq}$, where PE-eq stands for primary energy equivalents (Raugei et al. 2016).

The alternative approach is to express the energy delivered in units of electrical energy, without any conversion, with the resulting EROI being referred to as $EROI_{el}$ (Raugei et al. 2016). However, since the nominator (electrical energy delivered) and the denominator (primary energy invested) are, strictly speaking, not measured in the same units, the EROI ratio is no longer dimensionless, and the interpretation of an EROI being larger than 1 being the absolute minimum requirement for a net energy source, is lost (Arvesen & Hertwich 2015).

This study expresses the energy delivered in units of electrical energy, in line with other contributions from literature (cr. Raugei & Leccisi (2016); Arvesen & Hertwich (2015a); Weissbach et al. (2013). In this way, the calculated EROI values do not hinge on national grid conversion factors, which may be subject to changes in the future.

3.2 Methodology and data

3.2.1 The ecoinvent database

Founded in Switzerland and compiled by Swiss Federal Offices and renowned research institutes like the Swiss Federal Institutes of Technology (ETH) Zurich and Lausanne, the ecoinvent database is widely recognized as a leading data source for life cycle assessment studies, which aim to quantify and compare the environmental impact of products or services. The database comprises life cycle inventory (LCI) data on a wide range of economic activities in all sectors and contains currently over 12’800 datasets (Ecoinvent Association 2016).

Ecoinvent is a well suited source of data for the present study, since the providers are committed to high standards in terms of transparency and consistency, and the data coverage for Switzerland and other Western European countries is good, with a large availability of country-specific data. Also, it is already being used extensively, not only in LCA studies, but also in EROI analysis (cf. e.g. Arvesen & Hertwich 2015).

In order to facilitate internal consistency, this study uses ecoinvent as the source of data for almost all calculations in the static analysis. The most recent version of the ecoinvent database at that time, version 3.3, has been used for the subsequent calculations. Only for wind onshore and solar PV the data provided by ecoinvent has deemed to be too outdated given the rapid technological development for these technologies, so newer data sources have been used for complementary analyses as described below. These calculations are consistent with the ecoinvent methodology.

3.2.2 Calculation of nr-CED

The non-renewable Cumulative Energy Demand (nr-CED) can be derived very easily from the ecoinvent database, since the CED is one of the impact assessment methods implemented in ecoinvent. The CED impact assessment method can therefore be applied to the ecoinvent datasets, which describe the electricity production from various energy sources for a specific location (e.g. Switzerland). Since the data is cumulative, all upstream processes (and associated direct and indirect energy requirements, e.g. in form of materials) and the resource’s energy content are included in the

CED. The nr-CED, the non-renewable share of the CED, is the sum of the categories fossil, nuclear and primary forest.

Although the concept of cumulative energy demand is very popular and applied in several life cycle assessment databases, there are diverging concepts on how to compute the indicator from an inventory of inputs of energy carriers (Frischknecht, Wyss, et al., 2015). The main question related to the cumulative energy demand indicator is what primary energy equivalent in MJ should be attributed to one unit of energy carrier in its natural state (e.g. 1 kg of uranium extracted from ground, 1 m^3 of natural gas extracted from ground), i.e. how to aggregate the different energy sources in energy units. The approach implemented in ecoinvent is based on detailed considerations by Frischknecht et al. on a consistent approach for the accounting of energy sources (1998; Frischknecht, Wyss, et al., 2015). The basis for this accounting method is the "energy harvested", which quantifies the amount of energy extracted from the environment, which is then weighted with the energy content. This is assumed to be the maximum amount of energy extractable with today's technologies.

For fossil fuels, the primary energy harvested is the amount of fossil energy resources extracted from the ground. This is weighted with the higher heating value[3], since this is assumed to be the maximum amount of energy extractable with today's technologies.

For natural uranium, the determination of the energy content is controversial[4]. The ecoinvent database aggregates the amount of fissile resources extracted, and weights this with the energy which can be extracted from fissile uranium in light water reactors. The energy content of the natural uranium which ends up as "lost" fissile uranium during enrichment and in spent nuclear fuel is not accounted for, since it is assumed that, to date, it is not economically viable to extract fissile uranium from depleted uranium or from spent fuel. In addition, it is argued that those resources are still available for energy conversion in the future. If the energy content of those losses were to be included in the CED for natural uranium, the energy value per kg of natural uranium would be much higher (by about 50%).

For renewable energies, the energy input equals the amount of energy delivered by the energy collecting facility, thus the amount of energy harvested is considered at the exit of the harvesting facility. For photovoltaics, this equals the electric energy produced by the photovoltaic panel and delivered to the inverter. Therefore, the efficiency of the panel to convert solar energy to electricity is not taken into account. This energy input is not further weighted, since "the use of sustainably used renewable energy resources is assumed to be unproblematic and therefore a zero value is attributed to them" (Frischknecht et al. 1998, p. 270)

[3] The heating value is the amount of heat that is produced by the combustion of a specific amount of fuel. The lower heating value (LHV) is obtained when all the water formed by combustion is in vapour form, whereas the higher heating value (HHV) is obtained when all water formed by combustion is in liquid form, i.e. all water vapor has condensed (Moran et al., 2014)

[4] Hischier et al. (2010) give an overview over the different methods used in the literature, and gives a justification on the approach adopted in the ecoinvent database.

3.2.3 Calculation of EROI

The EROI for power generation technologies relates to CED data found in ecoinvent and other LCI databases. However, there is a fundamental difference between the CED and the EROI that needs to be accounted for: the CED expresses the total primary energy withdrawn from nature, comprising the primary energy invested and the primary energy harvested for transformation to electricity. Since the EROI only considers the primary energy invested, the CED values as found in the ecoinvent database need to be adjusted by the primary energy harvested by the power generation technology.

There are two possible ways for calculating the EROI from ecoinvent CED data. On the one hand, one can calculate the EROI bottom-up, by looking at the whole supply chain for a power generation system, dissecting it into sub-processes, and identify the energy investments for those sub-processes. By summing up the discrete energy investments, compliance with the definition of the EROI is ensured. However, the procedure for this is complicated since a large number of processes need to be followed, and there is a risk that this is not done in a consistent way for the different technologies, or that important energy investments are neglected.

On the other hand, the EROI can be determined top-down. This approach is in accordance with the best practice guidelines set out in Arvesen & Hertwich (2015a). In this approach, which is applied for the present analysis, the CED is read off at the very last step of the supply chain for a power generation technology, the electricity production. The cumulative dataset for the electricity production aggregates all the upstream processes that provided intermediate inputs, e.g. the resource extraction, feed stock processing, feed stock delivery to the power plant. The CED at this stage therefore measures all the primary energy consumed during this supply chain (including direct uses of energy, but also indirect consumption of energy due to the use of materials) and the resource's energy content. From this aggregated and comprehensive CED value, the portion of the CED attributable to the primary energy harvested, is then subtracted. Specifically, this is done by tracing back the whole transformation chain (as it is documented in ecoinvent) of the energy carrier. Starting from the feedstock/fuel input, that is required to produce 1 kWh of electricity, the transformation steps are followed in reverse order, taking into account the losses that occurred during those transformation steps. The losses must be considered, since they contribute to the total amount of energy that needed to be extracted from the environment in the first place.

At the end of this procedure, the primary energy equivalent that needs to be extracted from the environment for the provision of the fuel input for power generation is estimated. Since the accounting for energy carriers in ecoinvent is done in mass or volume units (m3 of natural gas, kg of hard coal etc.), a conversion in energy units (using the primary energy equivalents for energy carriers as shown in Table 4) is required to calculate the CED of the energy harvested.

The advantage of this method is that the calculation of the total CED is based on the ecoinvent methodology, which ensures that the starting value for all power generation technologies is calculated consistently. The possible error sources when determining the portion of the CED that needs to be subtracted from the total are relatively small, since the number of transformation steps is very manageable for most energy carriers (with natural uranium undergoing the most complicated transformation chain, see Chapter 3.2.5.3). Hence, the procedure is more easily reproducible than the bottom-up approach.

Subsequently, an example calculation is provided for natural gas. When reading off the CED at the last transformation step (conversion to electricity), all direct and indirect energy uses associated with the current step plus all upstream energy transformation steps and infrastructures are included in the indicator. In order to obtain the non-renewable CED, only the non-renewable share of this is considered. For example, the summed up CED of 1 kWh electricity produced from natural gas, in Germany, is 8.14 MJ-eq (see Table 1. The non-renewable share of the CED amounts to 8.09 MJ-eq per kWh. Finally, instead of the non-renewable CED per kWh, the CED per MJ_{el} is calculated by dividing by a factor of 3.6 (1 kWh= 3.6 MJ_{el}), in order to ensure consistency with the electrical energy units used for the EROI:

For the calculation of the EROI, the top-down approach is applied. The CED equivalent of the primary energy extracted from the environment (to supply the natural gas fuel input to the power plant) needs to be quantified, taking all the losses along the way into account. This is then subtracted from the total CED to make sure that the remaining CED is only associated with energy investments (the direct and indirect energy inputs in the form of materials that are required to implement and operate the whole supply chain).

(I) Extracted amount of natural gas in natural state per kWh

$$= \left(\frac{1\,kWh}{0.164\,m^3} * \frac{1\ \mathrm{m}^3}{1.115\ \mathrm{m}^3} * \frac{1\ \mathrm{m}^3}{1.01\ \mathrm{m}^3} \right)^{-1} = \frac{0.185\,m^3}{kWh}$$

$CED\ (natural\ gas, in\ ground) = 38.29 \frac{MJ-eq}{m^3}$ (see Table 3)

(II) CED equivalent for primary energy extracted from environment, including all losses ("Adjustment for EROI")

$$= \frac{0.185\,m^3}{kWh} * \left(38.29\ \frac{MJ-eq}{m^3} \right) = 7.07\ \frac{MJ-eq}{kWh}$$

(III) EROI[5]

$$EROI_{el} = \frac{3.6\ \frac{MJ}{kWh}}{CED_{total,ecoinvent} - Adjustment}$$

$$= \frac{3.6\ \frac{MJ}{kWh}}{8.14\ \frac{MJ-eq}{kWh} - 7.07\ \frac{MJ-eq}{kWh}} = 3.36$$

[5] The calculation shown here is simplified, since all the natural gas is assumed to be produced in Germany. For the results shown in section 1.1 the supply mix of German natural gas has been considered, which have different assumptions in terms of the losses. A slightly lower EROI results from this more comprehensive calculation.

Table 1: Example of the calculation of EROI and nr-CED from ecoinvent data.

LCA results from ecoinvent			
	Unit	MJ_{PE}/kWh	
Cumulative Energy Demand	total		8.14
Cumulative Energy Demand	non-renewable		8.09
Cumulative Energy Demand	renewable		0.05
Adjustment for EROI (calculated)			
	Unit	MJ_{PE}	7.07
EROI (calculated)			
	Unit	MJ_{el}/MJ_{PE}	**3.36**
nr-CED (calculated)			
	Unit	MJ_{PE}/Mj_{el}	**2.25**

3.2.4 Limitations of approach

From a methodical point of view, the handling of the losses is a very sensitive point of this analysis. When calculating the EROI based on CED data obtained from LCA databases or studies, variations in the losses inevitably have a large impact on the resulting EROI, since they are deducted from the CED, decreasing the energy investments and increasing the EROI. When comparing the results of this study with the findings by Raugei and Leccisi (2016), who analysed an overlapping set of technologies and adopted a very similar methodology, but without consistently considering the losses, it is striking that the nr-CED values are in the same order of magnitude, but EROI values are deviating, which further underlines this point. However, according to Arvesen & Hertwich (2015a), the losses do not form part of the energy investments considered for the EROI, and the authors therefore recommend the approach of systematically deducting the losses, which has been pursued in this analysis.

With regard to the data basis of the static part of the present study, the results inevitably rely on the timeliness and quality of the data provided by the ecoinvent database, which is used as the single data source. In this context, the technology status plays an important role: in order to ensure a fair comparison, all technologies should be compared on the same basis, i.e. comparing the most recent technology or comparing the “average” technology of technologies deployed today. However, this would require that the most up-to-date data for all processes and technologies is utilised. The ecoinvent database is periodically updated, and the most recent version of the database at the time of conducting the analysis was used. However, as stated by Jungbluth et al. (2012) who provided the LCI data for PV in ecoinvent, the rapid technological development for some technologies makes it is very difficult, if not impossible, to keep all datasets for all technical processes fully up-to-date. When examining the documentation and assumptions of the data sets for new renewable technologies such as solar PV and wind onshore, it has become clear that not all assumptions in the datasets are consistent with the most recent technology status of these technologies. For example, the dataset for wind offshore is based on a turbine type which is not representative for offshore wind parks of the newest generation.

In general, for each dataset, ecoinvent indicates a time period for which the data is intended to be valid (Weidema et al., 2013). For some datasets, this validity time period starts as early as in the 1980s. However, it is difficult to infer a technology status from this data validity period, as a technology, which has been in use for a long time, can still be the most competitive technology, depending on the technological domain (Weidema et al., 2013). It was beyond the scope of this study to verify in detail technology whether technology characteristics and process data in ecoinvent are consistent with the most recent status of all power generation technologies. However, the information as to the data validity provided by ecoinvent has been collected and is compiled in Table 2 and Table 3. In addition, the static analysis was complemented with additional, up-to-date estimates of solar PV and wind, as technological progress over the past decade has been more rapid for these technologies than for other technologies. These additional data points (based on recent LCA sources) are intended to provide a reference for the technology of the newest generation.

However, even if it were to be based on the most recent data, the present static analysis can still be regarded as a snapshot of current conditions only. Its results are strongly time dependent, and the picture might once more look fundamentally different in the future, as, for example, technological advancements in the domain of solar photovoltaics are rapid. Significant improvements, not only in terms of increased cell efficiencies, but also in terms of less energy and material intensive production processes (e.g. manufacturing of ever thinner wafers, recycling of silicon, development of better purification technologies etc.) can be expected due to increased deployment. The second part of this study is therefore dedicated to a dynamic analysis of the energy performance of power generation technologies, taking into account energy learning effects over time as a function of increased deployment (cf. Chapter 4).

Table 2: Data validity of datasets for fuel based power generation technologies as indicated in the ecoinvent database.
Key components only**.** Source: adapted from ecoinvent v. 3.3 (2016).

Technology	Location	Ecoinvent Version	**Data validity as indicated in Ecoinvent** (only key components shown)
Hard coal	DE	v. 3.3 (2016)	Hard coal mine operation **1990**-2016 Hard coal power plant construction **1980**-2016 Power generation in a hard coal power plant **1980**-2016
Natural gas CCGT	DE	v. 3.3 (2016)	Natural gas production, various countries **1989/1990/1996/2000**-2016 Gas power plant construction **1990**-2016 Power generation in a natural gas power plant **2000**-2016
Nuclear	CH	v. 3.3 (2016)	Uranium mine operation, open cast / underground mines **1980**-2016 Uranium production, milling of uranium ore **1980**-2016 Uranium production, in-situ leaching **2005**-2016 Uranium hexafluoride production **1982**-2016 Uranium production with diffusion method, enriched 4.2% **1980**-2016 Uranium production with centrifuge method, enriched 4.2% **1993**-2016 Uranium fuel element production, enriched 4.2%, for light water reactor **1980**-2016 Nuclear fuel element production, for pressure water reactor, UO2 4.2% & MOX **2002**-2016 Power generation in a nuclear pressure water reactor **1990**-2016
Solid Oxide Fuel Cell	CH	v. 3.3 (2016)	Natural gas production, various countries **1989**-2016 Solid Oxide Fuel Cell production, future **2000**-2016 Solid Oxide Fuel Cell maintenance, future **2000**-2016 Storage tank production **1987**-2016 Power generation in a solid oxide fuel cell 125kWe, future **2000**-2016

Table 3: Data validity of datasets for renewable power generation technologies as indicated in the ecoinvent database.
Key components only**.** Source: adapted from ecoinvent v. 3.3 (2016).

Technology	Location	Ecoinvent Version	**Data validity as indicated in Ecoinvent** (only key components shown)
PV multi-crystalline	CH/ES	v. 3.3 (2016)	Production of panel (multi-Si wafer) **2005**-2016 Production of mounting system for slanted-roof installation **1992**-2016 Inverter production **2004**-2016 Installation on slanted roof **2000/2004**-2016 Power generation of a 3kWp multi-Si planel, mounted on a slanted roof **2005**-2016
PV multi-crystalline (updated)	CH	v. 3.3 (2016); further data (Frischknecht, Itten, et al., 2015; Stolz et al., 2016)	Production and installation of multi-Si PV system **2011** Power generation of a 3kWp multi-Si panel, mounted on a slanted roof **2005**-2016
PV CdTe	CH/ES	v. 3.3 (2016)	Production of photovoltaic laminate (CdTe) **2004**-2016 Production of building integrated module for slanted-roof installation **1992**-2016 Inverter production **2004**-2016 Installation on slanted roof **2004/2008**–2016 Power generation of a 3kWp CdTe laminated panel integrated into slanted roof **2005**-2016
PV CdTe (updated)	CH	v. 3.3 (2016); further data (see PV multi-crystalline updated)	Production and installation of CdTe PV system **2010**-2011 Power generation of a 3kWp CdTe laminated panel integrated into slanted roof **2005**-2016
Geothermal	CH	v. 3.3 (2016)	Geothermal power plant construction (**2008**-2016) Power generation in a deep geothermal enhanced plant (**2015**-2016)
Hydro reservoir	CH	v. 3.3 (2016)	Hydro power reservoir plant construction **1945**-2016 Power generation in a hydro reservoir power plant in an alpine region **1945**-2016
Hydro run-of-river	CH	v. 3.3 (2016)	Hydro power run-of-river plant construction **1945**-2016 Power generation in a hydro run-of-river power plant **1945**-2016
Wind onshore	CH/DK	v. 3.3 (2016)	Onshore wind turbine construction (2MW) **2008**-2016 Wind turbine network connection **2008**-2016 Power generation of a 1-3MW onshore wind turbine **2005**-2012
Wind onshore (updated)	CH	Further data (Bundesamt für Energie BFE, 2015)	Construction of wind turbine components, onshore **2015** Power generation of a 1-3MW onshore wind turbine, onshore **2014**
Wind offshore	DK	v. 3.3 (2016)	Offshore wind turbine construction, (2MW) **1991**-2016 Power generation of a 1-3MW offshore turbine **2000**-201

3.2.5 Data per power generation technology

3.2.5.1 Hard coal based

For hard coal, the analysis bases on ecoinvent data for Germany, since in Switzerland, to date no hard coal power plants exist (and there are no plans to build such a plant in the foreseeable future). The cumulative ecoinvent dataset “electricity production, hard coal”, valid for the German context, describes power generation in an average hard coal power plant in the year 2012. This “average” power plant represents approximately the current mix of German hard coal power plants (in terms of installed capacity per power plant) – 7% are assumed to belong to the 100 MW class, and 93% belong to the 500 MW class.

The following sections discuss each process step of the hard coal based power generation system – the extraction of the energy carrier, the processing and delivery of the feedstock and the conversion to electricity - individually and in greater detail, in order to illustrate the assumptions made in ecoinvent in a transparent way. As a summary, Figure 7 schematically depicts the most important components and process steps of the hard coal based system which are captured by ecoinvent data, and thus, by the present analysis.

Extraction

Hard coal is assumed to be supplied entirely from underground mining in Western Europe. During the coal mining process, methane, which was formed during coal formation, is released from the coal seams. This is listed in ecoinvent as “off-gas”. Since this is not an energy investment in the sense that it is required to operate the mining infrastructure, it is considered a loss, which is attributed to the initial primary energy extraction (and is therefore not considered for the EROI calculation).

Processing

The ecoinvent data does not include a processing step for coal.

Delivery

The coal is assumed to be transported via freight trains. As opposed e.g. to natural gas, which requires pipelines to transport the natural gas, no specific transport infrastructure is needed for coal. Energy requirements associated with the transport are included in the calculations. Dust losses from transport and load/unload operation are included, and average coal losses are included.

Conversion

For the conversion to electricity, an efficiency of 37.3%[6] is assumed, which is equivalent to a hard coal input of 0.4 kg per kWh.

[6] Net electrical efficiency based on the lower heating value (LHV)

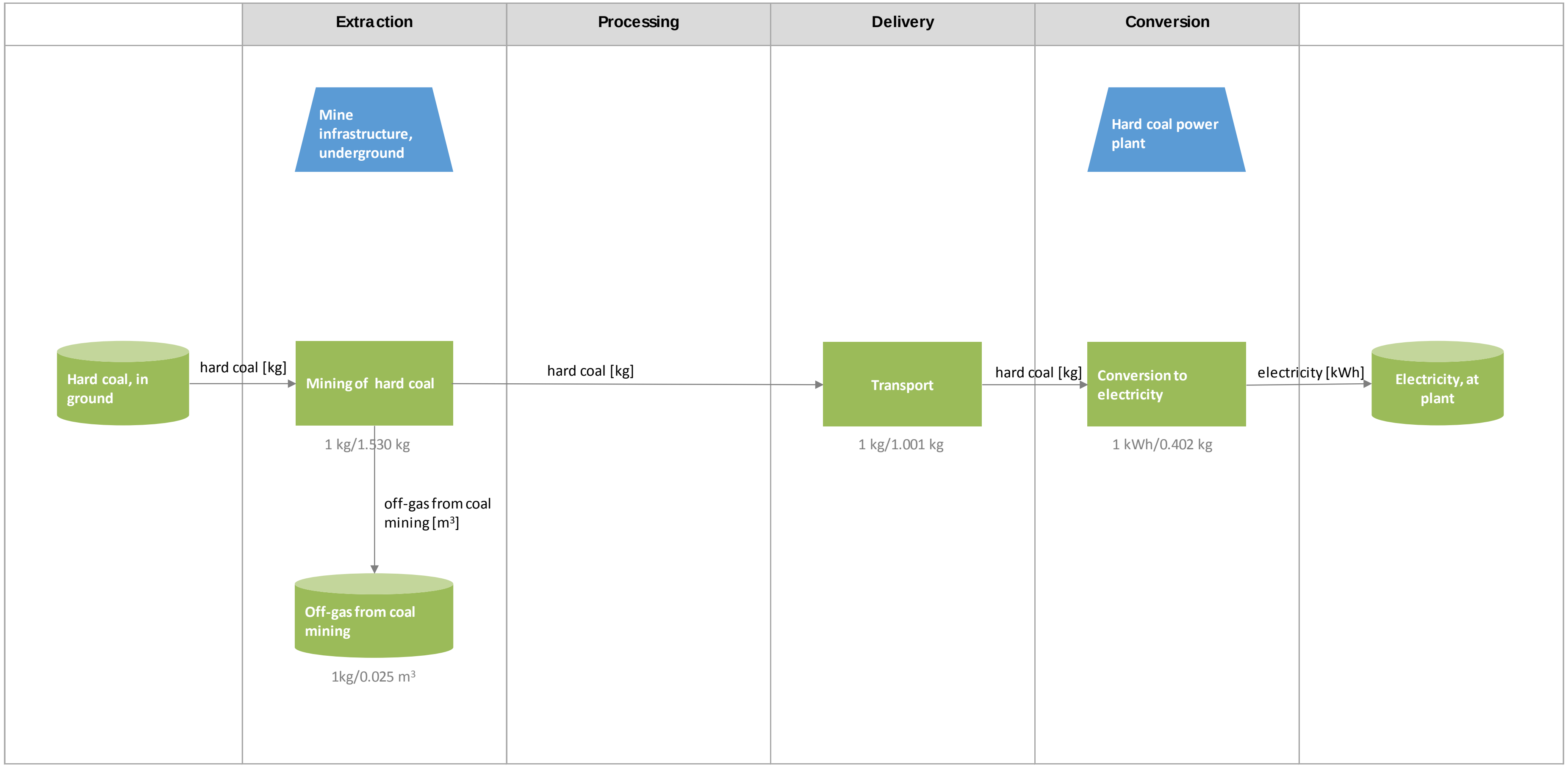

Figure 7: Representation of the hard coal based power generation system in ecoinvent.
Source: based on data from ecoinvent, v3.3 (2016).

3.2.5.2 *Natural gas based (CCGT)*

As far as natural gas is concerned, the analysis focuses on power generation in modern natural gas combined cycle (CCGT) power plants. Those power plants use both a gas and a steam turbine, so that the waste heat discharged by the gas turbine can be used to generate steam for additional power generation via the steam turbine. Combining two power generation cycles significantly enhances the efficiency of the plant, so that electrical efficiencies of 60% can be reached. Ecoinvent does not provide life cycle inventory data for electricity production in such NGCC plants specifically for Switzerland, since, to date, no such gas power plants exist. For the analysis, data for gas power plants in Germany has therefore been used.

The basis for the analysis was the cumulative dataset “electricity production, natural gas, combined cycle power plant”. The data refers to a typical 400 MW natural gas power plant operating in 2012 in Germany, without combined heat and power[7] (CHP).

Extraction

The data captures the exploration and production process of the natural gas. For a natural gas power plant in Germany, it is assumed that the natural gas is supplied by imports from Russia (38%), Norway (25%), the Netherlands (20%) and domestic production (18%)[8]. The production of natural gas in the different countries is captured in separate datasets in ecoinvent, and sometimes even a regional distinction is made between onshore and offshore production. The country specific datasets do not have an entirely uniform structure (for example, reporting of the losses is not uniform, or for Germany, the dataset for natural gas production includes the processing step, whereas for Norway this is split up in separate datasets etc.), however, they do report on the same aspects.

During the extraction phase, not all of the recovered natural gas is sent to processing. Some of the natural gas is not deemed economic, practical or safe to conserve, and is therefore either flared (burned) or directly released into the atmosphere. For the calculation of the EROI, this waste natural gas is considered a loss and not an energy investment. However, waste natural gas that is burned on site in gas turbines instead of being flared, is considered an energy investment, in the sense that it produces electricity, which is required to keep the operations running.

Life cycle inventory data is also provided on the necessary infrastructure for this process step, e.g. the natural gas field infrastructure and well. The corresponding infrastructure datasets cover the whole lifecycle of the infrastructure, including material and energy uses during the construction, operation and decommissioning phase.

[7] Cogeneration or combined heat and power (CHP) combines power generation with heat provision for industrial processes, district heating and other uses (Moran et al., 2014). Cogeneration is a highly efficient form of energy conversion, however, it is difficult to find users, located nearby, that need large amounts of heat throughout the year. For this reason, gas power plants without CHP are studied in this analysis.

[8] Rounded figures, excluding losses.

Processing

In this process step, the natural gas is purified. Ecoinvent captures both the “drying”, the removal of the water vapour in natural gas, and the “sweetening”, which refers to the removal of hydrogen sulfide from “sour” – sulphur containing- natural gas.

Delivery

Both the long-distance transport and the regional distribution of the natural gas are included in the data. The necessary infrastructure is captured in pipeline datasets, which take into account the requirements for the construction, operation and decommissioning of the pipelines. The transport of the natural gas to the German market via pipelines is assumed to entail losses, which are estimated based on leakage estimates for the European Union.

Conversion

For the conversion of the natural gas fuel to electricity in the power plant, an efficiency of 56.4%[9] is assumed, which corresponds to a fuel input of 0.164 m^3 natural gas per kWh.

[9] Net electrical efficiency based on the lower heating value (LHV)

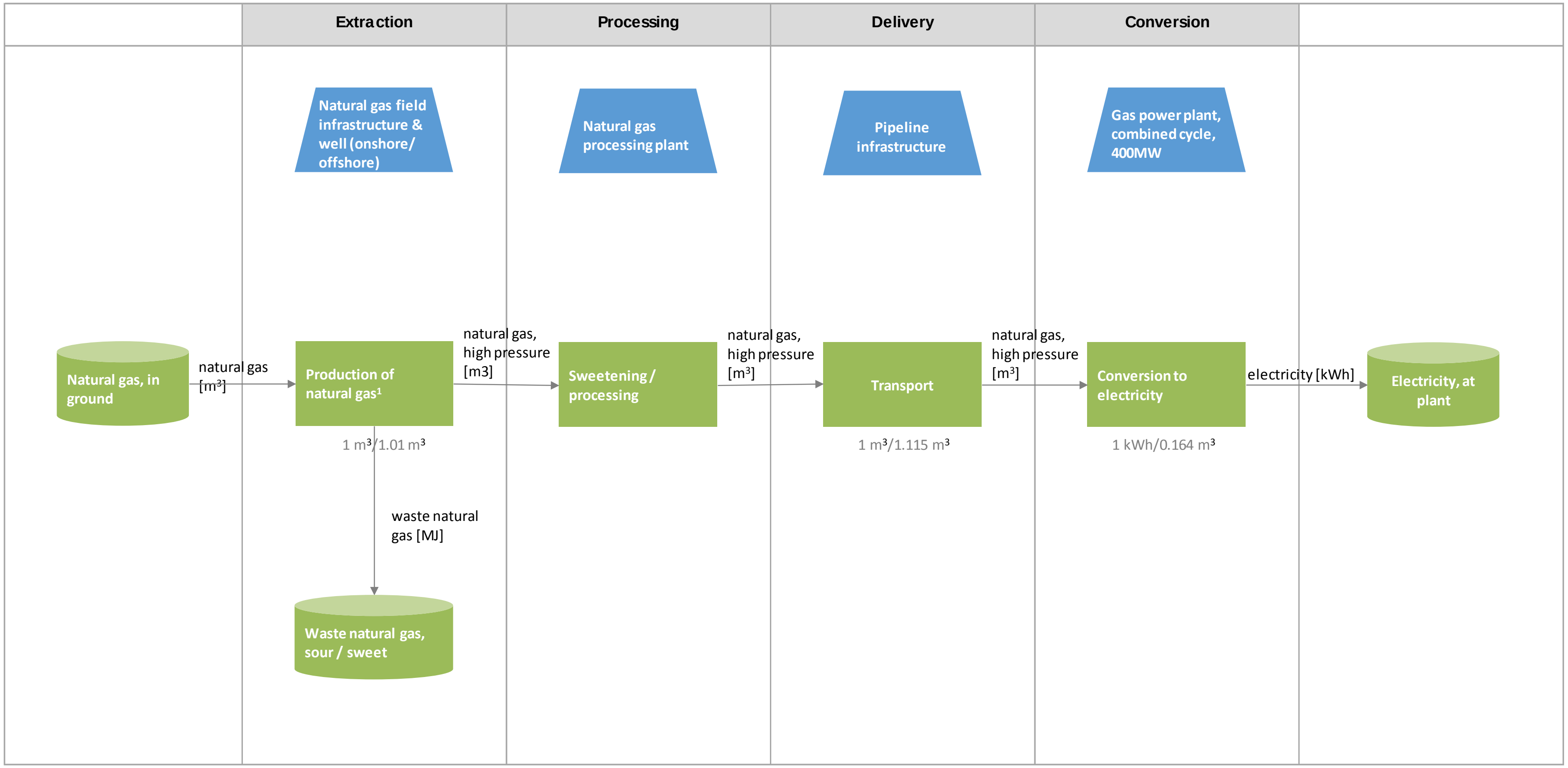

Figure 8: Representation of the natural gas (CCGT) based power generation system in ecoinvent.
Source: based on data from ecoinvent, v3.3 (2016). Note: The ecoinvent datasets for natural gas production in DE, NL, NO, RU have varying structures and losses during exploitation and production are not reported in a coherent way. For this graph, figures for the losses have been taken from the dataset for gas production in DE. However, all datasets with their respective assumptions in terms of losses have been included in the calculation.

3.2.5.3 Nuclear

There are five nuclear power plants in Switzerland, three pressure water reactors and two boiling water reactors, with a total capacity of more than 3000 MW . Ecoinvent provides datasets for electricity production in both pressure water reactors (PWR) and boiling water reactors (BWR) in Switzerland. For the modelling of power generation in BWRs, the operating power plant Leibstadt served as the basis, while for PWRs, the focus was on the Gösgen power plant.

The main difference in the modelling of the two reactor types concerns the type of nuclear fuel used. Both reactor types use enriched uranium, but in the boiling water reactor, only “fresh” nuclear fuel is used, whereas in pressure water reactors, the assumption is made that over the lifetime of the plant 8% of the energy will be produced by “recycled” MOX fuel elements. MOX fuel (mixed oxide fuel) is a nuclear fuel that consists of plutonium oxide from the reprocessing of spent nuclear fuel and depleted uranium from the enrichment process. The Swiss PWR power plants Beznau and Gösgen can partly operate on MOX fuels since 1978 and 1997 respectively.

Subsequently, the ecoinvent data on pressure water reactors is further discussed and analysed, which also fed into the calculations. Figure 9 illustrates components and process steps of the nuclear energy system which are captured by ecoinvent data.

For each modelled process step, an infrastructure dataset exists, which takes into account the requirements for the construction, operation and the decommissioning of the infrastructure (e.g. the uranium mill, uranium enrichment facility etc.).The radioactive wastes, which are generated during the individual process steps, are accounted for and categorised in four different classes: mill tailings, other low active wastes in near-surface depositories, low and medium short-lived waste, and high and intermediate long-lived radioactive waste including spent fuel. The last two types are assumed to require disposal in deep geological repositories.

Extraction

Uranium can be exploited from open pit mining, underground mining and by in-situ leaching (ISL). Ecoinvent provides data for both underground and pit mining, which yields uranium ore. It is assumed that 25% of the global uranium ore is exploited by open pit mining, and 75% by underground mining. The third process, in-situ leaching, is a mining process in which an oxidising solution is pumped into an underground uranium deposit, oxidising insoluble $U4+$ to soluble $U\ 6+$, which is then pumped to the surface. For this process, data is provided in ecoinvent as well. Since this process directly yields yellowcake, the process step of milling the uranium ore and processing it to yellowcake is not necessary.

Processing

Uranium processing involves three main steps. The first step is the processing of uranium ore to a concentrated precipitate named yellowcake. After the milling, the uranium ore undergoes a chemical leaching process to release the uranium in the form of yellowcake. Losses of uranium during this milling process are assumed to be 5% of the input uranium. In total, ecoinvent models 65% of the yellowcake to originate from traditional mining and processing, and 35% from in-situ leaching of uranium ore. The second step is the conversion of yellow cake to gaseous uranium hexafluoride, which is required for the subsequent step – the enrichment of the uranium. The required infrastructure to do this, the uranium conversion facility, is accounted for as well. During the third step, the enrichment, the proportion of 235U in the uranium is increased, from a natural share of 0.7% to about 3-4%. Two techniques are applied for this, the centrifuge process and the diffusion process. They are captured in two separate datasets in ecoinvent due to their great variability in energy intensity, the origin of the electricity supply and the cooling fluid used. The diffusion process is very energy intensive and is steadily replaced with the more modern centrifuge technology, which uses about 60 times less energy than gaseous diffusion. Ecoinvent assumes that only 2% of the uranium enriched to a content of 4.2% still originate from the diffusion process (for the PWR dataset, the required level of enrichment is assumed to be 4.2%). The infrastructure requirement is accounted for as well (uranium enrichment diffusion/centrifuge facility).

The nuclear fuel is then assumed to consist of 92% of "fresh" nuclear fuel and 8% of the MOX fuel. Additionally, the requirements in terms of material, infrastructure and energy for the reprocessing of the MOX fuel are considered as well.

Delivery

Transport is included in the respective steps (for example the transport of the nuclear fuel is attributed to the nuclear fuel processing step). No specific transport infrastructure is needed.

Conversion

The infrastructure dataset for a 1000 MW nuclear power plant describes the Swiss unit Gösgen. The net efficiency is assumed to be 32%. The estimates of the amounts of radioactive waste generated during the operation and decommissioning of the power plant are based on an evaluation which was performed by the Gösgen operators in the 1980s. For the spent fuel, two methods of treatments are considered: 40% of the total Swiss spent fuel is assumed to be recycled, leaving 60% for "conditioning", the direct disposal of untreated spent fuel.

Ecoinvent models the disposal of spent fuel and other high and intermediate long-lived radioactive waste in a geological final repository based on the concept developed by Nagra (Nationale Genossenschaft für die Lagerung radioaktiver Abfälle). Included in the considerations are the amount of overburden, the material and energy uses for mining the tunnels, placing the wastes and for the final sealing of the repository.

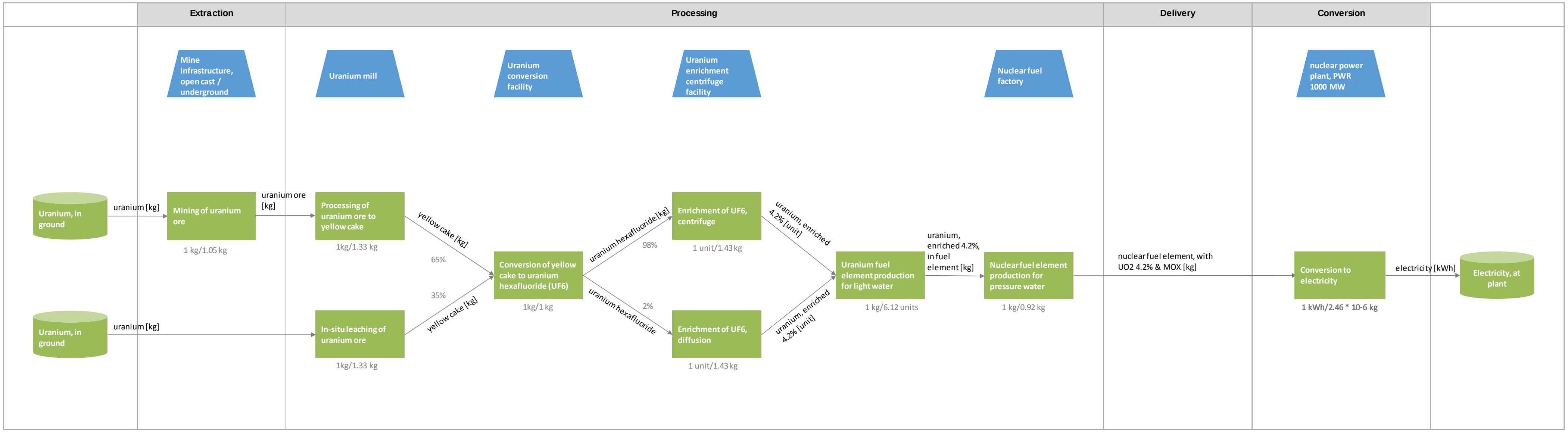

Figure 9: Representation of the nuclear power generation system in ecoinvent.
Source: based on data from ecoinvent, v3.3 (2016).

3.2.5.4 *Multi-crystalline silicone photovoltaics*

For solar PV roof installations, a wide range of datasets exists in Ecoinvent. Distinctions are made between different cell types (mono-crystalline silicon, multi-crystalline silicon, amorphous silicon, ribbon silicon, CIS and cadmium telluride), the type of installation (building-integrated, i.e. frameless laminate, or mounted, i.e. framed panel) and the roof type, on which the panel is installed (slanted roof vs. flat roof vs. facade installations). This results in more than 30 datasets for electricity production from solar PV in Switzerland, each describing a 3kWp installation.

For this analysis, two PV technologies were chosen: multi-crystalline silicon, since it represents the first, wafer-based generation of PV panels and cadmium-telluride, which belongs to the newer, second generation thin-film technology. The main differences between the two technologies are the amount of active material used, which influences manufacturing costs, and the efficiencies in converting the incident solar radiation to electricity. Since for solar PV, the process steps extraction, processing and delivery of the fuel are not needed, there is only one process step considered - the conversion of solar energy to electricity – plus the requirements for the construction, operation and decommissioning of the associated “infrastructure”. The LCI data includes processes that are required to manufacture the panel, the electric components, and the mounting system. A lifetime of 30 years is assumed for all cell types. Also, a decreased yield over the lifetime is taken into account in the output data. The end-of-life treatment of PV plants is modelled based on expected figures, not on real estimates due to a lack of such data.

The production of a solar PV panel is dependent on solar irradiation and thus, highly location-dependent. For comparison, this analysis considers both a site in Switzerland and a site in a high insolation region in Europe for each technology.

Jungbluth et al. (2012), who provided the LCI data for PV in ecoinvent, state that the production technology for photovoltaic power plants has constantly improved over the last few decades, (e.g. the amount of silicon required, capacities of production processes) and continues to improve rapidly. Due to the rapid technological development, they argue that it is not possible to keep the datasets for all technical processes fully up-to-date.

Multi-crystalline silicon PV in Switzerland

Figure 10 illustrates the components of a multi-crystalline silicon PV system included in the ecoinvent data. Processes included are, for example, the quartz reduction, the purification of the silicon, the production of wafer, panel and laminate and the manufacturing of the inverter, mounting and cabling. For each of those processes (for example, for the purification of the silicon), the inventory includes energy consumption, required materials and the transport thereof, dismantling of all components, the infrastructure for the production facilities and waste treatment for production wastes.

All PV datasets refer to a 3kWp installation. The cell’s efficiency to convert solar irradiation to electricity feeds into the calculation of the necessary amount of panel area to provide this specific power. For multi-crystalline silicon, assuming a cell efficiency of 14.9%, a panel area requirement of 22.1 m^2 is assumed.

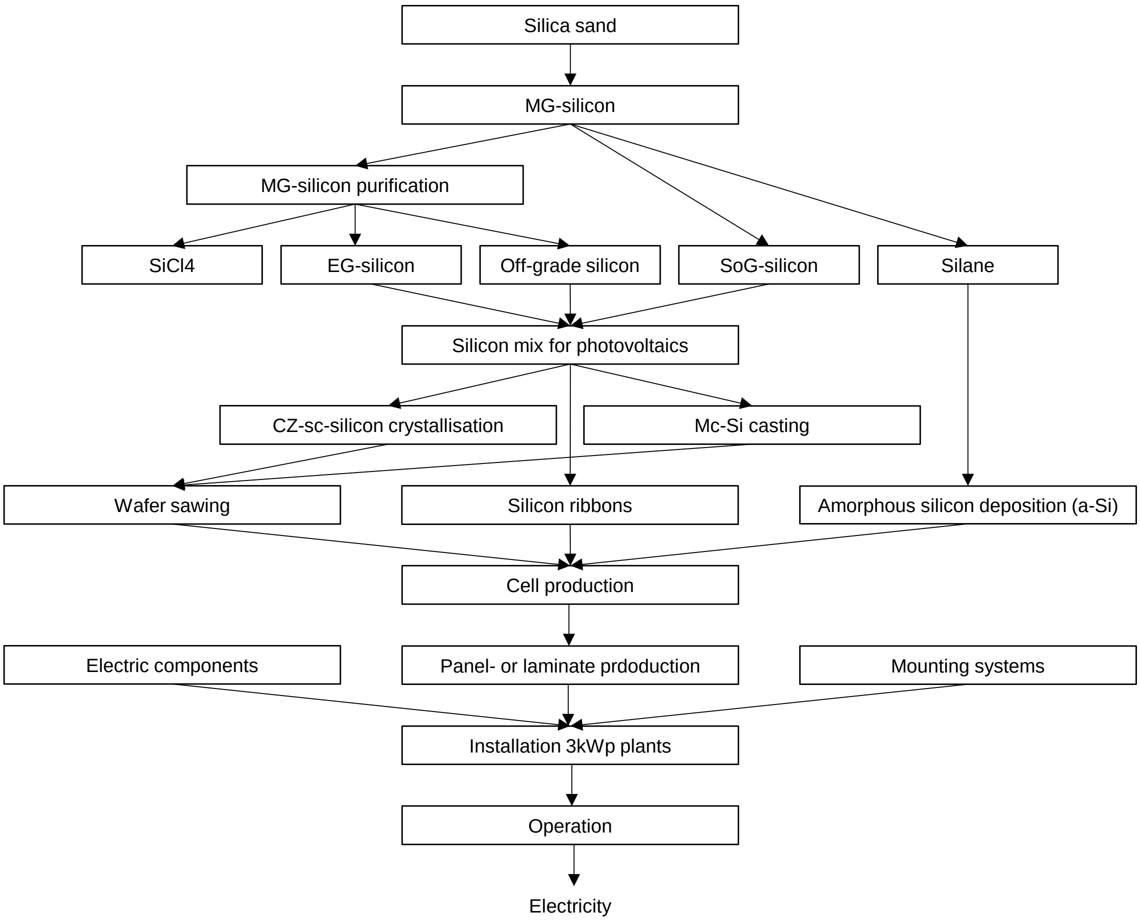

Figure 10: Components of a crystalline silicon PV system covered by ecoinvent.
MG-silicon = metallurgical grade silicon, EG-silicon = electronic grade silicon, SoG-silicon = solar-grade silicon). Source: Jungbluth et al. 2012

The Ecoinvent estimate of the annual production of a multi-crystalline silicon PV panel in Switzerland is based on data from operating photovoltaic panels in Switzerland for the years 2000 to 2005. The average production values for these 6 years range from 800 to 875 kWh/kWp, due to changing meteorological conditions. For the calculation in ecoinvent, the mean value of those 6 values is assumed, resulting in an average yield of 820 kWp/kWp. Thus, the figures in ecoinvent represent an average operation scenario, and are considerably lower than the expected yield for an installation in optimum orientation at an optimal location

The lifetime production of a multi-crystalline silicon PV panel is then obtained by multiplying with the assumed 30 years of operation and the assumed size of the installation (3 kWp).

The data on the production of photovoltaic multi-Si PV panels and other key components provided by ecoinvent cannot be considered entirely up-to-date: For example, the production data for multi-Si wafers dates back to the year 2005. A complementary calculation has therefore been conducted with the aim to obtain an estimate for a more recent technology status for the Swiss context, drawing on LCA studies providing manufacturing data for the status of 2011 (Frischknecht, Itten, et al., 2015; Stolz et al., 2016). With regard to the electricity yield data, the same data as provided by ecoinvent has been used for this calculation.

Multi-crystalline silicon PV in high insolation regions in Europe

For the analysis of a high insolation region in Europe, a wide range of datasets for various European countries are available. For this analysis, data for Spain was chosen.

The Ecoinvent estimates of the yield per kWp installed PV capacity in different countries are based on annual output data published by the IEA. However, this data describes the yield of newly erected plants, whereas the data for Switzerland is based on the whole stock of operating PV plants. A correction factor of 0.92 is therefore applied on the IEA data in Ecoinvent to obtain consistent values referring to the average yield.

For Spain, an annual average yield of 1183 kWh/kWp results in Ecoinvent, which is 44% higher than the assumed value for Switzerland. The remaining data that feeds into the calculation for Spain is the same as the data used for the calculation for Switzerland.

3.2.5.5 Cadmium-telluride thin film photovoltaics

Cadmium-telluride thin film PV in Switzerland

The following figure shows the components of a cadmium telluride thin film PV system, which are covered by ecoinvent data. For a cadmium telluride PV system, a lower cell efficiency of 11.7% is assumed as compared to multi-crystalline PV, which corresponds to a larger required panel area of 25.6 m^2 to provide the reference power of 3 kWp.

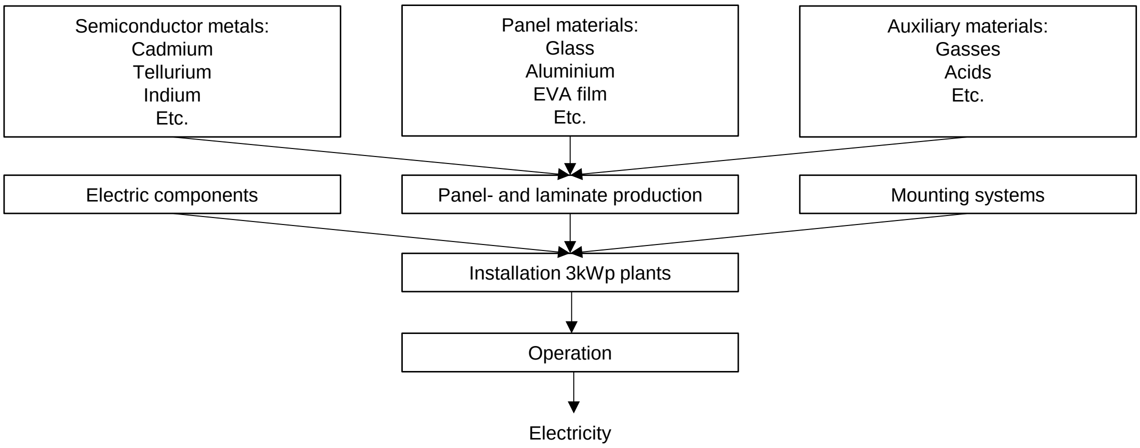

Figure 11: Components of a cadmium telluride thin film PV system covered by ecoinvent.
Source: Jungbluth et al. 2012.

Photovoltaic plants with good performance form the basis for the estimates for the yield per kWp of a cadmium-telluride PV panel in Switzerland in ecoinvent. Thus, an average installation would achieve a lower, while an optimum installation would achieve a higher yield. For cadmium telluride PV systems, the electricity yield assumed in the ecoinvent database is calculated via a top-down approach: The total production volume by PV panels in Switzerland in the year 2012 (127 GWh) is taken, and is distributed to the different photovoltaic installation types according to their respective market shares, which can be found in Jungbluth et al. 2012. The resulting annual yield per kWp is 918 kWh/kWp.

The data on the production of photovoltaic laminate and other key components in ecoinvent is not entirely up to date: For example, the production data for the CdTe laminate dates back to 2004. In order to get an impression of the performance of the recent technology status for the Swiss context, the calculations were in addition conducted with more recent LCA data. In Frischknecht et al., (2011) and Stolz et al., (2016) manufacturing data representing the technology status 2010 for the CdTe technology is provided, which was used for these complementary calculations. The electricity yield data for the Swiss context, as provided by ecoinvent, has not been changed for these calculations.

Cadmium-telluride thin film PV in high insolation regions in Europe
For cadmium-telluride thin film PV plants, only 2 datasets exist – one for locations in Switzerland and one for locations in the rest of the world.

The electricity yield data in the dataset for the rest of the world is therefore highly aggregated, consisting of a weighted average (on the basis of installed capacity in kWp) of performance data of 30 countries. The resulting yield value (1011 kWh/kWp) is strictly speaking not representative for high insolation regions in Europe. Therefore, the yield data has been corrected by taking the disaggregated yield value for Spain, instead of taking the 30 country average, from the same source which served as the basis for the yield data captured in ecoinvent (IEA, 2008a). This gives a value of 1183.1 kWh/kWp.

To summarize, Figure 12 illustrates the PV system as captured in ecoinvent. For the conversion efficiency, the point of reference for the primary energy harvested is the energy that is delivered to the inverter. Since the inverter is assumed to produce losses, the conversion efficiency is 93.5%. Therefore, an input of 3.85 MJ of primary energy is required to produce one unit of final electricity output (1 kWh, equivalent to 3.6 MJ).

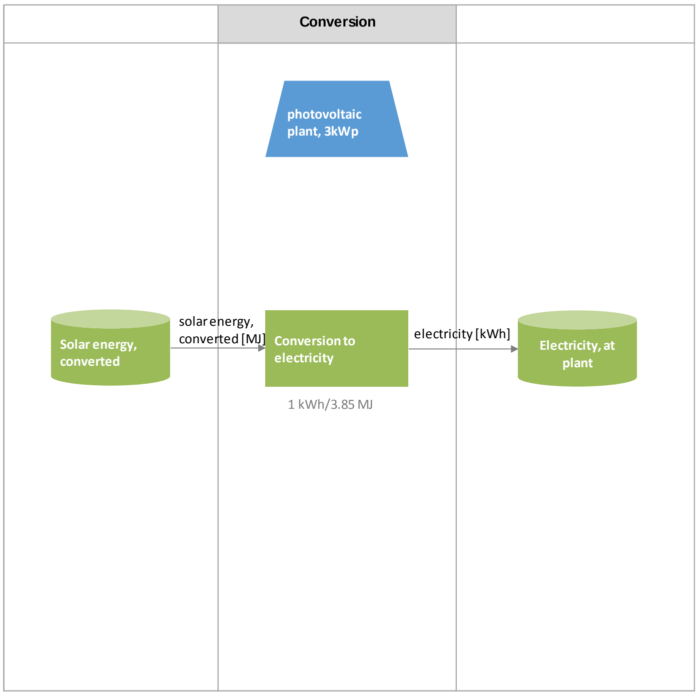

Figure 12: Representation of the solar PV system in ecoinvent.
Source: based on data from ecoinvent v3.3. (2016).

3.2.5.6 Geothermal

The term “deep geothermal power”, as it appears in the Ecoinvent database, denotes the technology that extracts heat energy from hot rock formations, which is subsequently exploited for power generation. It comprises the use of hydrothermal, petrothermal and geothermal resources, of which hydrothermal and petrothermal systems are assumed to offer the greatest potential for power generation in general (Hirschberg et al., 2015). Geothermal heat probe means the use of a single, deep borehole heat exchanger. Using a single well, however, limits the scope of heat production, and is therefore not a viable option for large scale power generation (Hirschberg et al., 2015).

Hydrothermal resources are geologic layers with a natural presence of (hot) water, which can be directly exploited. However, according to a report of the Swiss Centre for Technology Assessment (Hirschberg et al., 2015) on the potential of deep geothermal resources, saturated formations or structures with suitable conditions, e.g. with temperatures high enough for sufficient hot water productivity, are of relatively low abundance in Switzerland.

Petrothermal resources (also known as hot dry rock or enhanced geothermal) are hot, dry and impermeable rocks, in which water circulation is restrained. In order to enhance the efficiency of heat extraction, the rocks of the reservoir must be fractured by injecting a highly pressurized fluid (‘well stimulation’), creating microcracks, so that the heat exchange medium can circulate. This technology is assumed to bear the greatest potential for power generation in Switzerland (Hirschberg et al., 2015). An enhanced geothermal project in Basel for both power and heat generation, was abandoned in 2009 after seismic events occurred, induced by the well stimulation (Hirschberg et al., 2015).

The available data in Ecoinvent does not explicitly model the exploitation of one of the aforementioned types of geothermal resources, but rather a set of key parameters describing the geothermal power plant design, which are summarised in Table 4.

Table 4: Characteristics of geothermal power plant.
Source: ecoinvent v3.3 (2016), Hirschberg et al.(2015).

Net plant power	5.5 MWel
Number of wells	6 (2 well triplets during total lifetime)
Well depth	5 km
Geothermal gradient	35 °C/km
Surface plant life time	30 years
Well (reservoir) life time	20 years
Pipe inside diameter	25.4 cm
Production flow rate	147 l/s
Electrical efficiency	14%
Rock stimulation[10]	yes
Surface system / Power generation unit	Organic Rankine Cycle (ORC) with benzene as working fluid

The infrastructure dataset for the 5.5 MW geothermal power plant comprises all parts necessary to build a geothermal power plant: the deep well drilling, stimulation and surface power generation installations (Hirschberg et al., 2015).

For the deep well drilling, the following elements are included:
- Energy use for drilling (energy source is assumed to be electricity from the grid, with diesel only acting as back-up)
- Drilling for exploratory wells
- Material and energy use for the casing (consisting of steel and cement) of the borehole
- Treatment of the drilling fluid
- Transport and treatment of the drilling cuttings
- Transport of drilling infrastructure, casing material, and drilling fluid ingredients
- End-of-life of borehole
- Energy requirements for the infrastructure on the drill site (e.g. the drilling rig)

For the surface power generation unit, material use for the turbine and generator, requirements for the production of benzene (working fluid) and the dismantling of the unit are considered. Yearly losses of the working fluid of 8% are taken into account.

Figure 13 depicts the geothermal power system as captured in Ecoinvent. Since the conversion efficiency of the power generation unit is assumed to be 14%, an input of 7.14 MJ of geothermal primary energy (considered renewable) is required to produce one unit of electricity (3.6 MJ).

[10] Since rock stimulation is assumed, the data does not completely correspond to hydrothermal plants

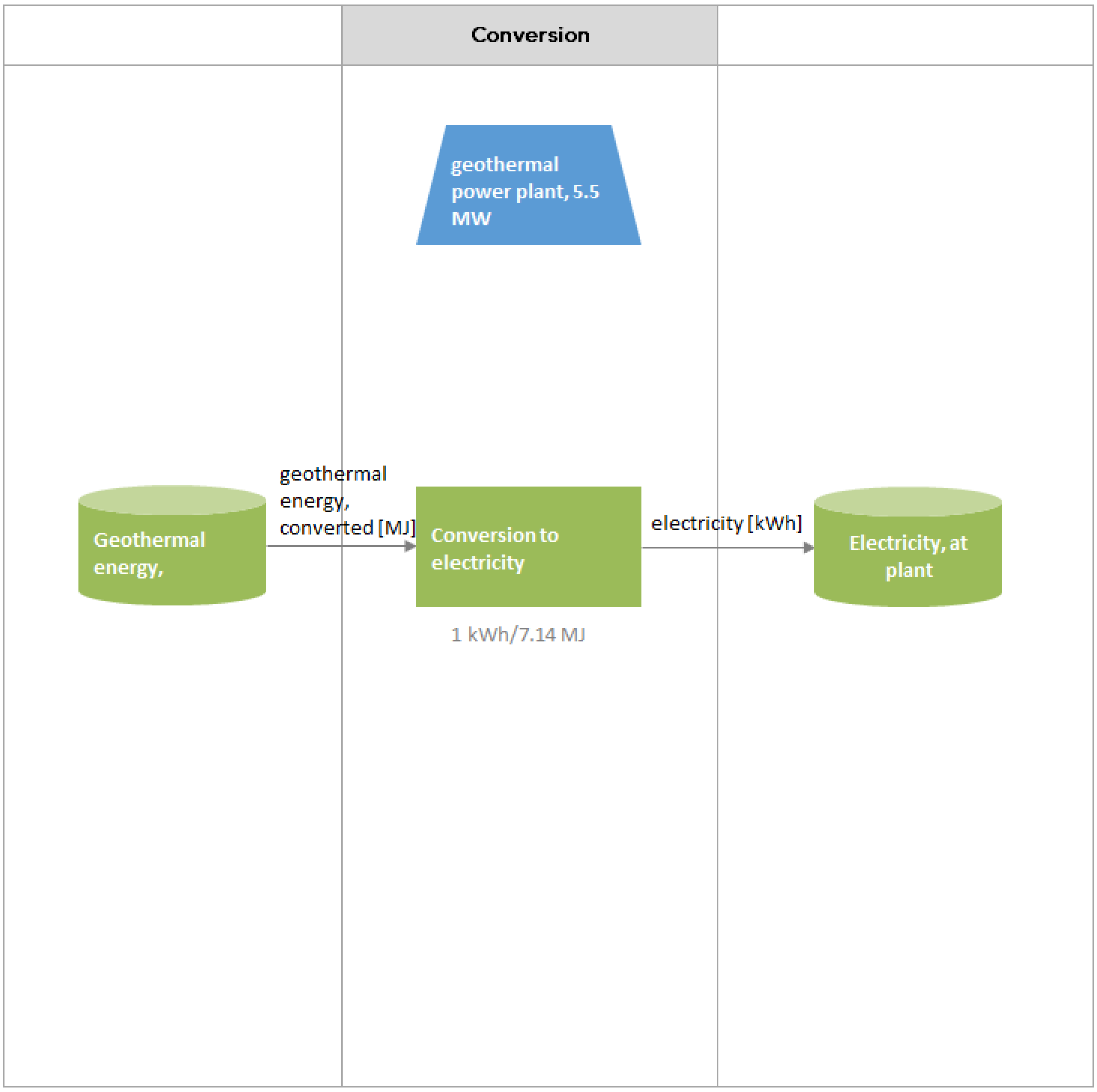

Figure 13: Representation of geothermal power system in ecoinvent.
Source: based on data from ecoinvent, v.3.3 (2016).

3.2.5.7 *Hydro reservoir*

Two types of hydro power plants have been considered in this analysis. On the one hand, reservoir hydro power plants, which convert the potential energy of water stored in dams to electricity, and on the other hand, run-of-river hydro power plants, which harvest the energy of flowing water (e.g. streams or rivers). The following figure schematically depicts the hydro power system. No other infrastructure than the hydro power plant itself is required. Maintenance and decommissioning of the hydro power plant is included in the data. As to the conversion, the point of reference for the energy harvested is the rotation energy of the turbine. The conversion efficiency of the primary energy harvested to electrical energy is assumed to be 95% (that is, an input of 3.79 MJ of primary energy is required per kWh), since the generator is assumed to be lossy.

The data for reservoir power plants in Ecoinvent is based on a representative sample of Swiss dams with a height of more than 30 meters. More specifically, 52 reservoir power plants with an annual gross production output of 17.8 TWh and a total installed capacity of 9130 MW form the basis for the analysis. The infrastructure dataset for the reservoir hydro power plant is both used for reservoir power plants and pumped storage power plants, due to the fact that the construction efforts are comparable. Lifetime is assumed to be 150 years for the dam and 80 years for the rest of materials. The data refers to the above-mentioned sample of dams, which were built between 1945 and 1970. The data can therefore not be assumed fully representative for reservoir power plants of the newest generation.

The overall efficiency of the reservoir power plant is composed of the efficiency of the works water channel, the turbine, the generator and the transformer. The following table shows the assumed efficiencies of the components, as compared to efficiency values for more modern reservoir power plants (in brackets), as provided in Ecoinvent.

Table 5: Characteristics of the considered reservoir hydro power plant.
Values for modern power plants in brackets. Source: ecoinvent, v.3.3 (2016).

Works water channel efficiency[11]	95% (95%)
Turbine efficiency	87% (91%)
Generator efficiency	96% (98%)
Transformer efficiency	98% (99%)
Reservoir power plant efficiency without works water channel	82% (88%)
Reservoir power plant efficiency with works water channel	78% (84%)

The data incudes operation and maintenance activities of the power plants, including required materials to conduct maintenance, such as lubricating oil or mass of water passing through the turbines.

[11] Losses along the works water channels are primarily caused by friction

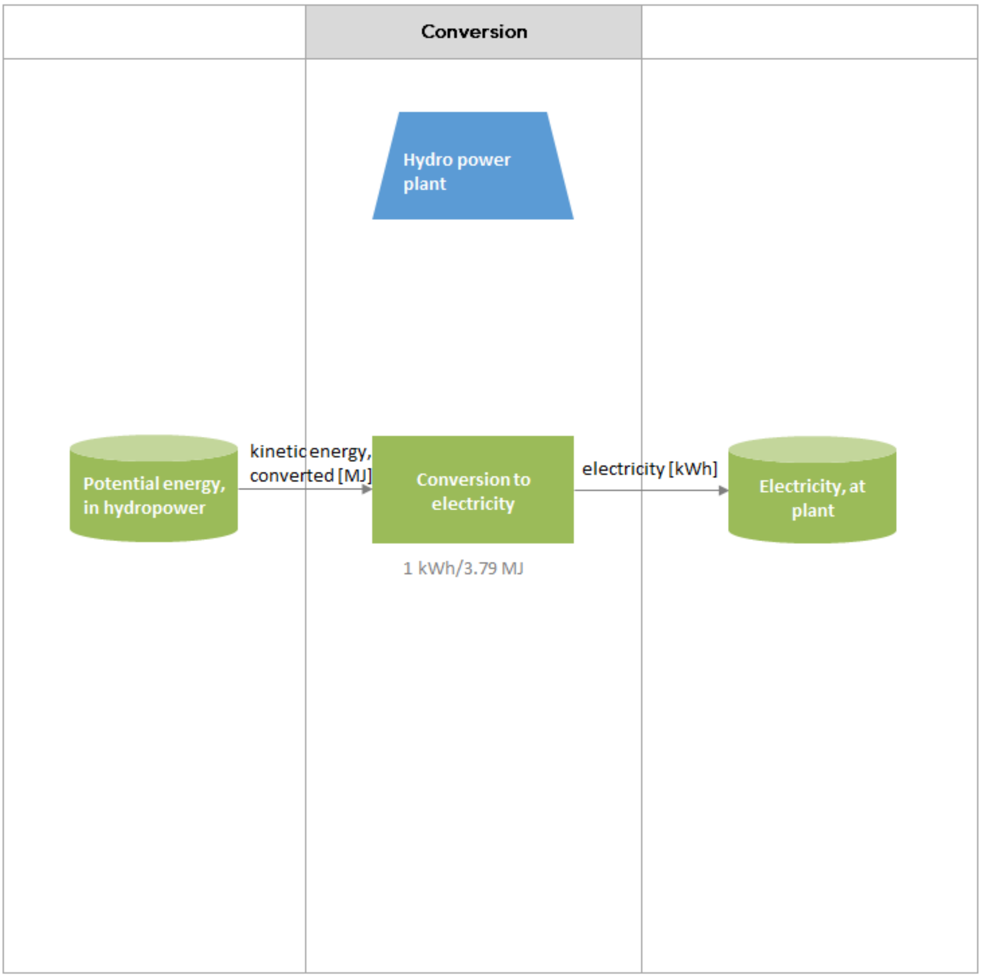

Figure 14: Representation of the reservoir hydro power system in ecoinvent.
Source: based on data from ecoinvent, v.3.3 (2016).

3.2.5.8 *Hydro run-of-river*

A representative sample of run-of-river power plants in Switzerland and Austria forms the basis for the dataset in Ecoinvent, including the following power plants: Rupperswil-Auenstein (CH), Wildegg-Brugg (CH), Birsfelden (CH), Donaukraftwerk Greifenstein (AT), Rheinkraftwerk Albbruck-Dogern (CH), as well as Ruppoldingen (CH), all built between 1945 and the beginning of the 1980s. The data might therefore not be fully representative for more modern types of run-of-river power plants.

The run-of-river infrastructure dataset assumes a lifetime of 80 years for the structural parts (including materials such as cement and reinforcing steel) and 40 years for all remaining parts. The following table shows the assumed efficiency of components of the run-of-river power plant in Ecoinvent (with efficiency values for more modern run-of-river power plants indicated in brackets for comparison).

Table 6: Characteristics of the considered run-of-river hydro power plant.
Values for modern power plants in brackets. Source: ecoinvent, v.3.3 (2016).

Works water channel efficiency	100% (100%)
Turbine efficiency	87% (91%)
Generator efficiency	96% (98%)
Transformer efficiency	98% (99%)
Overall run-of-river power plant efficiency	82% (88%)

The data incudes operation and maintenance activities of the power plants, including required materials to conduct maintenance, such as lubricating oil, and mass of water passing through the turbines.

3.2.5.9 *Wind onshore*

Ecoinvent offers datasets on both on- and offshore wind power generation in a range of countries and regions. For each country, data is available for three turbine size classes: smaller than 1 MW, 1-3 MW and larger than 3 MW. In order to analyse the effect of regionally varying wind conditions, it has been decided to analyse two wind locations:

1. Onshore wind power generation in Switzerland
2. Onshore wind power generation in high wind speed regions in Europe

Wind onshore in Switzerland

Choosing the turbine size class 1-3 MW as unit of analysis is deemed useful, since the majority of wind turbines installed in Switzerland belong to this size class (91.2 %, based on figures of 2014 in Ecoinvent). The turbine size class is approximated with a Vestas V80 turbine with a 2 MW rating. Table 7and Table 8 provide the characteristics and operational data of this reference wind turbine.

The infrastructure dataset for the reference wind turbine includes both the moving and the static parts of the wind turbine, such as the rotor, the nacelle (which in turn consists of the generator, the gear, main shaft, yaw system etc.), the electronics, the steel tower and the foundation. All materials for the construction of these components are included, plus the energy for erection of the turbine. According to the common practice in ecoinvent, the infrastructure dataset further includes the energy requirements for the maintenance and for the dismantling of the wind turbine. Maintenance work is assumed to be conducted twice per year, including a change of the lubricating oil once per year. Since it is assumed that all parts will hold for a period of 20 years, no replacement is necessary during the lifetime of the wind turbine (which amounts to 20 years as well).

The grid connection of the wind turbine to high or medium voltage grid is considered in a separate infrastructure dataset, including components such as cables, the transformer, substation with the circuit breaker and the electricity meter.

Table 7: Characteristics of reference onshore wind turbine.
Source: ecoinvent v3.3. (2016).

Type	Vestas V80
Capacity	2 MW
Diameter of the rotor	80 m
Swept area	5’027 m^2
Number of rotor blades	3
Rotor weight	37’000 kg
Rotor blade weight	6’500 kg
Nacelle weight	61’000 kg
Tower type	Tubular steel tower
Tower weight	165’000 kg
Material of the tower	Steel
Tower hub height	78 m
Tower diameter	4 m
Foundation weight	805’000 kg
Cable for network connection (per turbine)	1000 m
Lifetime	20 years

Table 8: Operational data of reference onshore wind turbine (2 MW Vestas V80).
Source: ecoinvent v3.3. (2016).

Cut-in wind speed	4 m/s
Rated wind speed	16 m/s
Cut-out wind speed	25 m/s
Nominal revolutions	16.7 rpm
Generator type	4-pole doubly fed generator, slip rings
Gearbox type	Three-stage planetary/helical
Power regulation	Pitch regulated with variable speed

Figures for the electricity yield of a wind turbine in Ecoinvent are taken from a 2012 report on the status of wind energy in Switzerland. The number of equivalent full load hours for wind turbines in Switzerland is calculated from the total amount of installed capacity (45.2 MW in 2012, 12 wind turbines, only wind turbines > 1 MW considered) and their average yearly production (77 GWh). Taking into account a 1% loss from gross electricity production, the resulting equivalent full load hours[12] amount to 1686.5 h. The reference wind turbine's total lifetime yield is then calculated by multiplying the total lifetime with the rated capacity and the equivalent full load hours.

The ecoinvent manufacturing data for the production of turbines and network connections date back to 2008. In order to gain an additional, more up-to-date estimate for comparison, the calculations have been repeated with recent data from a report by the BFE (2015) on the life cycle impact of Swiss wind energy. The BFE study examines 10 currently operating Swiss wind parks, which cover 98.8% of the Swiss wind energy production (Bundesamt für Energie BFE, 2015). Among the wind parks covered by the study, two parks employing wind turbines with ratings around 2 MW (to allow for a meaningful comparison with the ecoinvent data), and of the newest generation (built between 2010 and 2017), have been selected. As a result, the data referring to the wind parks Mt Croisin and Peuchapatte has been used as a basis for the calculations, including the actual yield per turbine as reported by the study. The resulting additional data point (see Chapter 1.1 for results) thus represents a performance average of current wind technology employed in two Swiss wind parks of the newest generation.

Wind onshore in high wind speed regions in Europe

In order to analyse the influence of varying regional wind conditions, the calculation has been repeated with the dataset for Denmark. A report by the European Environment Agency (2009) investigating Europe's onshore and offshore wind energy potential, found the highest observed annual mean wind speeds for the geographical region comprising Denmark, Germany and the Netherlands.

In Ecoinvent, the reported full load hours vary significantly. For Denmark, the full load hours are reported to be 2443 hours, for Germany 1602.3 hours and for the Netherlands 2063 hours. Since this

[12] Theoretical number of hours that the wind turbine has to run at full load in order to produce the annual yield

figure feeds directly into the calculation of the lifetime yield of the wind turbine, the dataset for Denmark was chosen to be best suited for representing a high wind speed location.

The calculation for wind onshore in Denmark differs from the calculation for the Swiss context only in the assumed lifetime yield of the wind turbine. The data for the infrastructure requirements, specifically the reference wind turbine, is the same.

3.2.5.10 Wind offshore

Up to the present, ecoinvent data on offshore wind power generation is only available for the turbine size class 1-3 MW, which is approximated with a 2 MW turbine of the type Siemens/Bonus 2 MW. However, the average capacity rating of offshore wind turbines under construction in the year 2016 was 4.8 MW (WindEurope, 2017). The data available in Ecoinvent is therefore not fully representative of offshore wind turbines of the newest generation, however, to date this is the only data available in ecoinvent. Table 9 and Table 10 summarise characteristics and operational data of the offshore reference wind turbine.

Table 9: Characteristics of reference offshore wind turbine.
Source: ecoinvent v3.3. (2016).

Type	Bonus 2 MW
Capacity	2 MW
Diameter of the rotor	76 m
Swept area	4536 m^2
Number of rotor blades	3
Rotor weight	52’000 kg
Rotor blade weight	n.a.
Nacelle weight	82’500 kg
Tower type	Conical steel tube mast
Tower weight	113’210 kg
Material of the tower	Steel
Tower hub height	60 m
Tower diameter	n.a.
Foundation weight	2’300’000 kg
Cable for network connection (per turbine)	n.a.
Lifetime	20 y

Table 10: Operational data of reference offshore wind turbine (Bonus 2 MW).
Source: ecoinvent v3.3. (2016).

Cut-in wind speed	n.a.
Rated wind speed	n.a.
Cut-out wind speed	n.a.
Nominal revolutions	17 rpm
Generator type	Asynchronous generator
Gearbox type	Three-stage planetary
Power regulation	n.a.

The datasets for offshore wind power generation in different European countries are all based on data for the Danish Offshore wind park Middelgrunden, built in 2000, without further, regional variation between the datasets. Maintenance is included in the data.
Two infrastructure datasets are available, one describing the fixed parts, the other describing the moving parts of the reference wind power plant. The datasets include required materials, construction and disposal of all components, except for the foundation and the network connection, which are assumed to be left in the ocean upon dismantling.

The following figure schematically depicts a wind power system (valid for both onshore and offshore wind power systems). For the conversion, the point of reference for the energy harvested is the rotation energy of the rotor. Of this incoming energy, 93% is converted to electricity by the generator, assuming a loss of 7%.

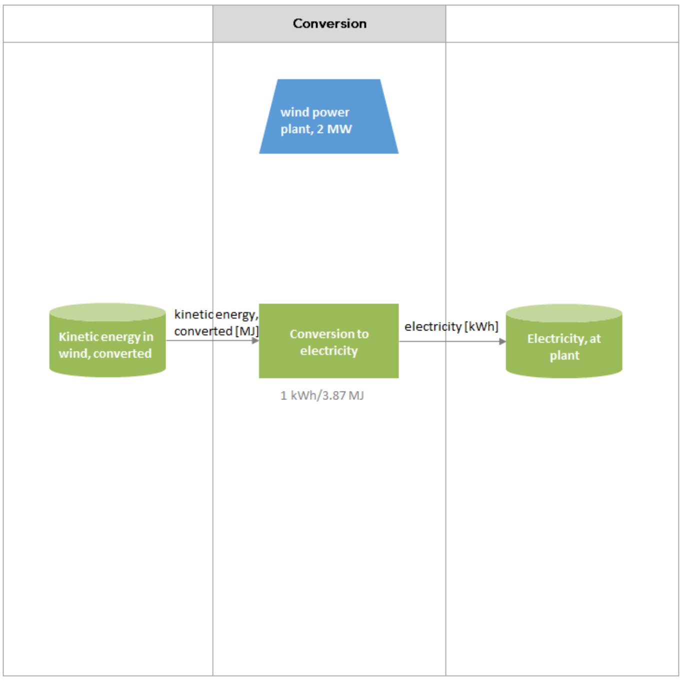

Figure 15: Representation of the wind energy system in ecoinvent.
Source: based on data from ecoinvent, v3.3 (2016).

3.2.6 Data per power storage technology

As far as data is concerned, Ecoinvent has turned out not to be a sufficient data source for the energy performance analysis of storage technologies, since some of the technologies are not or insufficiently covered (e.g. lead acid batteries, power-to-gas), or the data does not specify the storage capacity of the technology under investigation (e.g. in the pumped hydro storage dataset). This part of the analysis therefore draws on additional sources of data.

There is one important difference between the (previously applied) calculation method for the EROI and the calculation method for the ESOI. In the EROI calculations, the energy requirements for construction, operation and maintenance, and decommissioning of all infrastructure was considered, following a so-called cradle-to-grave approach. However, with regards to operation and maintenance, energy requirements for the operation of the energy storage often feed directly into the round-trip-efficiency. For example, the electrical energy used for operating the pumps in a pumped hydro storage plant often feeds into the round-trip efficiency of the plant, and is therefore classified as an energy loss instead of an energy investment.

Furthermore, LCI data on the decommissioning of energy storage devices is often not available for all technologies. Therefore, for ESOI, only the energy requirements (direct and indirect energy in the form of materials) for the construction of the infrastructure are considered, following the cradle-to-gate logic.

3.2.6.1 Lead-acid battery

The cycle life (the number of times the battery can be charged and discharged), the round-trip efficiency and the depth-of-discharge of the battery determine how much of the stored energy the battery returns over its lifetime (per unit of storage capacity). The number of cycles is, in turn, dependent on depth-of-discharge.

In comparison with lithium-ion batteries, lead acid batteries have a shorter life cycle, which can be drastically reduced at deeper depth-of-discharge. The parameters shown in Table 11 were used for the calculation. Values between 0.7 and 0.9 have been suggested for the round-trip efficiency of lead acid batteries (Gallo et al., 2016). This analysis uses a mean value of 0.8.

Table 11: Characteristics of lead acid batteries considered in analysis.
Sources: Rydh & Sanden (2005); Barnhart & Benson (2013).

Lead acid battery		
Roundtrip-efficiency η	-	0.8 (0.7-0.9)
Total cycle life λ	-	700
Depth-of-discharge	-	0.8
Embodied energy $e_{battery}$	MJ_{PE}/MJ_{el} storage capacity	456
Electrical energy returned over lifetime per unit of storage capacity e_{el}	MJ_{el}/MJ_{el} storage capacity	470

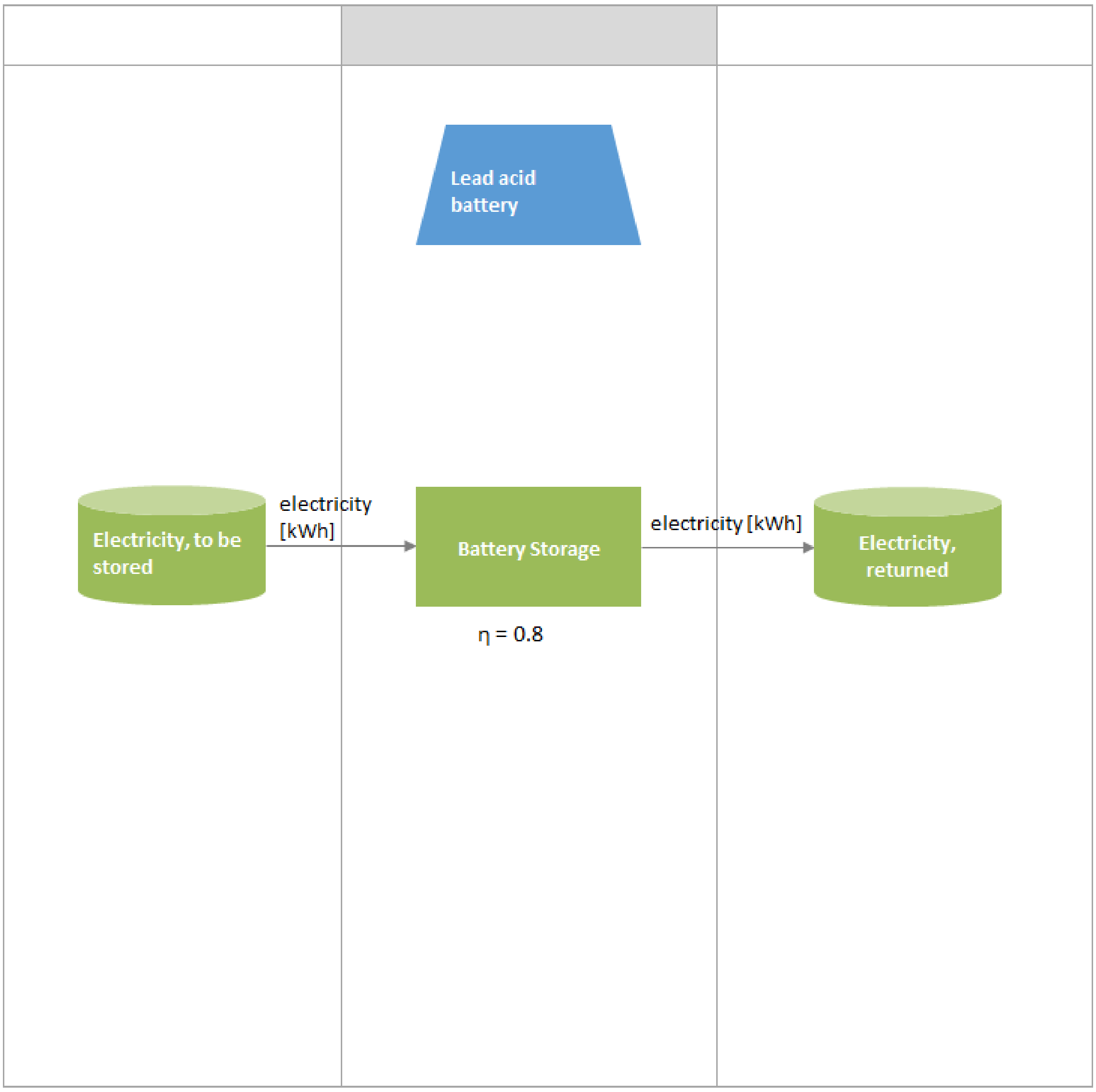

Figure 16: Representation of the lead acid battery storage system.

3.2.6.2 Lithium-ion battery

Barnhart & Benson (2013) report the number of cycles for lithium-ion batteries at three different depths of discharge: 33%, 80% and 100%. For this analysis, the pair of depth-of-discharge and number of cycles, which maximises the energy returned by the battery over its lifetime, was chosen (6000 cycles at 80% depth-of-discharge). For the roundtrip-efficiency, Gallo et al. (2016) suggest values between 0.85 and 0.95. For the analysis, a mean value of 0.9 is used.

For the embodied energy of a lithium-ion battery, primary energy values per storage capacity reported by Rydh & Sanden (2005a) were taken, and the unit for storage capacity was converted from Wh to MJ_{el}. Table 12 summarizes the assumed characteristics for lithium-ion batteries.

Table 12: Characteristics of lithium-ion batteries considered in analysis.
Sources: Rydh & Sanden (2005); Barnhart & Benson (2013).

Lithium-ion battery		
Round-trip efficiency η	-	0.9 (0.85-0.95)
Total cycle life λ	-	6000
Depth-of-discharge	-	0.8
Embodied energy $e_{battery}$	MJ_{PE}/MJ_{el} storage capacity	606
Electrical energy returned over lifetime per unit of storage capacity e_{el}	MJ_{el}/MJ_{el} storage capacity	4560

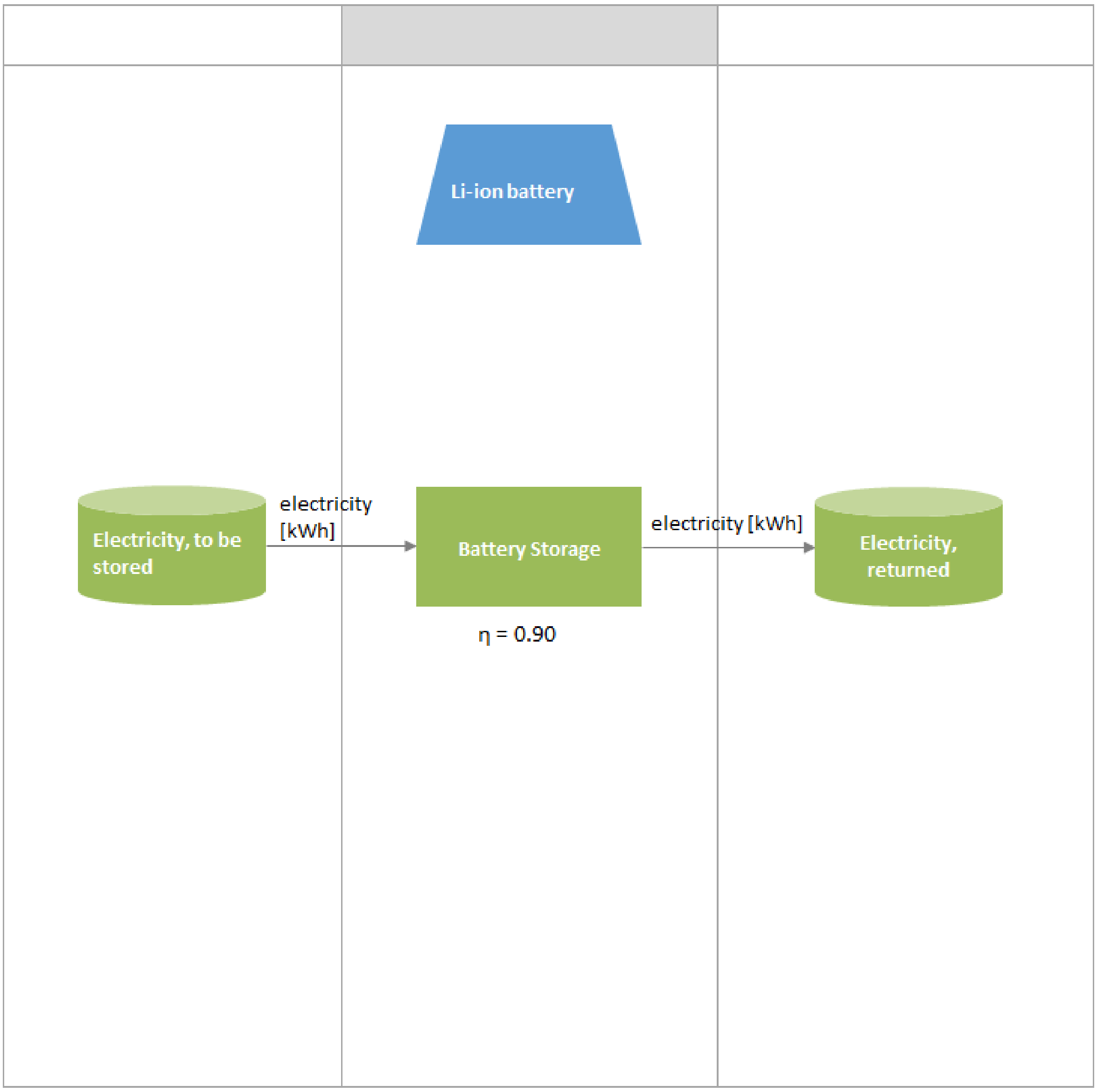

Figure 17: Representation of the lithium-ion battery storage system.

3.2.6.3 *Pumped hydro storage*

Since pumped hydro storage power plants have long lifetimes, the number of cycles for charging & discharging is significantly higher than for batteries. The depth-of-discharge is assumed to be 1, with a round-trip efficiency of 0.75 (Barnhart and Benson, 2013; Gallo et al., 2016).

The calculation of the ESOI for pumped hydro storage considers only the energy requirements for the construction of the pumped hydro plant, which were taken from Denholm & Kulcinski (2004). Table 13 summarizes the characteristics and energy requirements which were considered in the analysis.

Table 13: Characteristics of pumped hydro storage plant considered in analysis.
Sources: Denholm & Kulcinski (2004); Barnhart & Benson (2013).

Pumped hydro storage		
Roundtrip-efficiency η	-	0.75 (0.65-0.85)
Total cycle life λ	-	25'000
Depth-of-discharge	-	1
Embodied energy $e_{PHS\ Plant}$	$MJ_{PE}/MJ_{el\ storage\ capacity}$	100.6
Electrical energy returned over lifetime per unit of storage capacity e_{el}	$MJ_{el}/MJ_{el\ storage\ capacity}$	21'250

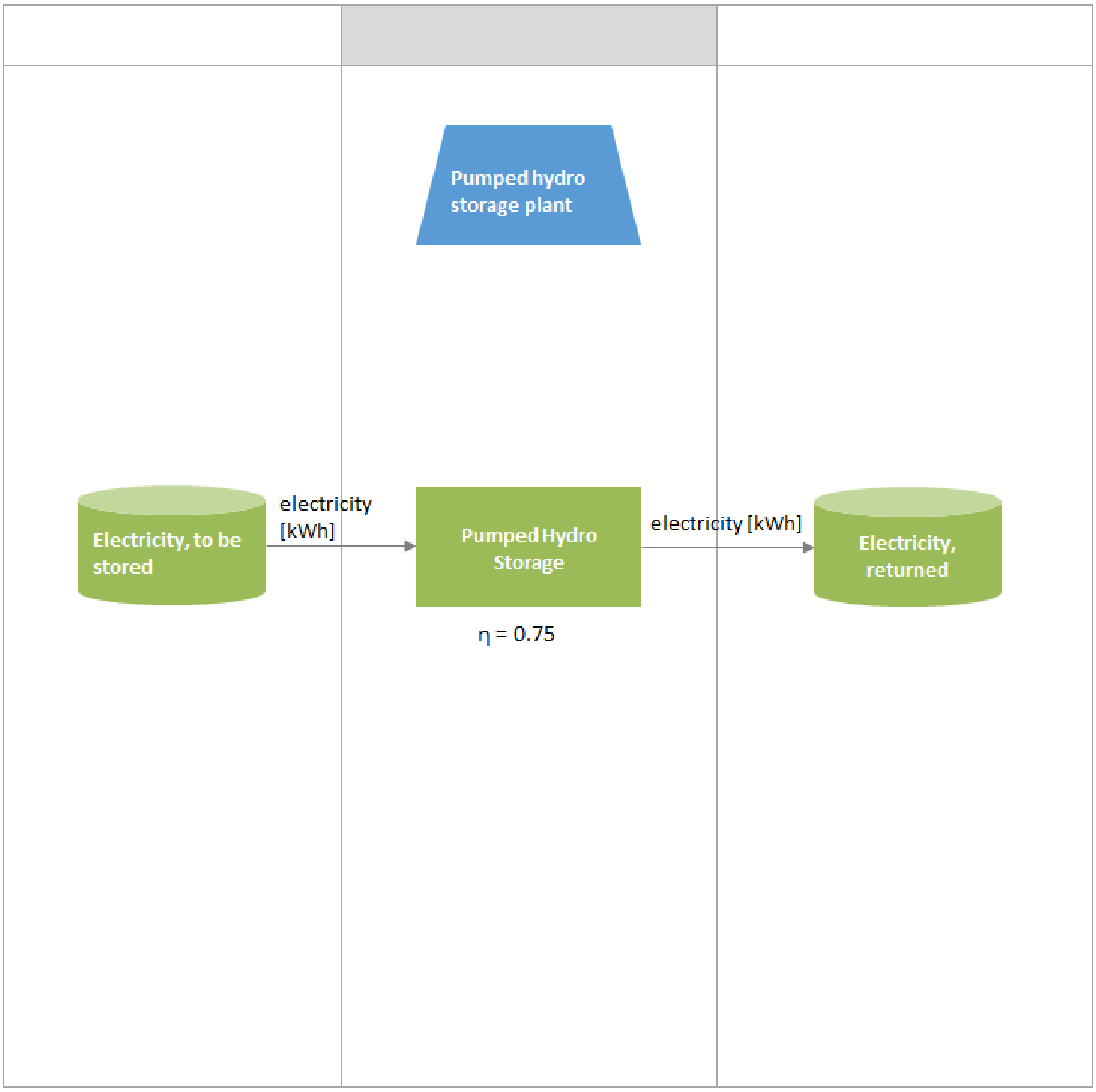

Figure 18: Representation of the pumped hydro storage system.

3.2.6.4 Excursus: Power-to-hydrogen-to-power

Another approach to store surplus energy is by converting electricity to hydrogen through water electrolysis. The generated hydrogen is then compressed and stored in high-pressure tanks. When needed, the hydrogen can then be reconverted to electricity in a fuel cell. Such a “power-to-gas-to-power” pathway is to date not yet covered by the Ecoinvent database. For example, to date no dataset exists for the generation of electricity in a fuel cell with hydrogen as fuel input. Thus, further data sources needed to be integrated in this analysis.

A study by Pellow et al. (2015) conducts such an ESOI analysis for an exemplary power-to-gas-to-power set up, laid out to accommodate the excess generation of a hypothetical wind farm[13]. The analysed power-to-gas storage system corresponds with a very common configuration among existing systems, consisting of an alkaline water electrolyser, a compressor, a hydrogen storage tank and a polymer electrolyte membrane fuel cell (see following figure). Based on the exemplary set-up proposed by Pellow et al., and using their values for energetic requirements for the single components, the ESOI has been established for this set up.

Since LCI data availability for power-to-gas systems is relatively limited, Pellow et al. (2015) compiled the data from various LCA studies, the Ecoinvent database and from own estimates. The following tables show the characteristics of the components of the power-to-gas set-up considered in this analysis.

The reported values in Pellow et al. (2015) for the embodied energy of the alkaline water electrolyser are based on an alkaline fuel cell, due to lacking LCA data for the electrolyser. This approximation is deemed useful, since the electrolyser and the fuel cell both employ Nickel as a catalyst, which is assumed to be the most energy intensive component. The authors recognise, however, that this assumption introduces uncertainty in terms of the embodied energy of the electrolyzer stack. Since Pellow et al. (2015b) report their embodied energy values in MJ_{el} (assuming a grid conversion efficiency of 0.3), the values have been converted to primary energy equivalents for the subsequent analysis. Table 14 summarises the characteristics of the alkaline water electrolyser.

[13] Hypothetical wind farm is producing 5 MW surplus power during eight hours per day. The hydrogen storage capacity is such that excess energy generated over three days can be stored. The fuel cuell rating is such that continuous power can be provided during five hours from a single day’s generation.

Table 14: Characteristics of alkaline water electrolyser in considered power-to-gas system.
Embodied energy values adapted. Source: Pellow et al. (2015).

Alkaline electrolyser		
Power	MW	5
Efficiency η_E	-	0.7
Embodied energy electrolyer stack	MJ_{PE}	6.8 *10^6
Embodied energy BOS	MJ_{PE}	5.5*10^6
Total embodied energy E_{lys}	MJ_{PE}	1.23*10^7

Table 15: Characteristics of hydrogen compressor and hydrogen storage tank considered in power-to-gas system.
Embodied energy values adapted. Source: Pellow et al. (2015).

Hydrogen compressor		
Power	MW	5
Efficiency η_C	-	0.89
Embodied energy compressor	MJ_{PE}	1.15*10^6

Hydrogen storage tank		
Hydrogen storage capacity	MWh	84
Hydrogen storage capacity (based on LHV)	Kg H_2	251 kg
Embodied energy storage tank	MJ_{PE}	8.06*10^5
Total embodied energy $E_{C\&S}$	MJ_{PE}	1.96*10^6

For the embodied energy of the hydrogen compressor and the hydrogen storage tank, a simplified approach is followed by the authors, assuming that they consist of a 100% steel. The compressor is assumed to weigh 1300 kg, while the storage tank is assumed to be a 58 kg steel cylinder. The embodied energy of the compressor and the storage tank is then calculated with the energy intensity of steel. Table 15 summarises the characteristics of the hydrogen compressor and the storage tank which form part of the considered power-to-gas system.

Data for the Polymer Electrolyte Membrane Fuel Cell is based on existing LCA literature. The fuel cell stack and the fuel cell BOS are assumed to have the same embodied energy (see Table 16).

Table 16: Characteristics of Polymer Electrolyte Membrane Fuel Cell considered in power-to-gas system.
Embodied energy values adapted. Source: Pellow et al. (2015).

Polymer Electrolyte Membrane Fuel Cell		
Power	MW	2.6
Efficiency η_{PEMFC}	-	0.47
Total fuel cell operating time	s	2.3*10^8
Lifetime of fuel cell stack	s	3.6*10^7
Fuel cell stacks over lifetime	-	7
Embodied energy fuel cell stack	MJ_{PE}	1.04*10^7
Embodied energy fuel cell BOS	MJ_{PE}	1.48*10^6
Embodied energy fuel cell E_{PEMFC}	MJ_{PE}	1.19*10^7
Electrical energy returned by fuel cell E_{el}	MJ_{el}	5.98*10^8

As compared to pumped hydro and battery storage, which consist of a single storage compartment with a given storage capacity, the power-to-gas system consists of several components. Some of those components are not necessarily determined by their (hydrogen) energy storage capacity, but rather by their rated power (e.g. compressor, fuel cell). The power-to-gas system therefore represents a special case within the considered storage technologies, requiring its specific formula, since the above-mentioned general formula is not applicable.

The total embodied energy per unit of storage capacity is therefore the sum of the embodied energy of all the components making up the power-to-gas system. The returned electrical energy, in turn, is measured at the exit of the last component, which is converting the hydrogen back to electrical energy– the fuel cell.

$$ESOI=\frac{E_{el}}{E_{lys}+E_{C\&S}+E_{PEMFC}}\left[\frac{MJ_{el}}{MJ_{PE}}\right] \tag{7}$$

With

E_{el}: Electrical energy returned by fuel cell over lifetime [MJ_{el}]

E_{lys}: Embodied primary energy of electrolyser [MJ_{PE}]

$E_{C\&S}$: Embodied primary energy of compressor and hydrogen storage tank [MJ_{PE}]

E_{PEMFC}: Embodied primary energy of polymer electrolyte fuel cell [MJ_{PE}]

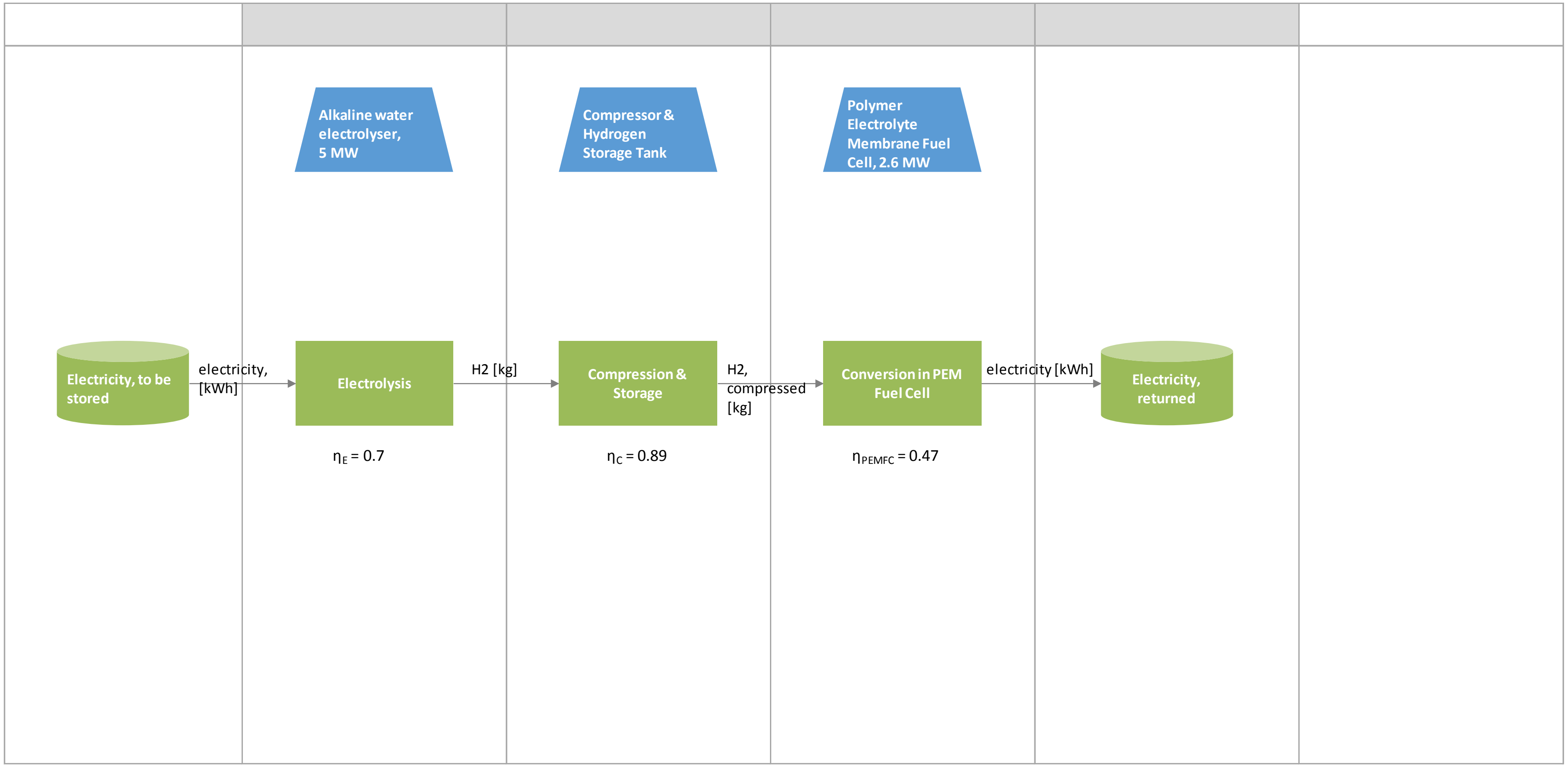

Figure 19: Representation of the power-to-hydrogen-to-power storage system.

3.3 Results

In the following, the results of the static energy performance analysis are presented. First, the results in terms of the nr-CED indicator are discussed, followed by an introduction of the results in terms of the EROI indicator. Then, the results for both indicator are combined in a matrix to gain an overall picture of energy performance. Lastly, the results for the ESOI indicator for storage technologies are discussed.

3.3.1 Results for nr-CED

Figure 20 summarises the results based on the nr-CED indicator. First of all, it is noteworthy that all fuel based power generation systems (shown on the left hand side of the figure) score high values for the nr-CED, hence, their non-renewable primary energy consumption is high per unit of electrical energy delivered. (It is important to keep in mind here that a high nr-CED score is associated with a worse energy performance). Among the four fuel based technologies, nuclear power performs worst in terms of the nr-CED (amongst others due to the low efficiency of the power plant and the fuel chain), followed by hard coal based system and natural gas based systems (CCGT).

When looking at the renewable power generation technologies (right hand side of the figure), it becomes clear that the values achieved by these technologies are one to two orders of magnitude lower than the fuel based technologies. Thus, they consume significantly less non-renewable primary energy per unit of electricity generated, as compared to their fuel based counterparts. Across the renewable energy power systems, PV systems exhibit higher nr-CED values, thus lower energy performance, than the wind and hydro technologies. Cadmium-telluride thin-film PV systems perform better than the multi-crystalline PV systems. Among the wind technologies, wind onshore under Danish wind conditions performs best, followed by wind offshore and wind onshore under Swiss wind conditions. Hydro power plants are the clear performance leaders in terms of the nr-CED: their non-renewable primary energy consumption only amounts to 0.01 units (run-of-river power plants) or 0.02 units (reservoir hydro power plants) per unit of electricity generated.

3.3.2 Results for EROI

Figure 21 presents the results for the EROI indicator. It is noteworthy that the EROI values are larger than 1 for all power generation technologies, thus, all technologies deliver significantly more (electrical) energy than was invested in them. The range of EROI values which is spanned by the technologies is relatively large, with the smallest value being 3 and the largest value being 78. In this context, higher values indicate a better energy performance.

For fuel based power generation systems, a low EROI value of 3 has been found for the natural gas based (CCGT) power system. For hard coal based systems, an EROI of 8 has been found, while for nuclear systems, an EROI of 12 has been calculated. It may seem surprising that the EROI of the natural gas based system is so much lower than the EROI of the hard coal based system. However, it must be kept in mind that the often rather high feedstock-to-electricity efficiency of modern natural gas plants does not play a role in the EROI calculations. In contrast, the numerous energy investments which are required during the extraction and processing phase of natural gas, and the required pipeline network for its transport, do enter into the calculations, and seem to penalise natural gas based systems as compared to hard coal based systems.

As far as renewable power generation technologies are concerned, an EROI of 3 has been found for geothermal systems, and an EROI of 4 for multi-crystalline PV under Swiss irradiation conditions. A higher EROI has been calculated for thin-film CdTe PV modules than for the wafer-based multi-crystalline PV technology: the EROI for CdTe PV under Swiss conditions has found to be 8. This finding suggests that for the thin film PV technology (cadmium-telluride PV), the “penalty” of a larger panel area required to generate the same amount of power (due to the lower cell efficiency), is not enough to offset the energy gains from a less energy intensive panel production process.

Interpreting figure 22, it needs to be recalled that numbers show an up-to-date estimate of the EROIs for PV systems and wind of the newest technology status in Switzerland based on more recent LCA data (but not for Spain due to limited data availability). For comparison, the figure also provides EROI values based on the (outdated) ecoinvent data for PV and wind in Switzerland, reflecting a technology status from ca. 2004 and 2008 for solar PV and wind, respectively.

Wind technologies have shown a very good energy performance with regards to the EROI indicator: Wind onshore under Swiss wind conditions was found to have an EROI of 18. For wind offshore, an EROI of 18 has been calculated, followed by wind onshore under Danish wind condition with an EROI of 20.

Among the best performing technologies in terms of EROI are by far hydro power plants: For run-of-river hydro power plants, an EROI of 78 has been calculated, which means that for every unit of primary energy invested roughly 78 units of electrical energy are returned. For reservoir hydro power plants, the EROI is 56, which is still considerably higher than the EROI of all other power generation technologies.

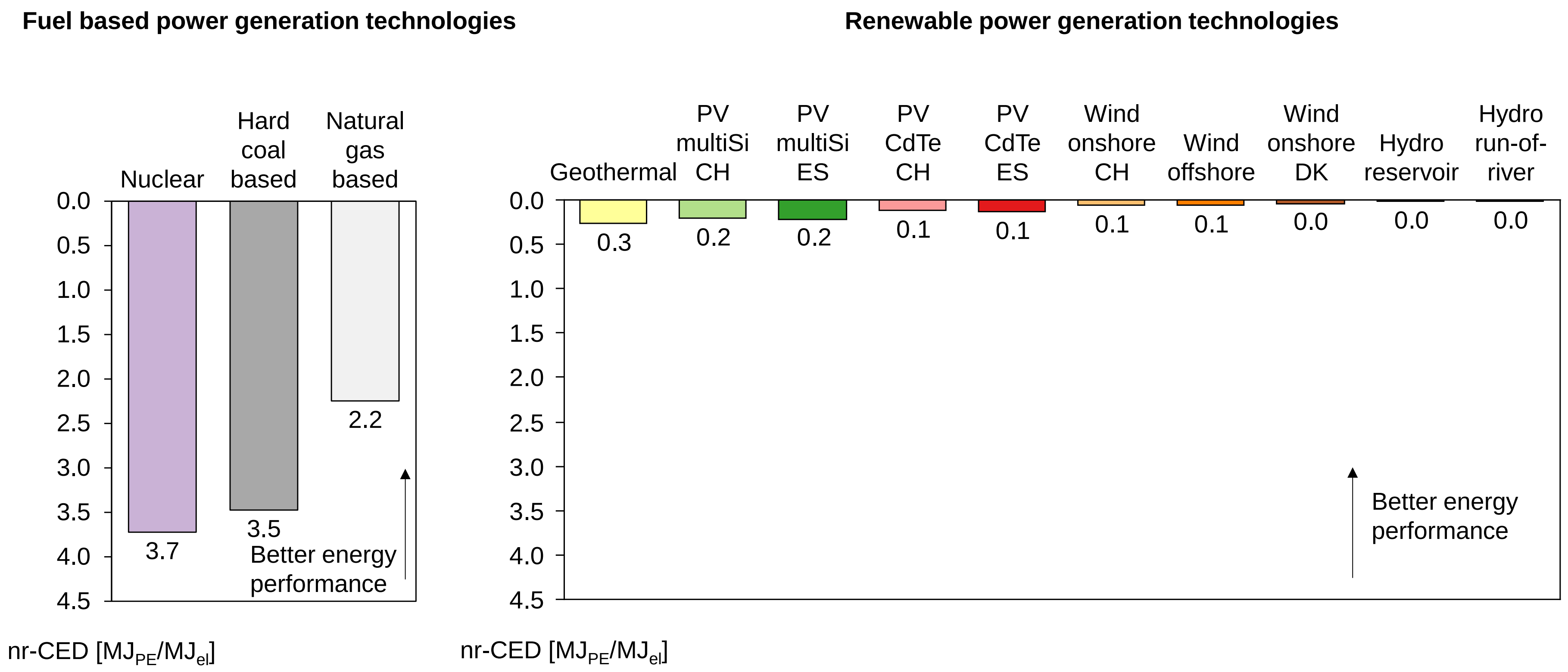

Figure 20: Results for the nr-CED indicator.
Left: Results for non-renewable power generation technologies. Right: Results for renewable power generation technologies.

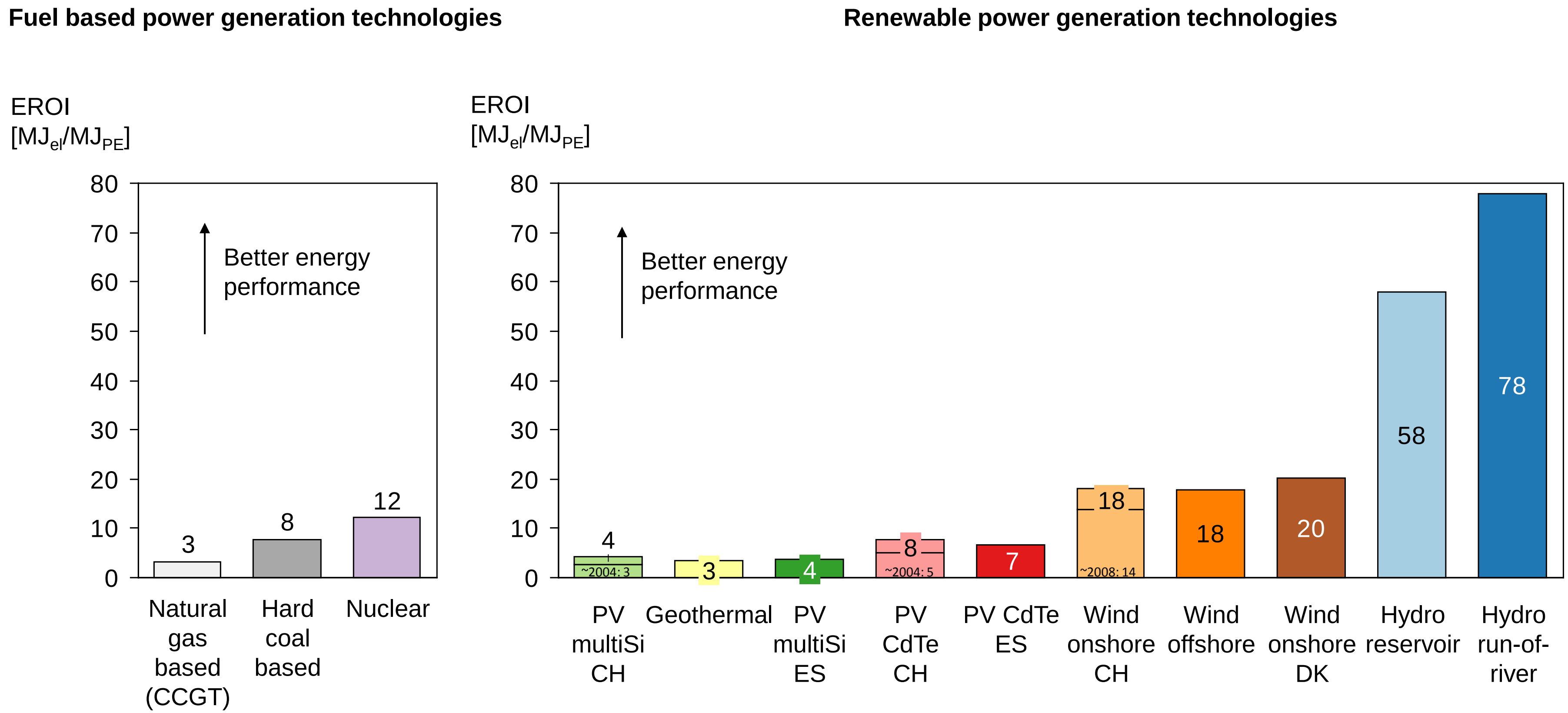

Figure 21: Results for the EROI indicator.
Left: Results for non-renewable power generation technologies. Right: Results for renewable power generation technologies. Vertical bars represent results based on more recent LCA data.

3.3.3 Combined results

In order to gain a better picture of the overall energy performance of power generation technologies, a matrix showing both the results in terms of the nr-CED and the EROI indicator is introduced and presented in Figure 22. On the x-axis of this matrix, the EROI indicator is plotted. The energy performance increases along this axis with increasing EROI values. On the y-axis, the *inverse* of the nr-CED is plotted, since this allows an easier interpretation of the matrix: the energy performance increases with increasing values along this axis as well, so that technologies showing a very good energy performance in terms of both indicators are placed in the upper right corner of the matrix.

It is immediately apparent from the matrix in Figure 22 that the two hydro power technologies (run-of-river and reservoir) show by far the best energy performance among all technologies studied, and combine very high energy returns with a low non-renewable primary energy consumption. Hydro run-of-river power systems show an even higher performance than the reservoir systems.

As the situation is less easily understood in terms of the remaining technologies, Figure 23 provides an enlarged view of the same matrix. From this, it can be seen that also wind power shows a very well and balanced energy performance, scoring well in terms of both energy return and the conservation of non-renewable primary energy resources.

For the fuel based power generation technologies, a clear performance trade-off is visible: on the EROI axis, their scores are rather high, although still lower than the EROI scores of wind power. However, they show a clear deficit as to the second axis of performance, consuming high amounts of non-renewable primary energy resources.

The PV technologies, in contrast, are associated with lower non-renewable primary energy consumption. In terms of their energy returns, they might be at present still lower than the best-performing fuel based systems (nuclear and hard coal), however, it can be noted that, under Swiss irradiation conditions, the multi-crystalline PV technology is almost competitive with natural gas CCGT, while the thin-film CdTe PV technology is already outperforming natural gas. The EROI of thin-film CdTe PV technology under favourable irradiation conditions is not far from the EROI of hard coal based power generation systems. Thus, these results suggest a small lead of fuel based power generation systems in terms of energy returns, however, the results also indicate fuel based technologies' deficits in terms of the conservation of non-renewable primary energy resources.

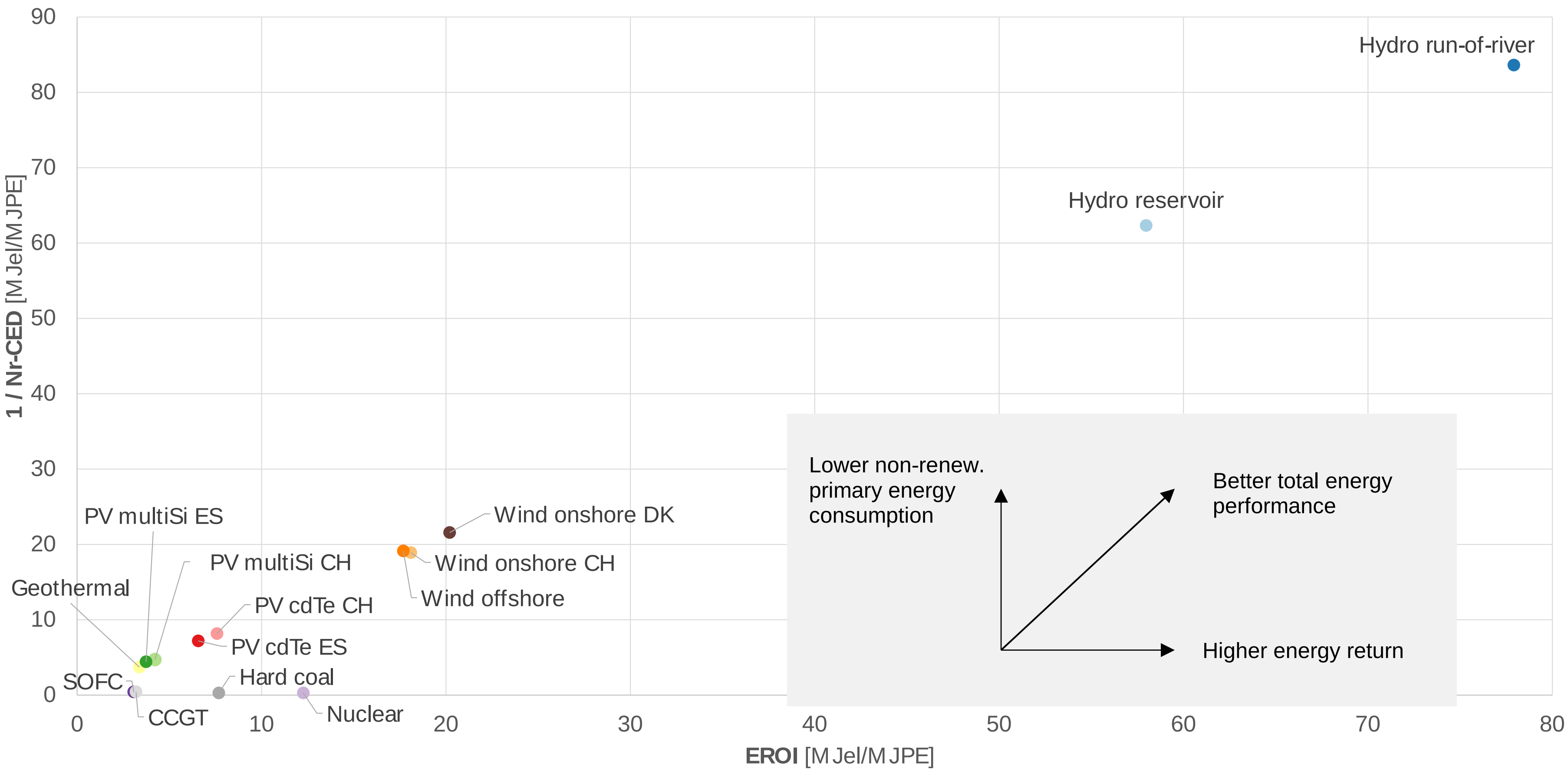

Figure 22: Combined results for the nr-CED and EROI indicators (Results Matrix).
Horizontal axis: EROI indicator. Vertical axis: Inverse of nr-CED indicator.

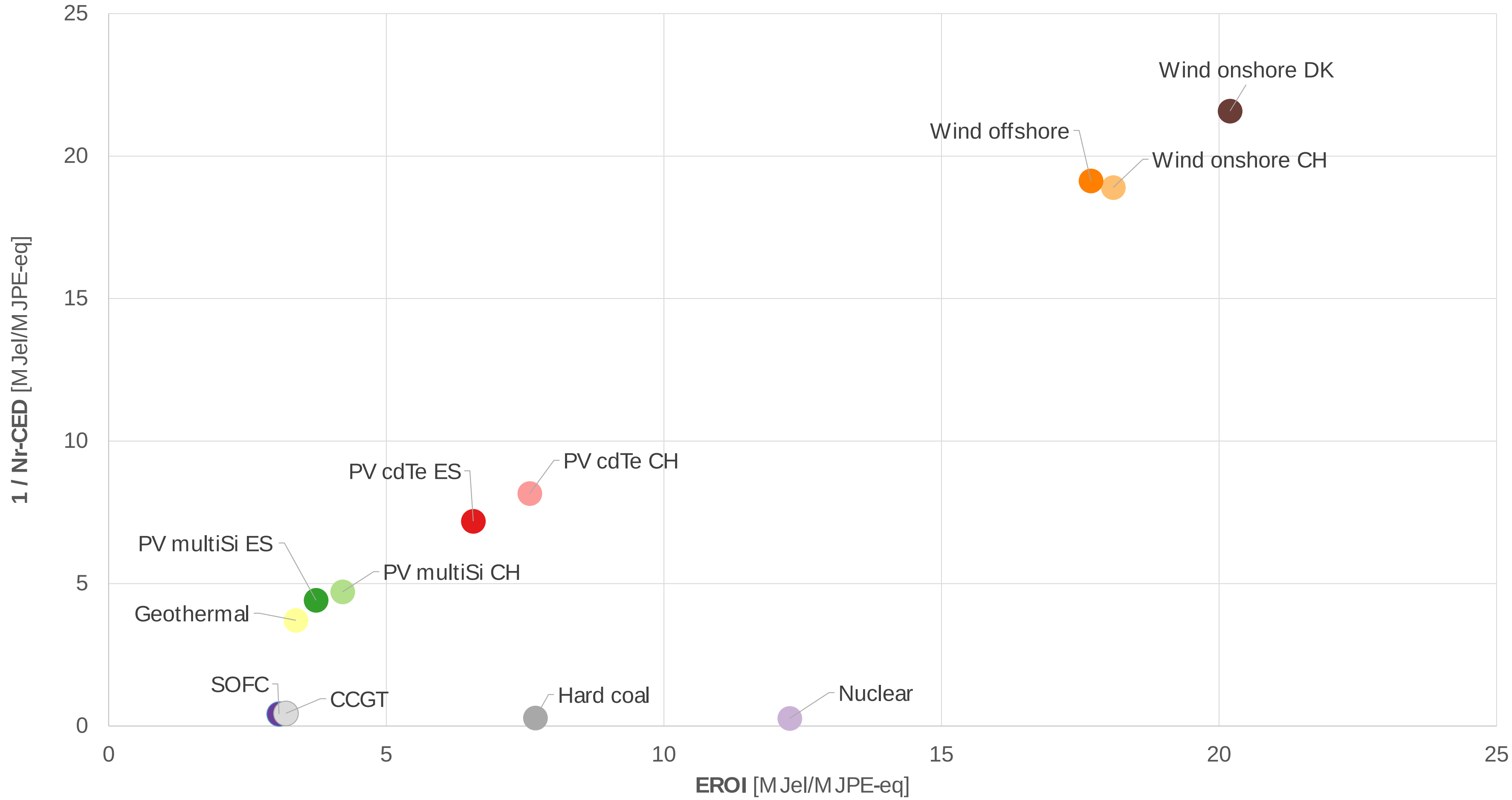

Figure 23: Enlarged view of Results Matrix.
Horizontal axis: EROI indicator. Vertical axis: Inverse of nr-CED indicator.

3.3.4 Results for ESOI

The results for the ESOI indicator, comparing the energy performance of storage technologies, are presented in Figure 24. Using the example of lead acid batteries, the results can be read as follows: The ESOI for lead acid batteries is 1, hence, one unit of electrical energy is returned by the lead acid battery per unit of primary energy invested in the construction of the battery

For lithium-ion-batteries, a higher ESOI value of 7 is achieved, thus, a lithium-ion battery returns 7 electrical energy units per unit of primary energy invested in the construction of the battery.

For pumped hydro storage, the achieved ESOI is very high. 186 electrical energy units are returned over the lifetime of a pumped hydro storage plant, per unit of primary energy invested in the construction of the power plant.

For the exemplary power-to-gas set up, an ESOI of 23 is calculated.

Hence, it can be noted that for batteries, the energy requirements are relatively large as compared the energy returned by the storage devices. Lithium-ion-batteries perform substantially better than lead acid batteries, due to their better longevity. Pumped hydro storage performs by far best, similar to the picture found in the analysis of power generation technologies. For the exemplary power-to-H_2-to-power, a rather favourable ESOI of 23 was found, however, these figures are tentative and based on an exemplary set-up, and more detailed studies analysing the energy requirement of such set ups must be carried out to confirm these results.

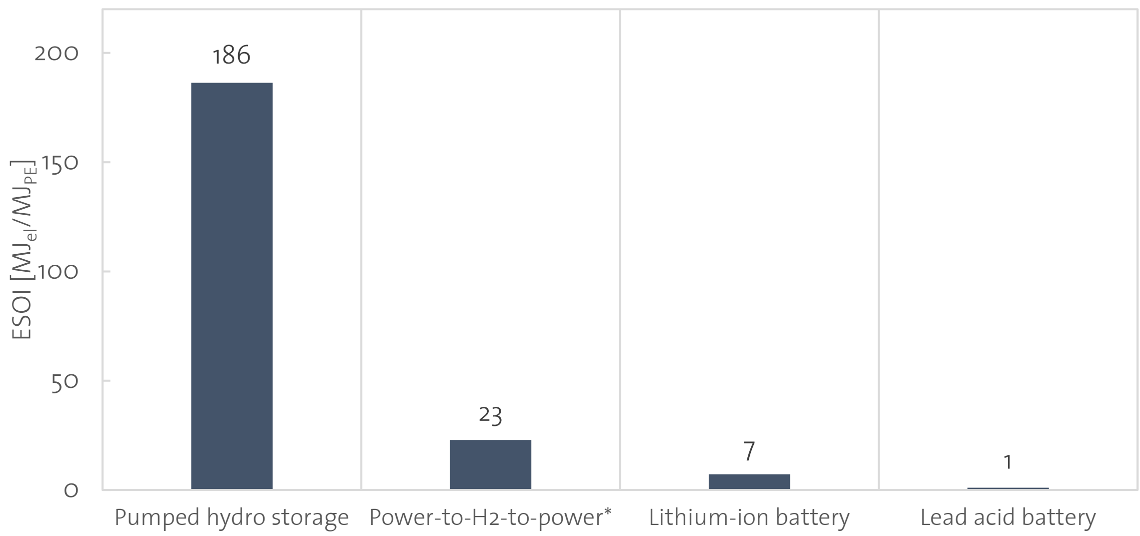

Figure 24: Results for the ESOI indicator.

4 Dynamic energy performance analysis for Swiss context

4.1 Towards dynamic energy performance indicators

While the static analysis already provides important insights, it remains a snap-shot. In order to provide input into the discourse/debate on *future* energy systems, it is crucial that potential improvements regarding the energy performance of technologies over time are considered. *Technological learning* is the driver behind the empirical phenomenon of decreasing technology cost as a result of increasing experience in manufacturing and from using a technology: For example, the costs of PV systems have decreased from several hundreds of $/W in the 1960s to costs of below 1 $/W over the last 50 years (Trancik et al., 2015). Also for wind energy the costs per installed capacity have declined significantly since the beginning of large-scale deployment in the 1980s (Wiser et al. 2011).

The underlying drivers of cost reductions for solar PV and wind power have been thoroughly investigated in bottom-up studies. For solar PV, drivers have been found to be the improving module efficiencies over time, which reduced the required surface area (and thus material requirements) for a given Watt of power output (Nemet 2006; Kavlak et al. 2016). Furthermore, the thickness of wafers has been reduced over time, which reduced the amount of silicon required per Watt. Improved production methods in silicon manufacturing have additionally led to higher silicon yields and reduced waste. Manufacturers have also made use of the ‘economies of scale” principle to bring costs down, enlarging their production facilities and significantly increasing the units produced per facility (Junginger et al., 2010; Kavlak et al., 2016; Nemet, 2006).

For wind power, the reasons for the cost decline rest in the growing size of the wind turbines (up-scaling of wind turbines), together with improvements in technology and manufacturing processes: for example the development and use of new materials, developments in power electronics and the specialization of standard components from other industry sectors, such as gear boxes, transformers and inverters, for wind turbines (Junginger et al., 2010).

Cost learning effects have also been observed for conventional power generation technologies. For example, economies of scale and improvements in the manufacturing processes have been found for important power plant components such as hard coal boilers and gas turbines (cr. Colpier & Cornland 2002; Yeh & Rubin 2007).

To quantify reductions in technology cost as a result of increased experience, the use of *learning curves* is well established. Many of the previously mentioned drivers for the cost reductions observed in the past also affect the energy balance of power generation systems, that is, they increase the material and energy efficiency of technologies. However, using the learning curve approach to investigate how the *energy performance* of technologies has developed as a function of increasing experience of manufacturers and users with a technology, is a novel approach (see Steffen et al. (2018) for further details).

In the dynamic part of this study, the learning curve concept developed by Steffen et al. (2018) is used to derive historical energy learning rates for power generation technologies. In a second step, the historically observed learning rates are extrapolated into the future, in order to estimate of the future energy performance of technologies. While the static analysis focussed on the Swiss context and took into account Swiss conditions where relevant, this narrow geographical perspective is abandoned for the dynamic analysis. Given the global nature of technological learning (Huenteler et al., 2016), the dynamic part of the analysis draws on global data and assesses worldwide dynamics. We do however extent the scope of Steffen et al. (2018) by including natural gas-based power generation as a technology that has greater importance for Switzerland than hard coal-based power generation (which has been analysed by Steffen and colleagues).

The next section provides an introduction to the topic of learning curves, and elaborates on how they have been applied to the energy sector. Furthermore, it summarises first attempts made in literature to extend learning curves to the domain of environmental and energy performance.

4.2 Use of learning curves for energy performance indicators

4.2.1 The learning curve concept

One approach to describe technological change is the learning curve concept. It is based on the hypothesis that a technology's economic performance improves as experience with the technology accumulates. *Learning curves* are a tool to represent the often observed empirical fact that the cost of a technology decreases as a function of cumulative capacity or production. The more a technology is being deployed, the more experience is gained by manufacturers and users, which can feed back into improvements of the next generation of that technology. Hence, learning curves are a tool to "measure" technological change in terms of cost reductions as a function of accumulated experience (Junginger et al., 2010).

Since the first observation of this phenomenon by Wright (1936) in the airframe manufacturing industry, empirical evidence for the cost-experience relationship has been found for a multitude of products and technologies in all industrial fields. In the meantime, efforts have been made to identify the learning mechanisms which are behind the cost reductions observed in learning curves. Examples of mechanisms include learning-by-doing, learning-by-researching, learning-by-using, economies of scale and inter-technology spill-overs (Kahouli-Brahmi, 2008; Nemet, 2012; Rosenberg, 1982). The following table aims at giving a brief overview of the most important mechanisms, but should not be considered as conclusive.

Table 17: Overview of important mechanisms of technological learning identified by literature. Adapted from Junginger et al. (2010), Kahouli-Brahmi (2008) and Nemet (2012).

Mechanism	Description
Learning-by-doing/ learning-by-manufacturing	Repetition of manufacturing process leads to improvements in the production process (e.g. increased labour efficiency and production methods)
Learning-by-researching	Basic or applied research and development activities enhance technology knowledge, which in turn leads to technology improvements
Learning-by-using	Experience from users and feedback effects help firms improve their products
Economies of scale	Mass production stage leads to learning effects (e.g. standardization of processes allows upscaling of production plants, and producing the same product in large numbers)
Inter-technology spillovers	Knowledge and technical developments from one domain can be transferred to another domain (e.g. jet engines developed for military aircrafts have provided the basis for the development of highly efficient combined cycle gas turbines for natural gas power plants)

The simplest way to represent this empirical phenomenon mathematically is in a **one-factor learning curve**. In equation (8), C stands for the costs at a specific level of cumulative production X, C_0 the initial production costs for the first unit, and b the (positive) learning parameter.

$$C(X) = C_0 * X^{-b} \quad (8)$$

Conveniently, when plotting this cost and cumulative production relation on a double logarithmic scale, a linear curve with a negative slope results. A crucial characteristic of the learning curve is the *learning rate*, which is defined as the fixed percentage reduction in cost which results from each doubling of cumulative production or capacity (Rubin et al., 2015). The learning rate is therefore often used to compare learning curves of different technologies or goods etc., and it can be calculated from the slope of the learning curve in the following way:

$$LR = 1 - 2^{-b} \tag{9}$$

This previous learning curve is classified as a one-factor learning curve, since it entails only one explanatory variable (cumulative capacity) which serves as a surrogate for all the underlying factors which can contribute to cost reductions (Rubin et al., 2015) [14].

Sometimes, technological learning which is induced by R&D ("learning-by-researching") is separated out from the other factors. Although R&D is present in all stages of development, it is particularly important in the early stages of technical development – without advances at this early stage, a technology might never enter the commercial phase (Jamasb, 2007; Sagar and van der Zwaan, 2006). Therefore, the one-factor learning curve model has been extended with the aim to disaggregate the effect induced by R&D and the effects of all other learning mechanisms subsumed under the term "learning-by-doing" (since they typically set in when a technology is deployed and practically used). The **two-factor learning curve** therefore includes cumulative R&D expenditures as a second variable, in order to separately describe the effects of learning-by-researching associated with R&D expenditures (Rubin et al., 2015). However, detailed data on both public and private R&D expenditures is often very hard to find, which limits the application of two-factor learning curves (Junginger et al., 2010).

A third type of learning curve is the **component-based learning curve**, which represent the total costs of a technology or a product as the sum of the costs of the individual components. With this approach, a separate learning parameter can be attributed to each technology component (Yeh and Rubin, 2012). Thus, the model allows some components to undergo faster learning than others, which can be the case for components that are at different stages of maturity (Rubin et al., 2015). This model is often used for early stage technologies, for which not enough empirical cost and cumulative production data is available to derive a learning rate for the whole system (Knoope et al., 2013). Since many components are not specific for one technology, but are also part of other technologies, a learning rate for the component can be derived from all the technologies which have that component in common. The learning curves of these separate components can then be combined to estimate the learning of the whole entity (Knoope et al., 2013).

[14] In turn, in the two-factor learning curve, the R&D part of learning (learning-by-researching) is separated from the other learning factors, which are then subsumed under the term "learning-by-doing". In order to indicate that all of these factors are taken into account in the one-factor-learning curve, the learning curve is sometimes more generally named „experience curve". In this work, the term „learning curve" is used. However, this shall refer to the general, overarching phenomenon of technological learning, and does neither specify the underlying mechanisms further, nor does it exclude the phenomenon of learning-by-researching.

Since the 1990s, the learning curve approach has increasingly been applied to the energy sector and energy technologies. In particular, learning curves have been used to describe the historical price developments of power generation technologies, both of emerging energy technologies like wind and solar PV and of mature technologies like gas and coal fuelled power plants. Especially for solar PV, evidence for very steep learning curves has been found. In the following, the application of the learning curve concept in the energy sector is further discussed, and the relative strengths and weaknesses of this approach are investigated.

4.2.2 Learning curves in the energy sector

For policy makers, learning curves provide a systematic methodology for following the historical development and performance of technologies, and in this context they can act as a monitoring tool to identify the present status or current market stage of the technology (IEA, 2000; Junginger et al., 2010). On the other hand, they can be used to forecast future costs, by extrapolating along the learning curve. This allows policy makers to assess the potential for future costs improvements of a technology, and it also allows to determine the scale of deployment required to make a technology competitive with incumbent technologies (Junginger et al., 2010). In this sense, learning curves can provide a rationale for the implementation of deployment policies for environmentally friendly technologies: learning curves provide evidence that costs decrease with increasing deployment, and decision makers can actively influence deployment rates through policies. Deployment subsidies are therefore expected to induce the “ride down” the learning curve (Schmidt and Sewerin, 2017). Furthermore, they also show the required investment in deployment to bring about the necessary amount of learning to make a technology cost efficient (Junginger et al., 2010).

Learning curves are also widely used in both top-down and bottom-up energy models, where they are incorporated to simulate the dynamic evolution of technologies (Junginger et al., 2010; Wiesenthal et al., 2012). In contrast, in models with exogenous technological learning the cost trajectories of technologies are exogenously specified, for example by assuming annually decreasing capital costs of a technology by a fixed percentage (Rubin et al., 2015). As highlighted by Taylor & Fujita (2013), incorporating technological change into models is essential, and they caution that, when evaluating the costs and benefits of new environmental and energy efficiency regulations, social cost of such regulations can be significantly overestimated if learning is not considered.

Limitations of the learning curve concept. Despite the broad application of learning curves, there are significant uncertainties associated with the approach, which make learning curves a useful, yet imperfect tool to represent technical change (Yeh and Rubin, 2012). Subsequently, three main critical points are discussed.

First, even if a strong negative statistical correlation between the cost of a technology and its cumulative installed capacity is observed, it is not necessarily a causal relationship. In general, learning curves offer little explanation as to how cost reductions occur, and the effect of the individual learning mechanisms (e.g. economies of scale, learning-by-using etc.) cannot be readily determined (Junginger et al., 2010; Rubin et al., 2015; Yeh and Rubin, 2012). However, an increasing number of studies try to remedy this problem (see Kavlak et al. (2016) and Nemet (2012) for examples). When extrapolating learning curves, it is nevertheless important to keep in mind that an observed phenomenon from the past is projected into the future without being able to determine its underlying drivers in detail (Wiesenthal et al., 2012).

Second, some authors challenge the assumed shape of the learning curve, i.e. its linearity in a double logarithmic plot (log-linearity assumption). They argue that especially at its beginning or end, the learning curve is not necessarily log-linear. E.g., Grübler et al. (1999) argue that during the early innovation phase of a technology, often high learning rates can be observed, but during later stages, learning flattens off, with a lower learning rate setting in. Guibert (1945) also made a case for a flattening out of the learning curve, with learning rates asymptotically reaching zero for large cumulative outputs. Other studies found that during the early phases of commercial deployment, the costs of immature technologies often increase rather than decrease. This is often explained with the scaling up from pilot projects to full-scale commercial plants, which brings about underestimated and unexpected costs. Rubin et al. (2004) found empirical evidence for this phenomenon for emission control technologies for coal power plants (e.g. flue gas desulfurization systems). Similar trends have been shown for the experience curve for combined cycle gas turbines by Colpier & Cornland (2002). Importantly, though, also with constant learning rates, learning will eventually slow down. Along the learning curve, for each doubling of the cumulative capacity, a fixed percentage reduction in cost (the learning rate) is achieved. Due to the log-linearity characteristic, each successive doubling requires adding substantially more installed capacity. However, there are limits to the expansion of cumulative capacity of technologies, for example market constraints: In the long run, markets may become saturated and the maximum market size may be reached (Junginger et al., 2010). Ferioli et al. (2009) additionally suggest that resource constraints set limits to the expansion of cumulative capacity: Fossil resources or the availability of suitable wind generation locations are limited natural resources, and once a majority is depleted, the costs of the technology may start to rise.

Third, another critique often brought forward is the variance of reported leaning rates for electricity generation technologies across studies, depending on the data source, the considered time period and the analysed geographical scope of the study (van Sark et al., 2008). Rubin et al. (2015) reviewed the corresponding literature for 11 electric power generation technologies, and concluded that the reported learning rates varied significantly. Furthermore, they reported that in several cases, the reported range included negative as well as positive values. However, the need to better characterize the uncertainties when deriving learning rates for technologies has been widely recognized, and several measures that can support this have been identified. The proposed measures include the consistent reporting of the errors for the derived learning rates, the systematic use of sensitivity studies when incorporating learning curves in energy models, and indicating ranges for learning rates rather than a single value (van Sark et al., 2008; Wiesenthal et al., 2012; Yeh and Rubin, 2012).

4.2.3 Learning curves for environmental and energy performance

The cost learning curve is a widely applied methodology, which is appreciated for its simplicity and for the fact that it seems to be applicable to a wide range of technologies and industries. Even though cost learning curves manage to reflect the empirically observed price developments in many industries fairly well (Junginger et al., 2010), they do not offer explanations per se as to how those cost reductions have come about.

In recent years, an increasing number of studies have started to open up the black box of "learning", by disentangling the underlying factors for the cost declines. For example, Kavlak et al. (2016) set out to investigate the causes of the dramatic cost reductions in the PV technology. Many of the underlying drivers identified in these studies could also have a direct impact on the environmental and energy performance of technologies, due to increased material and energy efficiency and higher energy yields. This suggests that technological change has not only the potential to bring down the costs, but also to significantly improve the energy and environmental impact of technologies. It therefore appears to be a logical step to analyse in detail how the environmental impacts have developed as experience with technologies has grown and technologies have improved – thus, applying the learning curve concept to the domain of environmental and energy performance analysis. However, at present relatively few studies exist which show how the different drivers of learning can influence the environmental impacts of technologies (Bergesen and Suh, 2016). The next sections present an overview of the research work which has already been conducted on this topic.

Many authors in LCA literature have acknowledged the need to account for technological change in LCA early on. For example, Weisser (2007) states in his comparative review of studies analysing life-cycle greenhouse gas emissions of power generation technologies that "technology experience curves potentially render older LCA inappropriate for reference use today, since the associated GHG emissions have fallen, especially for some renewable energy technologies (RETs) where the energy pay-pack ratio has improved significantly and continues to improve".

In several case studies, frameworks for incorporating technological change in prospective LCAs have been explored. For example, Pehnt (2006) applies a dynamic LCA approach to determine the future environmental performance of renewable energy technologies, using photovoltaics, forest timber in heating, and timber in steam turbines as examples. Pehnt's approach bases on a set of individual "dynamic" parameter per technology, which are assumed to improve over time. For PV, the prospective LCA for the year 2030 is calculated with a reduced wafer thickness, a higher module efficiency, an increased scrap share of the aluminium and steel production, and a more sustainable electricity mix, which results in a lower environmental impact. Gavankar et al. (2015) investigate how the scale of production and technological maturity influences the environmental performance of an emerging technology, using the manufacturing of carbon nanotubes as an example. They find significant reductions in all considered environmental impact categories, as the carbon nanotubes' manufacturing process scales up from small to mass production.

These extant studies incorporate some dynamic elements, and investigate how these would influence future environmental impacts of technologies. However, only in more recent contributions are the improved environmental impacts examined as a function of accumulated experience, and the terms "environmental experience or learning curves" introduced.

First, Bergesen & Suh (2016b) suggest that Solar PV might see substantial improvements in its environmental performance over the coming decades. They therefore propose a dynamic life-cycle assessment model which models the effects of technological learning in LCA, taking into account the entire supply chain of a technology. Their LCA framework incorporates the effects of changes in the direct and supply chain inputs required for producing a technology as a result of learning processes, and based on historical learning rates. This permits the computation of changing environmental impacts of technologies as cumulative production increases. Applying their mathematical framework to the case of CdTe photovoltaics, they find that life cycle GHG emissions decrease significantly with an increasing cumulative production volume.

Second, Caduff et al. (2012) investigate how the trend towards larger turbines influences the environmental performance of wind energy. They found an improved environmental performance for bigger turbines, and attributed this to two effects: an effect attributable to the growing size and in addition, a general learning effect over time due to increased experience with the technology. They derive an *environmental experience curve,* indicating that these two effects combined lead to a reduction of 14% of greenhouse warming potential per kWh of electricity produced, for each doubling of cumulative installed capacity.

Also in the Net Energy Analysis literature, first steps have been made to incorporate learning curves: For instance, Louwen et al. (2016) apply the experience curve concept to the energy demand, energy payback time and greenhouse gas emissions of PV systems (mono- and poly-crystalline silicon), and find significant improvements as a function of cumulative installed PV capacity. For the cumulative energy demand, they find a decrease by 13% for poly crystalline and 12% for mono-crystalline PV systems.

Similarly, Görig & Breyer (2016) aim to analyse the development of PV systems in terms of energy. They calculate learning rates for the energy demand of various PV technologies, and a separate learning rate for the BOS and the Panel.

To conclude, first steps have been taken to apply the learning curve concept to the environmental and energy performance of technologies. As far as the energy performance of technologies is concerned, studies are still lacking which systematically apply the learning curve concept to energy performance indicators, developing *dynamic* instead of static concepts. In particular, there is a lack of studies comparing different technologies based on such a dynamic indicator. In an attempt to fill this gap in the literature, the dynamic concept for the EROI indicator proposed by Steffen et al. (2018) compares a set of power generation technologies that are relevant for energy policy decisions in Switzerland and Europe in general.

4.3 Methodology and data

4.3.1 Dynamic EROI concept

Two static energy performance indicators, the EROI and the nr-CED, have been introduced in Chapter 2, and their relative strengths and weaknesses have been presented. One often mentioned critique of the EROI is that it does not take into account fuel inputs. However, it must be kept in mind that EROI and nr-CED address different questions, and that both concepts therefore have their merits. The nr-CED is better suited to quantify the full resource implications of a power generation system, and stands in the tradition of environmental indicators aiming to quantify the full environmental impact of technologies. The EROI, in turn, examines the precondition that a technology should return more energy than is invested in it, i.e. the societal energy viability of technologies. It also answers the question in which power generation technology one should invest already available materials and energy, expressed in units of energy, to achieve the highest possible energy return.

The EROI indicator is chosen to be the basis for this analysis, due to three main reasons. First, the EROI dominates current energy performance literature, and results can therefore be more readily compared with existing literature. Second, sufficient data showing developments over a longer period of time is only available for the EROI indicator, since the corresponding Net Energy Analysis literature had its beginning as early as in the 1980s. Third, the EROI is better suited to highlight energy learning: since the nr-CED of fossil fuelled power generation technologies is largely dominated by the fuel input, changes in the energy investment are not well visible. The EROI in turn, is more sensitive to changes, and is therefore better suited to track the evolution of technologies over time.

The dynamic concept on the basis of the EROI indicator aims at capturing the dynamics of technological learning. The dynamic EROI concept is based on the premise that the amount of energy delivered by a power generation technology, and the energy that has to be invested in it, change as experience with the technology accumulates. The power generation capacity, which cumulatively has been installed[15], serves as a proxy for the experience which manufacturers and users have accumulated with the technology (see Steffen et al. 2018). Hence the link between EROI and time is not a direct, but an indirect one, as the EROI is assumed to depend on the cumulative installed capacity, which in turn refers to a specific year in time. The following equation summarises the concept, with X being the cumulative installed power generation capacity of a technology in place in a specific year t.

$$EROI_{dynamic} = EROI\,(X(t)) = \frac{E_{delivered}\,(X(t))}{E_{invested}\,(X(t))} \tag{10}$$

[15] The cumulative installed capacity designates all generation units which have ever been built, irrelevant whether the capacity is still in operation or not. From one year to the other, the cumulative installed capacity can therefore only remain constant, or increase, but never decrease.

The study follows a two-step approach: In the first step, a *retrospective* analysis is conducted, which analyses the developments which occurred in the domain of energy in the past and derives historical learning curves for each technology. In the second step, the learning curves are projected forward in the *prospective* analysis, which aims at assessing the future energy performance of technologies. The prospective analysis also includes an uncertainty analysis which investigates the uncertainties which are associated with this methodical procedure.

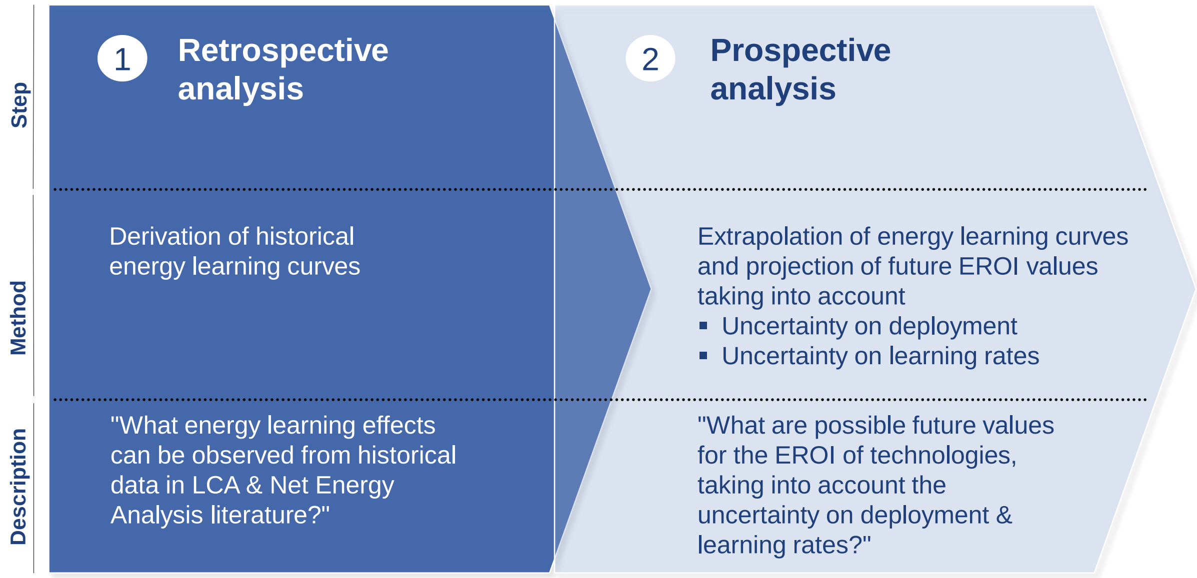

Figure 25: Overview of two-step research approach for dynamic EROI analysis.

4.3.2 Derivation of energy learning curves

General approach

It becomes apparent from the definition of the dynamic EROI (see equation (10)) that a technology's EROI can improve in two ways: The energy which is delivered over the entire lifetime can increase (thus, increasing the numerator of the EROI ratio), or the energy which needs to be invested in the system can decrease (thus, decreasing the denominator of the ratio). The retrospective analysis therefore analyses the developments of both influencing factors separately, and derives a learning curve for both energy invested and energy delivered for each technology. Those two learning curves are then combined in order to estimate the total learning effect in terms of the EROI. Figure 26 depicts the research methodology.

In its non-logarithmic form, the learning curves are assumed to take on the form of the following power law:

$$E(X) = E_o * X^{-b} \tag{11}$$

Where E is the energy invested or delivered at a specific cumulatively installed power capacity X, E_0 the energy invested or delivered of the first unit produced, X the cumulative installed capacity and b the learning parameter. If the equation is transformed to its logarithmic form, a linear curve with a slope –b results.

$$\log\left(E(X)\right) = -b * \log(X) + \log(E_0) \tag{12}$$

A linear regression is performed on the logarithms of the energy data (energy invested or energy delivered) and the cumulative deployment data, in order to obtain the parameters of the learning curve. In other words, linear learning curves are fitted to a set of collected data points in a double logarithmic plot relating energy to cumulative installed capacity. With this regression analysis, the slope and the intercept parameters -b and $\log(E_0)$ can be obtained. The slope can then be used to determine the learning rate, which is defined as the rate at which the energy delivered or invested "improve" for each doubling of cumulative installed capacity.

$$LR = 1 - 2^{-b} \tag{13}$$

"Learning" in the sense of an improvement in energy is inversely defined for energy invested and energy delivered: It is desired that the primary energy invested in the capture and delivery of the energy *decreases* over time, while the electrical energy delivered by the power plant is desired to *increase* over time to achieve the maximum possible improvement of the EROI. The desired slopes, and hence the learning rates, have an opposite sign. It is important to note that the slope of the learning curve can easily be converted into the learning rate (using Equation (13)), which offers a more intuitive handling than the slope.

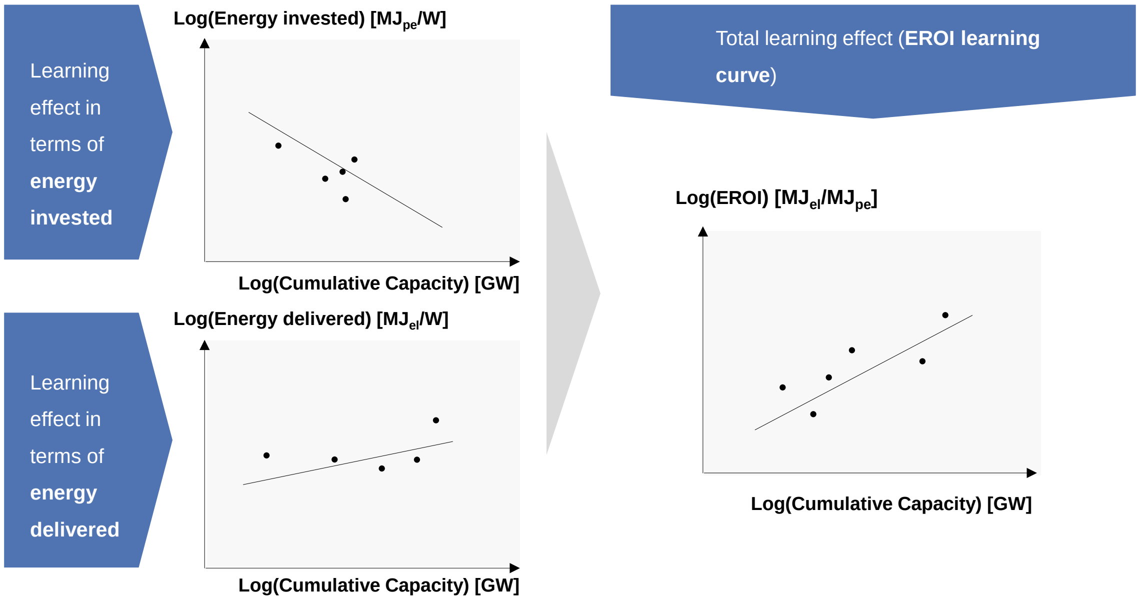

Figure 26: Overview of the research methodology for the retrospective analysis.
A learning curve for both energy invested and energy delivered is derived per technology to estimate the total learning effect for the EROI.

In order to derive the historical energy learning curves for a power generation technology, data on how the energy invested and energy delivered developed over time needs to be collected. However, since it is not the passage of time which leads to technology improvements, but rather the accumulation of experience with the technology, data on cumulative installed capacity over time needs to be gathered in addition. While the next section explains some fundamental choices in terms of the learning model, the subsequent section explains the process of sourcing and harmonising the data in greater detail.

Choice of learning model

When it comes to the implementation of the learning curve concept, there are a couple of fundamental decisions which greatly determine the learning model: the type of learning curve chosen, whether global or regional learning is assumed, and whether limits to technological learning are introduced, amongst others (Wiesenthal et al., 2012). The learning model chosen for this analysis is discussed in the following, referring to those three fundamental choices.

- **Type of learning curve**

For this analysis, a *one-factor learning curve* approach was chosen. The one-factor learning curve is the most established framework for following empirically observed technology evolutions (Wiesenthal et al., 2012), and there is no immediate benefit of using a two-factor learning curve for the research aim.

- **Global vs. regional learning**

Learning in power generation technologies is a global phenomenon, and it is the global experience with the technologies which determines learning effects (Huenteler et al., 2016). This also means that procurement, diffusion and spill over effects are assumed to occur *globally,* with improved technology design or energy savings in the manufacturing process eventually finding their way to all markets. The geographic boundaries for the learning curves are therefore chosen to be global, meaning that data from all over the world is collected and aggregated.

- **Limits to technology learning**

This analysis does not consider limits to technology learning, that is, no “energy floors” or “energy ceilings” are introduced which set limits to the learning potentials for energy invested and energy delivered. This would have the benefit of reducing the risk of overestimating the remaining improvement potentials. However, this would have to be done with bottom-up engineering estimates, which are beyond the scope of this study. Also, Wiesenthal et al. (2012) argue that bottom-up engineering estimates are normally based on current knowledge and state of the technology, and therefore tend to be too pessimistic, as they cannot foresee dramatic breakthroughs.

Sourcing and harmonization of data

In order to derive historical energy learning curves, three data components by technology are necessary:

1. Cumulative installed capacity over time
2. Historical data on energy invested
3. Historical data on energy delivered

The data on the cumulative installed capacity over time is used as a proxy for the experience that manufacturers have gathered. Data on cumulative installed capacity over time per technology had to be compiled from various sources, which are described in greater detail in section 4.3.5.

The data on energy invested and energy delivered was collected in two bodies of literature, in Net Energy Analysis literature and Life Cycle Analysis literature. Two searching methods were pursued in order to retrieve historical data on energy invested and energy delivered by technology. On the one hand, an extensive keyword search in both English and German in a variety of scientific databases and online search engines was conducted. [16,17] On the other hand, published review papers in the domain of LCA and Net Energy Analysis Literature were analysed and used as a starting point to find further useful references ("snowball method").

The results of the literature search were closely examined and filtered down based on a set of criteria to ensure sufficient data quality and comparability among the studies. In the first step, a set of general filter criteria were applied to all data sets. Each of these general filter criteria are discussed in detail below. In the second step, some technology-specific filters were applied to the data per technology, which are explained in the technology-specific sections 4.3.5.2 to 4.3.5.5.

Filter criterion 1: Completeness of technological scope

It had to be ensured that the historical data on energy invested collected from various studies covered the complete technological scope. The technological scope specifies what is included in the "energy accounting" for energy invested. Table 18 summarises the technological scope per technology for this analysis. For the fossil power generation technologies, the technological scope includes both the fuel supply chain and the power plant. For the renewable power generation technologies converting wind and sunlight, only the investments in the power plant are included. It was then examined if the collected data matches the defined technological scope. If it was apparent that the collected historical data on energy invested did not cover the entire technological scope, the data was excluded from the analysis. However, often the studies the data was taken from did not present their results in a disaggregated way, e.g. by breaking the energy investments down into energy investments for single power plant components or processes of the fuel chain. For example, for fossil power generation technologies, the energy investments for single power plant components were rarely listed, and if they were listed, then a variety of collective terms combining components were used, which made a comparison among studies difficult. Therefore, a pragmatic approach was followed to ensure that the entire technological scope was covered: if the study's description of the system considered matched the defined technological scope, the data was included in the analysis, even if the results were not presented in a disaggregated way. For fossil power generation technologies for example, it had to be evident that the fuel supply chain was covered in the analysis. For renewables, the description had to entail the major power plant components mentioned in Table 18.

Filter criterion 2: Methodological correctness

A correct estimation of the energy investments into fossil power generation technologies excludes the energy content of the fuel. It therefore had to be made sure that the collected data is in line with this. Whenever the energy content of the fuel was included in the figures for energy invested, but could easily be subtracted from the total results, this has been undertaken. Data which included the energy

[16] Scopus (Elsevier), Materials Science & Engineering Database, Science Citation Index Expanded (Web of Science), AGRIS (United Nations, Food and Agriculture Organization), American Chemical Society, nature.com (Nature Publishing Group), Cambridge Books Online, American Association for the Advancement of Science, PNAS (National Academy of Sciences)

[17] The used English key words were "life cycle energy", "net energy", "energy analysis", "net energy analysis", "EROI", "embodied energy", "cumulative energy" and "payback time". The German key words were "Energieaufwand", "kumulierte Energie", "Nettoenergie", "energetische Amortisationszeit" and "energetische Rückzahlzeit".

content of fuel, but did not provide enough information to correct the figures for this, was excluded from the analysis. Further, the studies had to specify whether the process chain analysis (PCA) method or the Input-Output (I/O) analysis method was used for estimating the energy investments[18].

In this analysis, attempts were made to separate those two methodological approaches as far as possible. As long as there was sufficient data available, covering a sufficiently long time-scale, results obtained with the PCA or the hybrid method were preferred, in order to allow a better comparison with the results obtained from the static analysis, which also bases on the PCA approach. However, for the technologies natural gas and hard coal, there was insufficient data available obtained by using the PCA method. In particular the earliest studies published around 1980 almost exclusively applied the I/O method, and not including this data in the analysis would mean omitting an important time period for the evolution of fossil fuel technologies. Therefore, data obtained by PCA and I/O method have been combined for natural gas and hard coal.

Filter criterion 3: Specification of technological status

It is essential that each collected data point could be assigned to the technology status of a specific year. Some studies explicitly stated for which time period or year the technology they examined is representative. However, the more typical case was that the technological status had to be estimated indirectly. This has been done by analysing the publication dates of crucial data sources used in the studies (for example of material and energy balances for studies with the PCA approach, or energy intensity tables for the I/O approach). If several crucial data sources with different publication years were referenced, an average of those publication years was taken. For studies, which claimed to represent the "present" technology status, the publication year of the study was taken and three years were subtracted from it to determine the year of the technological status. This has been done to take into account the time lag between the drafting of a study and its publication in a scientific journal, due to the review process and other possible delays. Excluded from the analysis were prospective studies analysing pioneering technologies which were not yet available at the time of publication, and studies which did not offer any indications on the technology status.

[18] Two methods can be distinguished in life-cycle energy analysis: process chain analysis (PCA) and input-output analysis (I/O). Hybrid assessment tools are a combination of both. PCA is a bottom-up technique, which examines all energy use processes in detail. The whole life-cycle is broken down into different stages, and complex processes are broken down into a series of more simple ones. An energy and material balance is established for each process. (Blok & Nieuwlaar 2017; Weisser 2007). By contrast, the I/O method is a top-down approach which is based on monetary flows, rather than physical flows of material and energy. It divides an entire economy into sectors, and it then assigns an energy intensity value to each sector. Based on the exchange of economic inputs and outputs between the sectors, I/O determines the energy flows. (Blok & Nieuwlaar 2017; Weisser 2007).

Table 18: Technological scope per technology.

Technology	Fuel supply chain	Major power plant components
Hard coal	Extraction, processing, delivery of hard coal	• Mechanical equipment (steam turbines, boiler) • Electrical equipment (generator) • Ancillary systems (environmental control systems, cooling systems) • Housing & other
Natural Gas CCGT	Extraction, processing, delivery of natural gas	• Mechanical equipment (steam turbines, gas turbines, boiler) • Electrical equipment (generator) • Ancillary systems (environmental control systems, cooling systems) • Housing & other
PV multi-crystalline	-	• PV module • Balance of system (inverter, power control systems, cabling, frame)
Wind onshore	-	• Rotor • Tower • Foundation • Electrical equipment (generator) • Transmission (pitch control, hub, mounting, main shaft, bearings and gear box)

Whenever needed, data was converted to the units used in the definition of the EROI. The unit for energy invested is MJ of primary energy per Watt of installed electrical (net) capacity. The unit for energy delivered is MJ of electrical energy per Watt of installed electrical (net) capacity.

Further details on power plant characteristics were collected from the studies. This has been done for several reasons: First, information on net power rating, the lifetime and capacity factors fed into the calculation of the energy delivered. Second, comparing the power plant characteristics for data points of the same estimated “technology status period” allows for a cross-check. For example, very large differences in the module efficiencies of two multi-silicon solar PV panels, which should represent roughly the same technological status, should not occur. Third, having further background information at hand sometimes allowed to explain anomalies in the data.

4.3.3 Prospective analysis and uncertainty analysis

While the previous section explained the general approach used to derive energy learning curves from historical data, this chapter focusses on the approach for projecting those energy learning curves into the future.

Even though the extrapolation of learning curves into the future is often done (e.g., Schmidt et al., 2017), and actually represents one of the advantages of the concept of learning curves, it is associated with uncertainties. In this study, a comprehensive uncertainty analysis is therefore undertaken to account for the uncertainties inherent to this methodological approach.

The first major source of uncertainty of this analysis is the future deployment of technologies, i.e. how much additional power generation capacity will be built per technology. The development of the cumulative capacity determines a technology's remaining "learning potential", and is therefore an important determinant of learning alongside the learning rate. This uncertainty is addressed by means of a **scenario analysis**, in which three alternative deployment trajectories are explored for each technology, assuming varying future energy and climate policy regimes which will be in place. The three scenarios considered are the *Business-as-usual Scenario*, the *Paris pledges Scenario* and the *2°C Scenario*. Two of these scenarios make rather extreme assumptions in terms of policy developments (the Business-as-usual scenario, representing the worst case in terms of global climate agreements, and the 2°C scenario, representing a rather ambitions case), so that a wide range of possible developments both in terms of policy regime and capacity additions lie in between. The historical learning curves from the retrospective analysis are then extrapolated along these deployment scenarios, assuming that the observed incremental learning effects from the past will continue in the future. The extrapolated values for energy invested and energy delivered are used to calculate EROI values for the period 2020 – 2040. By comparing the outcome in terms of EROI for these three alternative deployment scenarios, the impact of this source of uncertainty on the results can be broadly assessed.

The second major source of uncertainty for this study are the learning rates for each technology. On the one hand, there is uncertainty in the derived learning rates from historical data. On the other hand, even if the learning rates could be determined with absolute certainty, one could still not be certain that learning in the future occurs at the same pace as in the past - meaning that the learning rate for the future may not need to be the same as the one observed in the past. Therefore, a **Monte Carlo analysis** is conducted, which analyses the effect of randomly varying learning rates on the future EROI values, thus, estimating the impact of this source of uncertainty on the results.

In the next sections, both parts of the uncertainty analysis, the scenario analysis and the Monte Carlo analysis, are discussed in greater detail.

Scenario analysis

The three scenarios considered in the scenario analysis, sorted from least to most ambitious scenario, are the *Business-as-usual Scenario*, the *Paris pledges Scenario* and the *2°C Scenario*. These deployment scenarios are adaptions of scenarios published in the global long-term energy projections (World Energy Outlook WEO) by the International Energy Agency IEA.

The *Business-as-usual Scenario* represents the default scenario, and is an adaption of the WEO's Current Policies Scenario. In the 2016 version of the WEO report, only policies enacted as of mid-2016 are included, and no further changes in policies are assumed in this scenario. It therefore describes the "default setting" of the energy system, and provides a benchmark against which the impacts of new policies can be measured (IEA, 2016a, 2016b).

The *Paris Pledges Scenario* is the main scenario, and is adapted from the IEA's New Policies Scenario. It incorporates existing policies in the domain of energy, as well as policies or plans which have been announced, but not yet implemented: This includes for example the national pledges to reduce greenhouse-gas emissions, which have been submitted for the COP21 conference in Paris, or plans to phase out fossil-energy subsidies (IEA, 2016a, 2016b).

The *2°C Scenario* sets out a pathway which is consistent with the goal of limiting global warming to 2°C by limiting the concentration of greenhouse gases in the atmosphere to around 450 ppm of CO_2 (IEA, 2016b). This scenario is adapted from the IEA's 450 Scenario.

The IEA's World Energy Outlook

The IEA energy projections are generated with a large-scale simulation entitled World Energy Model, which models the global energy system in detail. It is designed to replicate the functioning of energy markets, in response to changing input parameters. Examples of such inputs to the modelling are described in the following (adapted from IEA (2016a)).

- *Future energy policies*: These are the policies in the domain of energy and climate policy that are assumed to be pursued by governments around the world. For example, the New Policies Scenario assumes that all net-oil importing countries phase out fossil-fuel subsidies completely within ten years. The Current Policy Scenario does not make such an assumption, unless a country has already implemented a programme to do so. The 450 Scenario assumes that all fossil-fuel subsidies will be removed in both net-exporting and net-importing regions, with the exception of the Middle East, within twenty years. Another source of variation between the scenarios is the scope to which carbon pricing mechanisms are introduced, and the carbon price that results from those mechanisms. This is assumed to have a major impact on the costs of the different fossil fuels. The New Policies Scenario, for instance, takes into account China's carbon trading scheme, which is due to come into force by the end of 2017 for six large energy consuming sectors.
- *Economic prospects:* Another important assumption is the development of economic activity in different regions and sectors. The global economy is assumed to grow by 3.4% per year

on average over the projection period in all scenarios. However, how this growth in economic activity translates into demand for energy is heavily dependent on the policy scenarios.

- *Demographic trends:* By 2040, the world population is assumed to grow to 9.2 billion, with an increasing share of the population living in cities and towns. The major share of this growth is assumed to occur in Africa, India, Southeast Asia and the Middle East.
- *International fuel prices and technology costs:* These parameters are endogenously modelled, that is, they are generated within the model itself. The fossil fuel prices (i.e. oil and gas prices) within the model are set in such a way that the long-term projections for demand and supply match. As far as technology costs are concerned, technological learning is accounted for, with the costs of power generation technologies like wind and solar decreasing with cumulative deployment.

Taking into account all these input parameters, the simulation determines the future mix of fuels and power generation technologies used to meet the world's energy demand. With respect to the electricity sector, the model makes sure that enough electrical energy is generated to meet the (peak) electricity demand in each region. The simulation adds new generating capacity to the existing capacities in order to meet the growing demand or to replace retired power plants (for reasons of age or due to policy-induced early retirement) (IEA, 2016a).

It is exactly this added generating capacity that is of interest for the prospective analysis of this study, as it determines the development of the cumulative installed capacity per technology. However, in the WEO only the *capacity in operation* is listed per year. This means that the difference in generation capacity from one year to the other represents the newly built generation capacity minus the capacity which has retired and no longer belongs to the capacity in operation, hence, the *net capacity additions*. However, for this analysis it is not the net capacity but rather the *gross capacity* added per technology which is of interest for the learning potential of technologies. This means that additional assumptions were needed to estimate trajectories for the cumulative installed capacity per technology for the time frame 2015 – 2040, based on the figures from the IEA's WEO.

Deriving scenarios for future cumulative installed capacities

In order to translate back to the *gross capacity additions* from the figures provided by the IEA, the capacity retirements per technology per year had to be estimated. In order to obtain an estimate of the capacity which will retire during the time period 2015 to 2040, the data on the technologies' historical cumulative installed capacities from the retrospective analysis was accessed once again. Based on these figures, the newly built capacity for each year in the time period 1980 – 2015 has been calculated. It was then assumed that this capacity is decommissioned after a certain amount of years, which represents the average technical lifetime of the power plants. The assumptions for the average plant lifetimes were taken from the IEA, which suggests 50 years for hard coal power plants, 30 years for CCGT natural gas power plants, and 25 years for wind turbines and solar panels (IEA, 2016a). The projected retired plant capacity was then added to the net capacity additions obtained from the IEA figures to obtain the gross capacity additions. The gross capacity additions, in turn, were added to the cumulative installed capacity, starting from the present and known value for the year 2015, to gain trajectories for the cumulative installed capacity per technology during the time period 2015 to 2040 in 5 year steps. Further details on the calculation approach can be found in Steffen et al. (2017).

Likewise, as the IEA provided figures for wind power and natural gas but no separate figures for onshore wind and natural gas CCGT, further assumptions had to be made regarding the split of these technologies. For further details, please refer to Steffen et al. (2017).

To sum up, the IEA scenarios form the basis for the three deployment scenarios used in this analysis (Business-as-usual Scenario, Paris Pledges Scenario, 2°C Scenario). However, for the IEA scenarios, readily usable figures for the development of the cumulative installed capacity per technology were not indicated. Additional calculations had to be performed to derive these figures, and a variety of assumptions had to be made, which justified the renaming of the scenarios. The scenarios are illustrated in Figure 27. The year 2015 is the baseline year, where the cumulative installed capacities correspond to the actual historical values for all technologies.

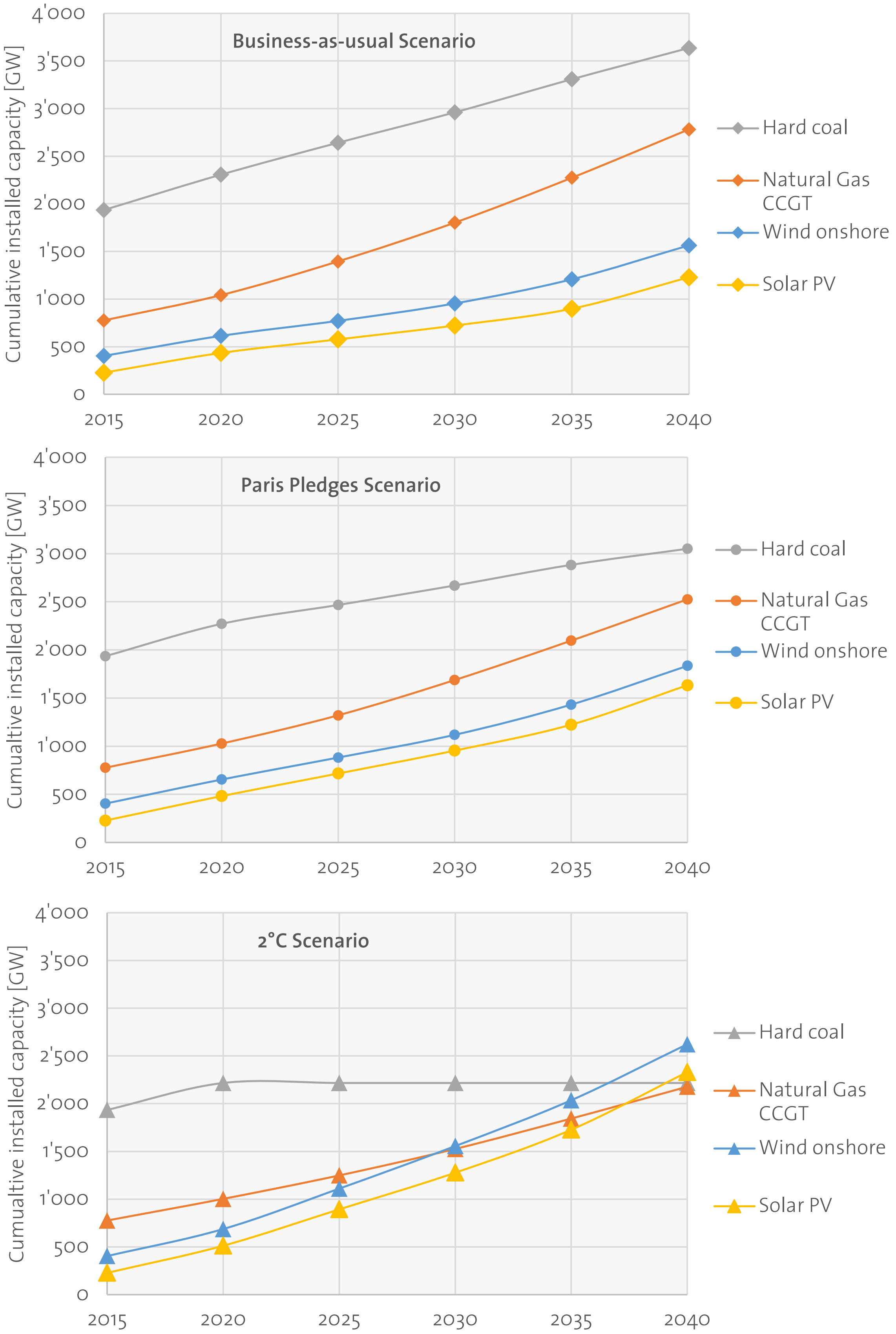

Figure 27: Scenarios for development of cumulative installed capacity per technology.
Top: Business-as-usual Scenario; centre: Paris Pledges Scenario; bottom: 2°C Scenario. Source: based on IEA WEO scenarios (IEA, 2016b).

Hard coal

For hard coal, the cumulative installed capacity is assumed to grow the most in the Business-as-usual Scenario, with a cumulative installed capacity of almost 3700 GW in 2040, as compared to the 1935 GW cumulatively installed in 2015. This represents almost a doubling of the cumulative installed capacity. In the Paris Pledges Scenario, the cumulative installed capacity in 2040 was calculated to be 3050 GW, which represents an increase of almost 60% as compared to the 2015 value. In the 2°C Scenario, the cumulative installed capacity is assumed to remain constant at a level of 2200 GW as of 2020, with no capacity additions after 2020.[19]

Natural gas

For natural gas, the difference in the cumulative installed capacity between the three scenarios is not as pronounced as for hard coal. In 2015, the historical cumulative installed capacity (data from the retrospective analysis) is 730 GW. In 2040, this is assumed to rise to 2800 in the Business-as-usual Scenario, to about 2500 GW in the Paris Pledges Scenario, and to 2200 GW in the 2°C scenario.

Wind onshore

The historical cumulative installed capacity of wind onshore was approximately 400 GW in 2015. The Business-as-usual scenario projects an increase to a level of 1600 GW in 2040. The Paris Pledges Scenario projects a slightly higher level of 1800 GW of cumulative installed capacity. In the 2°C Scenario, much more wind onshore capacity is expected to be added, so that in 2040 the cumulative installed capacity amounts to 2600 GW.

Solar PV

For solar PV, the three scenarios foresee widely diverging developments in terms of the cumulative installed capacity. The Business-as-usual Scenario assumes a cumulative capacity of approximately 1200 GW in 2040, which is almost five times the cumulative installed capacity of 2015 (230 GW). In the Paris Pledges Scenario, a level of almost 1600 GW is assumed, and 2°C Scenario even predicts a level of 2300 GW for the cumulative installed capacity of solar PV in 2040.

While the scenario analysis accounts for the uncertainty on deployment by presenting the resulting EROIs for varying future deployment scenarios, the Monte Carlo Analysis analyses the outcome for varying future learning rates, as the next section explains.

[19] Since the methodological approach only takes into account retirements for reasons of age, but not early retirements due to political reasons, these figures might underestimate the cumulative installed capacity of hard coal in the 2°C Scenario. However, there is no further information regarding policy-induced early retirements available. Also, these trajectories for the cumulative installed capacity should not be seen as forecasts, but rather as explorative pathways for the analysis.

Monte Carlo Analysis

The second source of uncertainty is the *uncertainty on the learning rate.* First of all, the underlying assumption of the learning curve is that the incremental learning process observed in the past, is going to continue in the future. However, this might not necessarily be the case, as disruptive innovations can fundamentally change the learning rate occurring in the future. Second, there is uncertainty in the historical learning rates which have been derived by fitting a linear learning curve to the historical energy data. In some cases, the scatter in the data was considerable, which led to a low quality of the fit of the curve to the collected data. Therefore, a Monte Carlo Analysis was conducted, which takes into account the uncertainty in these learning rates, and analyses the outcome for a large number of alternative learning rates, which are randomly selected and inserted into the model.

In order to model the uncertainty in the dynamic analysis with regard to the learning rate, the future slopes of the learning curves for both energy invested and energy delivered for all technologies were stochastically varied, i.e. defined as the stochastic input variables. It is important to note here, that the slopes of the learning curves, can be easily converted to equivalent learning rates, however, the calculations in the simulation model are based on the slope and not the learning rate for reasons of simplicity. In terms of the probability distribution, the assumption was made that the slopes of the learning curves are normally distributed, with the mean of the distribution being the slope of the observed historical learning curve. The standard deviation was taken to be the standard error of the slope from the “fitting” of the historical learning curve to the collected data points. The uncertainty was only applied to the future, not retrospectively. For the calculation of the 2015 values of energy invested and delivered, the parameters of the *historical* learning curve were used, that is, the slope –b and the intercept a from the regressions.

Finally, the EROI values for the years 2020 to 2040 were calculated by dividing the energy delivered and the energy invested values of the respective years. The output cells of the simulation were the resulting EROIs of the years 2020, 2025, 2030, 2035 and 2040 for each technology. After carrying out 5000 iterations of the simulation, a 95% confidence interval for the future EROIs per technology was provided, based on the simulation results.

4.3.4 Limitations of approach

This section presents four main limitations of the dynamic energy performance analysis conducted in this study, as well as possible areas of research, which other studies could follow up on.

First, an important limitation refers to the data basis of the present analysis. The collection of historical data was a time-consuming and laborious process, and despite these efforts only a limited amount of data was available for some technologies. In general, a shift in the focus of interest in assessments of power generation technologies over time has been observed: in the 1980s, many studies were investigating embodied energy and net energy topics, while in later years, the emphasis shifted to embodied greenhouse gas emissions, due to the increasing awareness of anthropogenic climate change. This means that the energy information required for this analysis has become scarcer over time, with less studies reporting on energy indicators. Also, for some technologies the scatter in the collected data is relatively large. This scatter in historical energy values may be due to methodological uncertainties, e.g. mismatching system boundaries, or differences in the methodology. To address this issue, filter criteria were applied to the collected data to exactly detect this, and to ensure the comparability of the data.

Second, a general assumption made in the learning curve approach which may not be necessarily valid is that the gradual learning process which has been observed in the past, continues at the same pace in the future ("incremental change"). Unforeseeable disruptive innovations may occur in the future, which would mean that the previous learning pathway is left, and the technology "jumps" to a new learning pathway which cannot be anticipated with accuracy. However, learning curves have demonstrated their ability to predict technology developments with reasonable accuracy in many cases, especially once a certain level of technological maturity is reached.

Third, each technology is analysed on its own in this work, and it is not considered that technologies are embedded in a system which could improve independently (i.e., has its own learning curve). Thus, systemic improvements such as less energy intensive transport, electricity or raw material (e.g. steel) sectors are not considered per se. Furthermore, cross-technological and cross-sectoral spill overs (e.g. from electronics or other industries), are not taken into account. However, as the four technologies are quite distinct, possible spill-overs are likely to be limited.

However, in this regard, the study opens up several possible avenues for future research. The analysis gives an indication where the learning effects primarily come from, that is, whether they affect the energy invested or energy delivered parameters of the EROI. In this regard, starting points are offered for further investigating the drivers for energy performance improvements in detail, which other research projects could follow up on.

Having outlined the research methodology in general terms in this chapter, the next chapter now moves on to provide technology-specific information on the research methodology. Besides information on technology-specific data and assumptions, the energy learning curves fitted to historical data are presented for the four power generation technologies considered in this analysis: hard coal, natural gas CCGT, solar PV and wind onshore.

4.3.5 Data per technology

In the first part of this chapter, the set of technologies chosen for the dynamic analysis are introduced, and a rationale for choosing this selection is provided. The following sections are then dedicated to the technology-specific data which was used to derive the historical learning curves for the dynamic EROI analysis. The chapter is therefore structured along the four power generation technologies, which are covered in the analysis. For each technology, detailed information on the data sources used for calculating the cumulative installed capacity and deriving the historical learning curves for energy invested and energy delivered, are provided.

4.3.5.1 *Choice of technologies*

Due to the complexity of the two-step methodological approach, it was necessary to limit the analysis to a selection of technologies. The following criteria were applied for the selection process (explained in greater detail below):

Selection criteria for technologies considered in dynamic EROI analysis.

1. **Relevance:** Technology relevant for European context
2. **Data availability:** Sufficient high-quality data accessible
3. **Reduction of methodological uncertainties:** Not including technologies which bear large methodological uncertainties
4. **"Archetype sampling**": Technologies at different stages of maturity and exhibiting distinctive learning patterns

First, the technology under investigation was required to presently be a relevant technology or a technology gaining increasing importance in the European energy system.

Second, it had to be ensured that sufficient historical high-quality data is available for the technologies from the different bodies of literature. For example, for hydro power, there was not enough data available to continue the analysis.

Third, the methodological uncertainties associated with conducting such an energy analysis should be minimised by selecting suitable technologies. For this reason, nuclear power was excluded from the analysis. The nuclear fuel chain is complex and includes mining and milling of uranium ores, enrichment of uranium, fuel fabrication and reprocessing or disposal of spent fuel. Energy consumption for mining and milling ores increases considerably if low-grade ores are processed. Depending on the enrichment method used, the electricity consumption of the enrichment stage can differ by a factor of 40 (Fthenakis and Kim, 2007). Also, the decommissioning of nuclear power plants is associated with significant amounts of energy. However, few studies estimate the energy requirement of the decommissioning phase, and the data which is currently available is associated with large uncertainty. Beyond nuclear, hydro power was excluded as the energy investments for hydro reservoir power plants depend significantly on the specific site at which they are built.

Fourth, the analysis aims at investigating a set of technologies, which are at different stages of maturity, and which are expected to exhibit distinctive learning patters, following the “archetype sampling” approach. For this reason, both fossil and renewable power generation technologies were included in the scope of the analysis.

Based on the four above-mentioned criteria, the following four technologies have been chosen and are described in the following:

1. Hard coal
2. Natural Gas CCGT
3. Wind onshore
4. Solar PV multi-crystalline silicon

4.3.5.2 Hard coal

Three types of coal-fired power plants can be distinguished: pulverised coal-fired power plants, fluidised bed combustion plants and integrated gasification combined cycle (IGCC) plants. Only fluidised bed combustion and pulverised coal-fired power plants have been included in the retrospective analysis. IGCC plants are a relatively new technology, which employ the principle of coal gasification: coal is converted into syngas, a fuel gas consisting of hydrogen and carbon monoxide, which is then passed to a combined cycle with a gas and steam turbine (Sarkus et al., 2013). The IGCC power plant technology rather resembles combined cycle natural gas power plants in its operation principle, and is therefore considered an innovation which is radically different from the other coal-fired power plant technologies. It is therefore not included in the pool of coal power plant technologies, which are analysed as an entity in order to estimate historical learning effects.

Cumulative installed capacity

Data on the historical cumulative installed capacity for hard coal power plants has been compiled from three different sources as described in Steffen et al. (2018). Figure 28 shows the compiled time series for the global cumulative installed capacity of hard coal for the years 1980-2015.

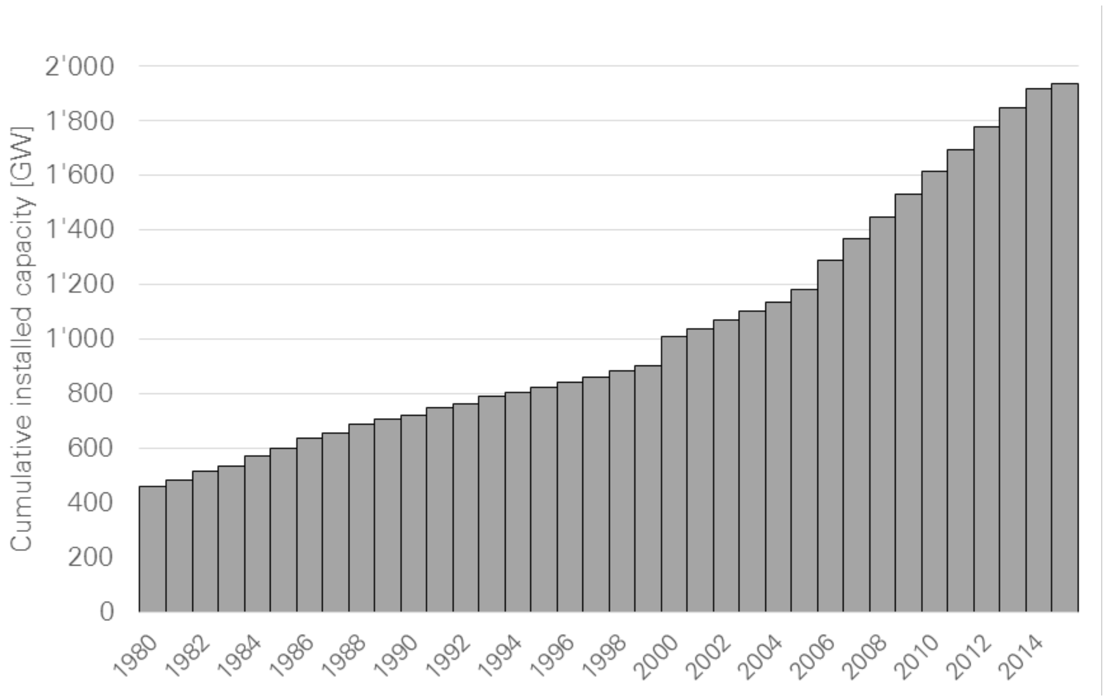

Figure 28: Cumulative installed capacity of hard coal based power generation 1980-2015.

Learning curve for energy invested

In order to derive the learning curve for energy invested, historical data has been collected from both Net Energy Analysis and LCA literature by Steffen et al. (2018). Since many of the earlier works were based on an I/O approach, and not enough data was available to limit the analysis to PCA studies, studies applying both methodologies were included. It was ensured that the energy investments indicated by the data covered the complete technological scope. Hence, energy investments in the coal supply chain (extraction, processing and delivery of hard coal), as well as the major components of hard coal power plants (mechanical and electrical equipment etc.) were considered.

A total of 18 data points was collected. This data was then connected to the historical data on cumulative installed capacities to construct the historical learning curve for energy invested, which is presented in Figure 29.

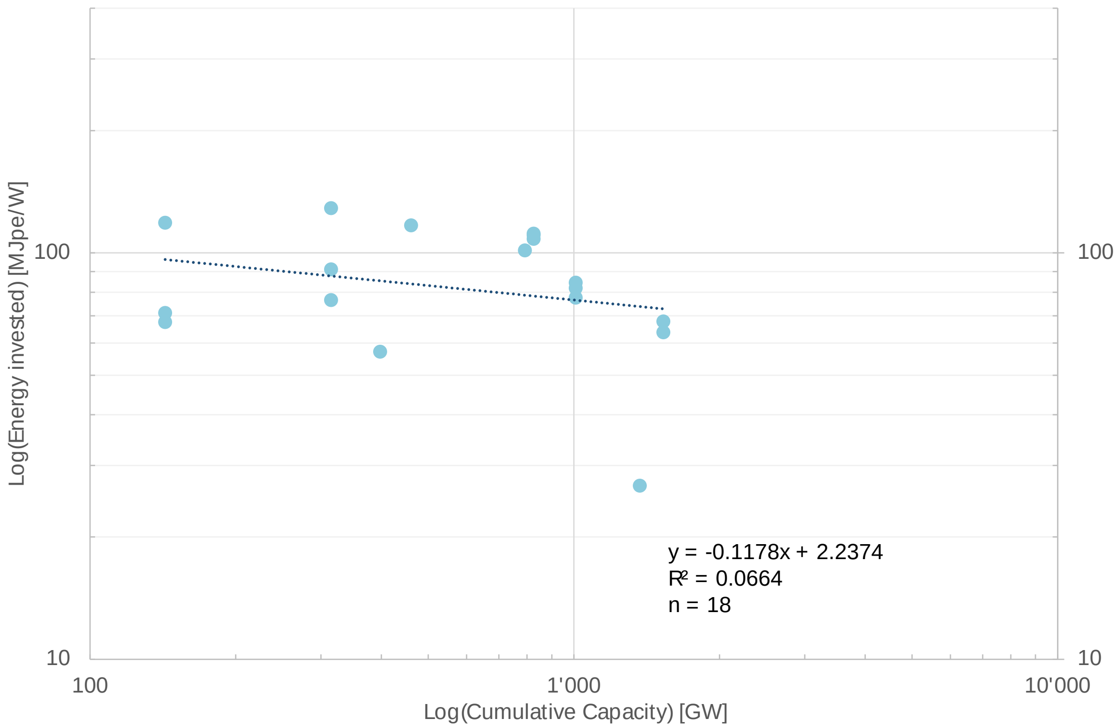

Figure 29: Historical learning curve for energy invested of hard coal.

Learning curve for energy delivered

The electrical energy which is delivered by a power plant over its entire lifetime is given by the following equation (cf. Steffen et al. 2018):

$$
\begin{aligned}
E_{lifetime} &= C_{Plant} * CF * 8760\ \frac{h}{y} * T_{lifetime} \qquad [kWh] \\
&= C_{Plant} * CF * 8760\ \frac{h}{y} * T_{lifetime} * 3.6\ \frac{MJ_{el}}{kWh} \qquad [MJ_{el}]
\end{aligned}
\tag{14}
$$

C_{Plant} denotes the installed net generation capacity of the power plant, in kW. The *capacity factor* (CF) of a power plant is defined as the actual energy produced over a year compared to the theoretical maximum of energy the plant could have produced, had it been operated continuously at its maximum rating throughout the whole year (8760 hours). $T_{lifetime}$ denotes the technical lifetime of the power plant. A conversion factor is needed to convert the unit of kWh in the unit of MJ.

$$
E_{delivered} = \frac{E_{lifetime}}{C_{Plant}} \qquad \left[\frac{MJ_{el}}{W}\right] \tag{15}
$$

In order to obtain the energy delivered in MJ_{el} per W of installed capacity, the electrical energy produced by the power plant over its lifetime is divided by the installed net generation capacity of the power plant, in W.

From every data source collected, information on the installed net generation capacity, the capacity factor, and the technical lifetime were gathered to calculate the energy delivered. Only one data source did not provide all necessary parameters to calculate the energy delivered, and was therefore not included for the derivation of the learning curve. Figure 30 presents the derived historical learning curve for the energy delivered of hard coal.

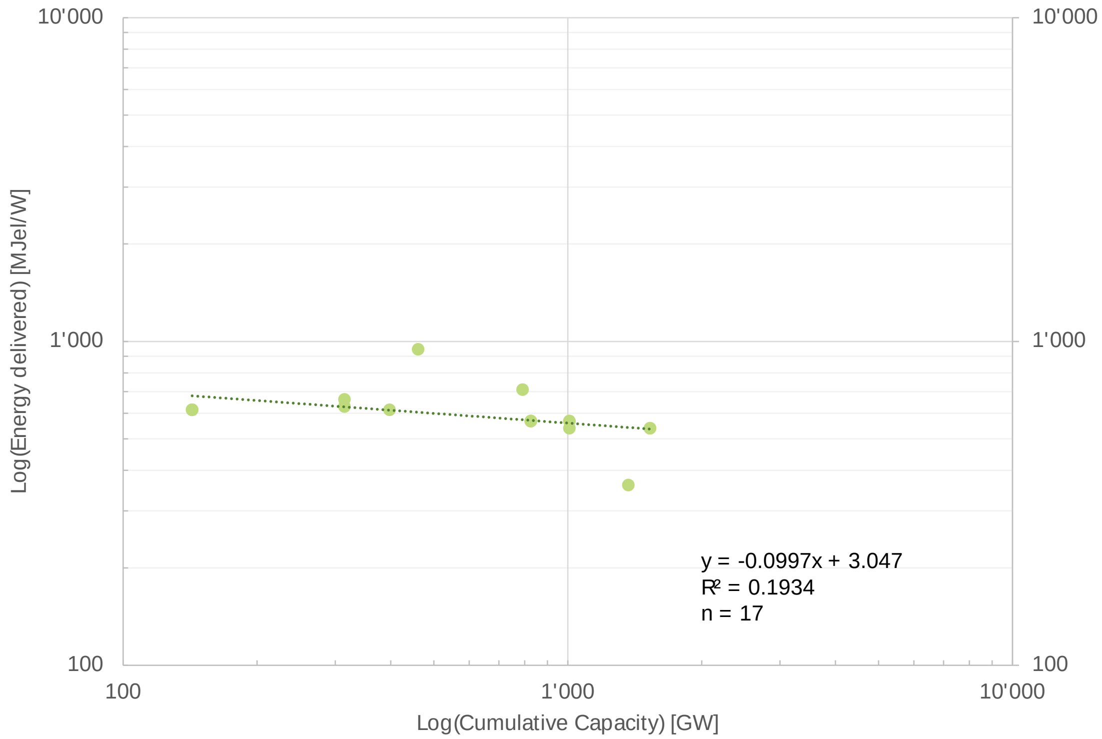

Figure 30: Historical learning curve for energy delivered of hard coal.

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4.3.5.3 Natural gas

Two types of natural gas power plants can be distinguished: open-cycle gas turbine (OCGT) plants and combined-cycle gas turbine (CCGT) plants. OCGT plants consist of a single gas turbine which is connected to a generator. Today, they are mostly used to meet peak-load demand (Seebregts, 2010). CCGT plants additionally use the remaining heat in the gas turbine exhaust to drive one or several steam turbines, which generate additional electric power. Therefore, CCGT plants have higher electrical efficiencies which can reach up to 52 to 60% (Seebregts, 2010). CCGT plants are predominantly used for intermediate and base-load generation.

Since the 1990s, CCGTs have become the preferred technology option for new gas-fired power plants, due to their high electrical efficiency and environmental advantages (IEA, 2008b). Therefore, this analysis focuses on CCGT power plants as the most important representative of natural gas power plants today.

Cumulative installed capacity

Data was retrieved from Van den Broek et al. (2009), who provided data on the historical cumulative installed capacity of CCGT plants from 1965 to 2001. This data was cross-checked with raw data for the years 1982 to 1994 used in a study by Colpier & Cornland (2002).The following figure shows the cumulative installed capacity of CCGT natural gas power plants for the years 1980 to 2001.

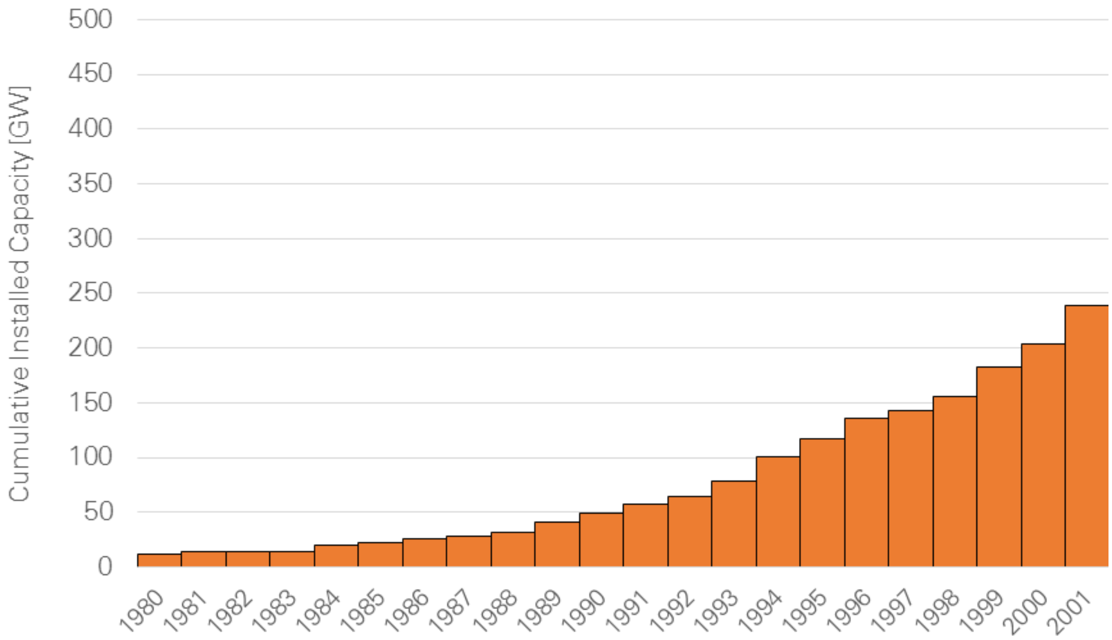

Figure 31: Cumulative installed capacity of natural gas CCGT 1980-2001.

Learning curve for energy invested

In general, only few studies were available which assessed the energy investments of natural gas power generation systems. In total, 9 data points were collected which satisfied the general filter criteria. The technological scope for natural gas power plant systems encompasses the natural gas supply chain (extraction, processing and delivery of natural gas) and major power plant components (mechanical & electrical equipment etc.), and studies were only included if both were covered.

The collected data has been taken from studies which applied both the PCA method and the hybrid method (which combines the PCA method and the I/O approach). The two earliest data points from 1974 and 1988 describe thermal natural gas power plants, which use a steam turbine (and a boiler) instead of a gas turbine. As the first CCGT power plants were only built at the end of the 1980s, thermal natural gas power plants and open-cycle gas turbine power plants can be seen as the precursor technologies. CCGT plants have then combined the simple gas turbine cycle of an OCGT with a steam turbine cycle, as employed in a thermal natural gas power plant in a further evolutionary step.

Additionally, information on the net efficiency of the power plant and the origin and type of the gas used (gaseous or liquid natural gas) was tracked if available. Figure 32 shows the derived historical learning curve for the energy invested of natural gas.

It should be noted that compared to the other technologies, the analysis for natural gas-based power generation rests on a small number of data points only. As there is a gap in the data between the first data point and the remaining data points, a sensitivity analysis has been conducted, to check if the results would drastically change when the first data point (from 1974) is omitted. However, the slope of the learning curve did not change much when omitting the earliest data point. Nevertheless, the limited data availability should be kept in mind when assessing the outcomes for this technology.

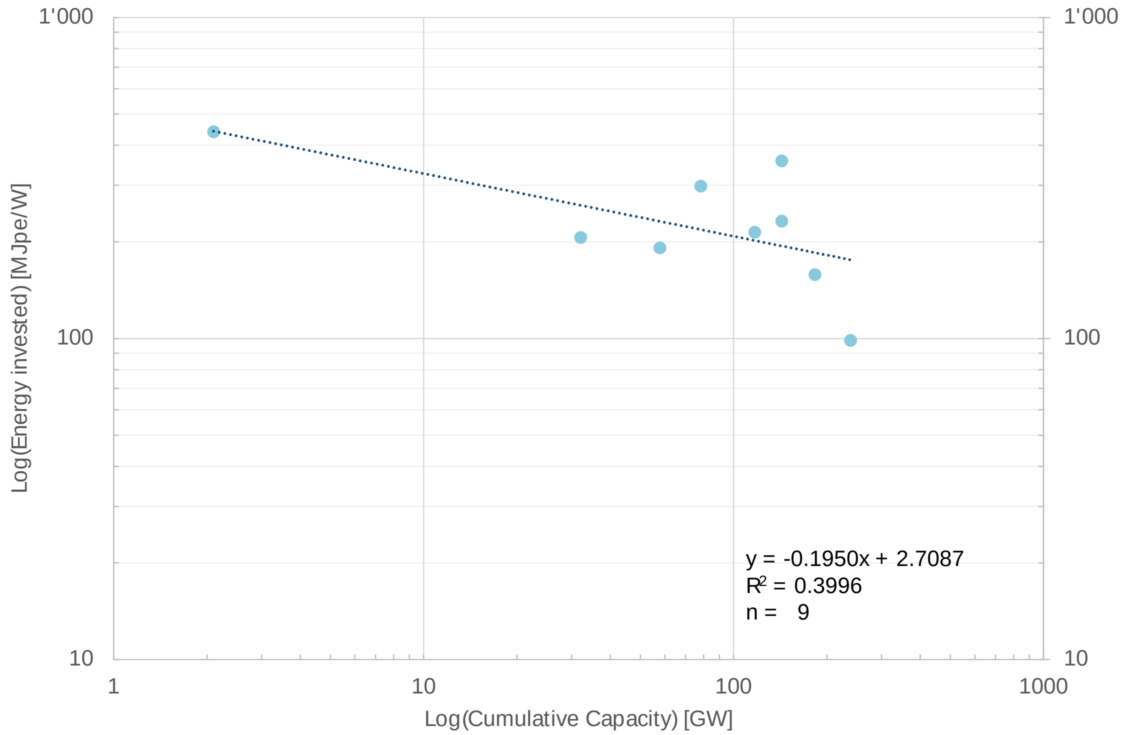

Figure 32: Historical learning curve for energy invested of natural gas.

Learning curve for energy delivered

The learning curves for the energy delivered by natural gas power plants and by hard coal power plants have been derived in a very similar manner, and the same equations were used for the calculation of the energy delivered from the parameters collected from the studies (net generation capacity, capacity factor and technical lifetime). Only one study did not indicate the capacity factor for the natural gas power plant under investigation and could therefore not be included in the analysis. Figure 33 shows the derived historical learning curve for the energy delivered of natural gas.

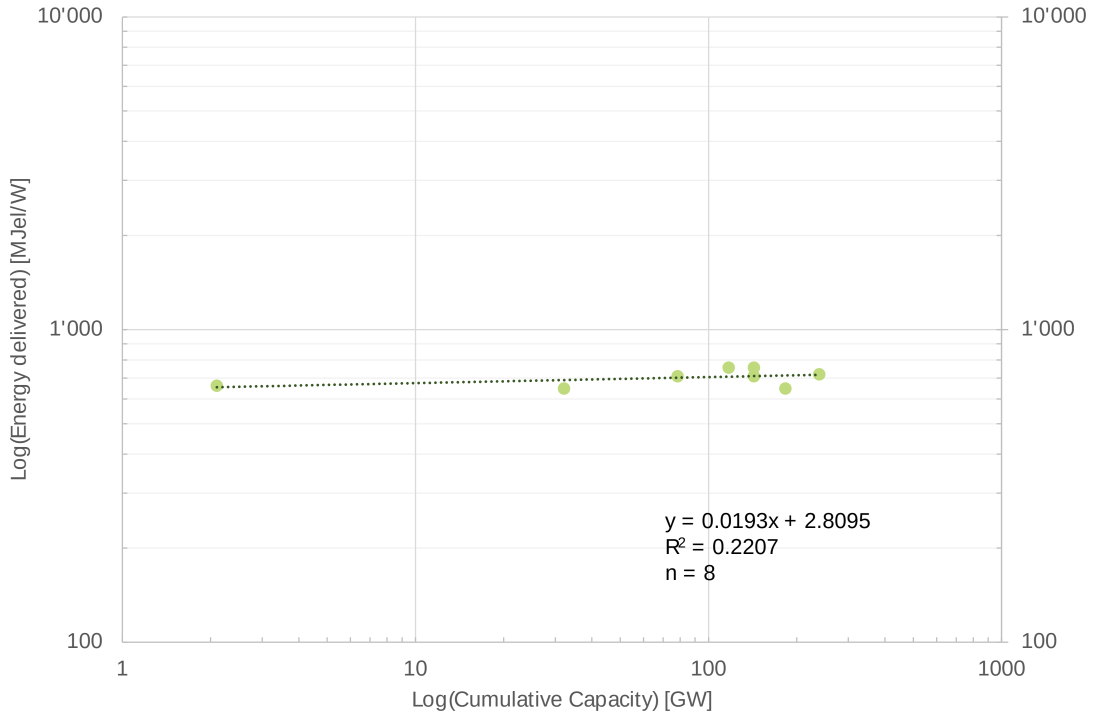

Figure 33: Historical learning curve for energy delivered of natural gas.

4.3.5.4 *Wind onshore*

Wind turbines exist in several vertical and horizontal axis designs. This analysis focuses on utility-scale wind turbines, which are commonly of the horizontal-axis wind turbine type with a power rating greater or equal to 100 kW. Niche applications, (such as roof-top wind turbines or small turbines[20] for stand-alone systems without grid connection) are considered to be a separate branch of the technology, and are not assumed to contribute to the learning effect of utility-scale wind turbines.

Cumulative installed capacity

Data on the historical cumulative installed capacity for wind onshore has been compiled from three different sources as described in Steffen et al. (2018). Figure 34 shows the compiled time series for the global cumulative installed capacity of wind onshore for the time period 1980 to 2015.

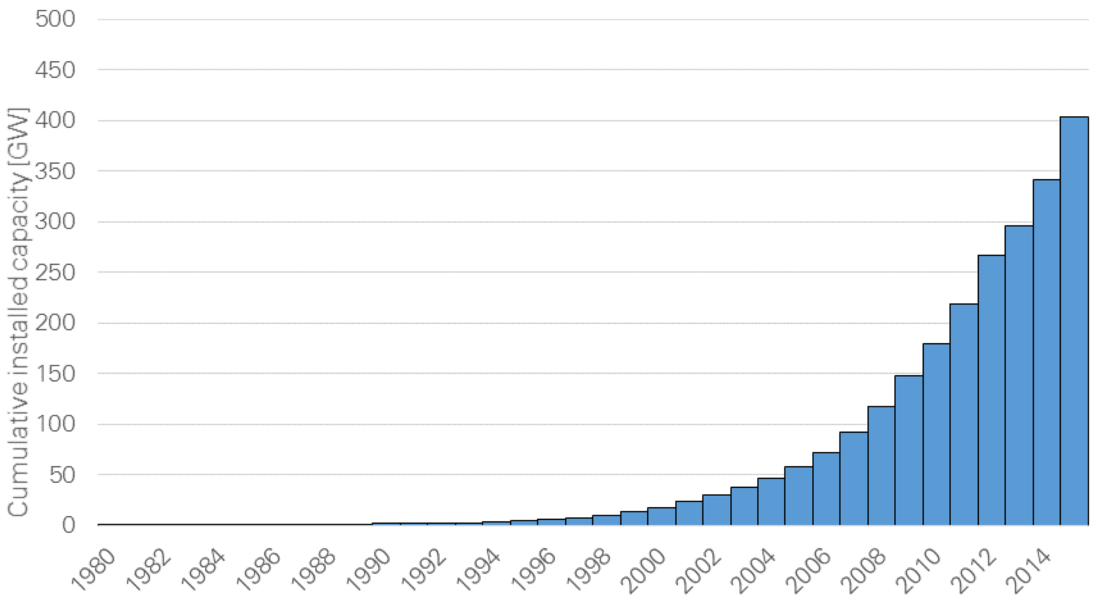

Figure 34: Cumulative installed capacity of wind onshore 1980-2015.

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Learning curve for energy invested

According to Steffen et al. (2018), collected data on the necessary energy investments for wind onshore was first checked on the completeness of the technological scope, which, for onshore wind, encompasses the following five major components of wind turbines: the rotor blades, the transmission, the generator, the tower and the foundation. Data was only included if all major components were covered.

[20] Small wind turbines are commonly defined as turbines smaller than 50 to 100 kW of rated power (IRENA, 2016a). Here, a cut-off point of 100 kW has been chosen.

Sufficient studies were available to justify the procedure of only including data obtained by the PCA method. In total, 39 data points have been collected for this analysis. Figure 35 shows the derived historical learning curve for energy invested of wind onshore, together with the collected data points.

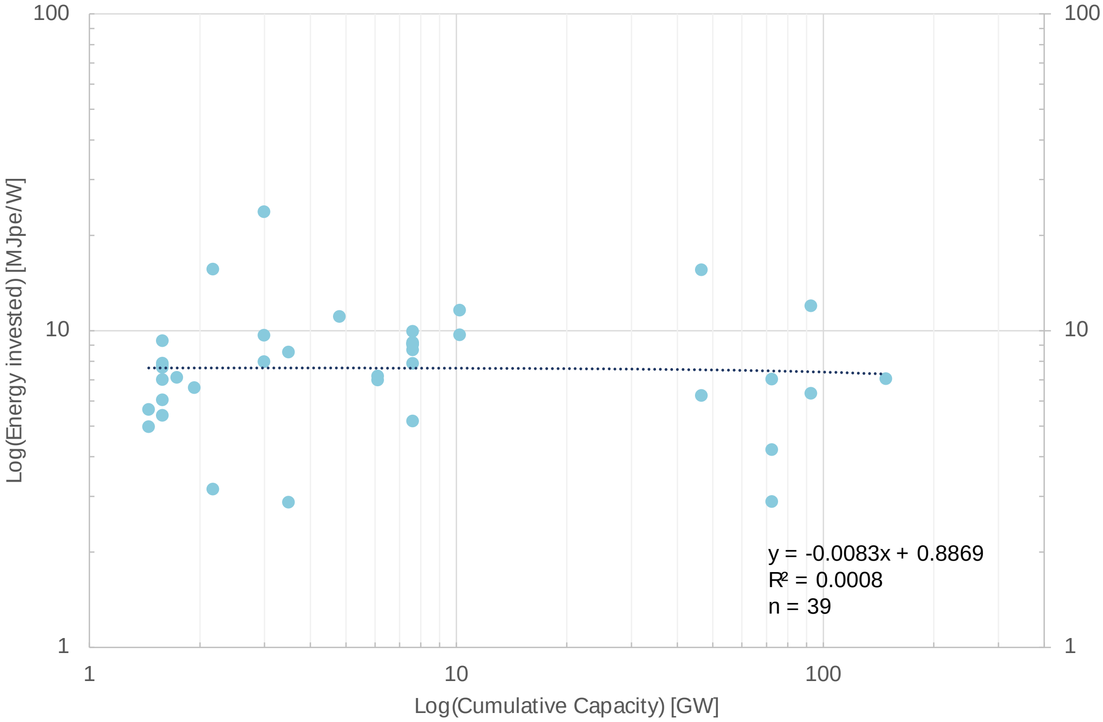

Figure 35: Historical learning curve for energy invested of wind onshore.

Learning curve for energy delivered

Deriving a learning curve for energy delivered for wind onshore is not trivial as the electrical energy yield of a wind turbine is highly dependent on its location and the wind conditions on site. In general, the amount of power generated by a wind turbine is proportional to the cube of the wind speed (IRENA, 2016a). The "windiness" of a site, meaning the occurrence of high wind speeds on a regular basis, is therefore crucial for the performance of a wind turbine.

Other factors which have an influence on the energy yield are related to the wind turbine design, namely the rotor diameter and the hub height of the turbine chosen for a specific site. The captured kinetic wind power depends on the area which is swept by the rotor, and the wind speed at hub height (and air density) (IRENA, 2016a). The larger the rotor diameter is, the more air can be moved through the rotors. The hub height[21] matters since wind speed increases with height above ground (Kubiszewski et al., 2010).

[21] Height of the wind turbine above the ground, without taking into account the length of the blades.

Comparing the yield data from operating wind turbines with different installation years, i.e. following the same plant-level approach as for hard coal and natural gas power plants, is problematic in the sense that it would mainly show the variance in energy yields due to differing wind conditions at various locations. However, the aim of this analysis is to abstract from the location of plants and to investigate if and how the electrical yield of an average turbine in a region with a specific wind regime would have changed if each year a turbine representing the most recent technological status would have been erected.

One parameter which permits the comparison of the performance of wind turbine of all sizes and at different locations is the *capacity factor*[22]. The definition of the capacity factor is very similar to the load factor: it is the actual annual electricity generated divided by the theoretical maximum, which is the electricity that could have been generated had the turbine been operating at its rated power throughout the whole year, calculated as the installed generator capacity times the number of hours in a year (8760 hours).

$$\mathrm{CF} = \frac{\text{Electricity generated during a year [kWh]}}{\text{Rated power [kW] * 8760 [h]}} \quad [\text{-}] \tag{16}$$

Wiser & Bolinger (2016) studied data on capacity factors for a large sample of onshore wind power plants in the US (covering 96.5% of installed wind capacity in the US at the end of 2014). They have found a clear trend towards higher *average* capacity factors for wind turbines with newer installation year when analysing the average capacity factors for the year 2015[23], differentiated by installation year of the turbines. The authors of the study see the two main reasons for this in larger rotor sizes and taller towers of newer wind turbines. For a given generator capacity, increasing the rotor diameter or the hub height will result in an increased capacity factor (Wiser et al., 2011).

Interestingly, capacity factors are increasing in value despite a counterbalancing trend: new wind projects are increasingly built in lower-quality wind resource areas (Wiser and Bolinger, 2016), where in general lower capacity factors are realised than in higher wind speed areas (keeping all other factors constant). This confirms the overall trend towards a new generation of wind turbines – with larger rotors and lower specific power[24] – which are increasingly optimised for lower wind speed sites and which can make good use of lower wind speed conditions (Zayas et al., 2015).

[22] The capacity factor as metric of performance also has some limitations. Most turbine manufacturers offer a certain type of wind turbine in different variations with respect to the generator capacity and the design. Very high capacity factors can "artificially" be achieved by combining a small generator with a very large rotor, which will be able to exploit very low wind speeds, at the cost of a low yearly energy output. However, wind turbines are normally chosen with the aim to maximise the yearly energy output, and the specifications are typically well adapted to the respective site-specific wind speeds (Molly, 2011).

[23] Wind conditions do not only vary geographically, but also temporally: The available wind resources vary from year to year, with a specific year having the potential to be a "good or a bad wind year". This is why data on capacity factors measured for different years cannot be readily compared.

[24] Specific power is the name plate capacity of the wind turbine (W) divided by the swept are of the rotor in square meters (m2).

Based on the data provided by Wiser & Bolinger (2016), Steffen et al. (2018) assigned an average capacity factor value to each “technology status year”, and thus, to each data point which has already been collected for the energy invested section. Adjustments have been made to account for the temporal variation of wind resources (i.e. “good” and “bad” wind years), and for regional variation of wind resources (i.e. scaling the capacity factors to typical conditions in Germany with on average significantly lower values than in the US). Figure 36 shows the average capacity factors, which were assigned to wind turbines representing the technological status of a specific year.

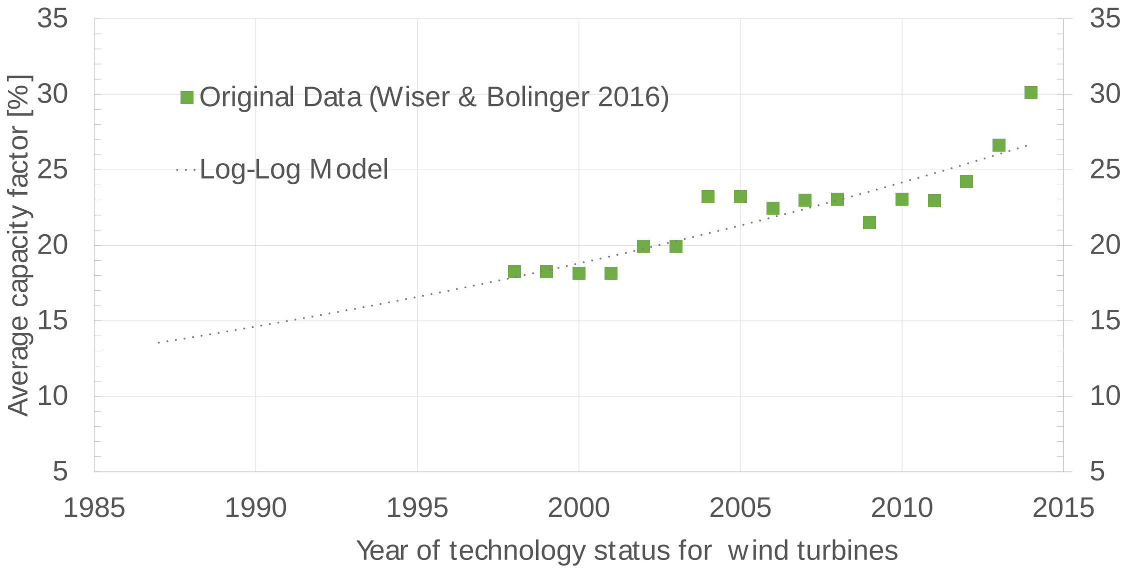

Figure 36: Average capacity factor of wind turbines over time under German wind conditions. Source: own calculations based on data from Wiser & Bolinger (2016). The original data was corrected for an average wind year using a Wind Resource Index, and for wind conditions in Germany.

Hence, for a wind turbine installed in 2015 a capacity factor of 30% is assigned. In order to check the plausibility of the derived curve for the average capacity factors, it seems worth analysing the average capacity factor which would be assigned to newly installed wind turbines in 2040. Based on the installed wind capacities projected by the three deployment scenarios from the prospective analysis, the following average capacity factors result for the year 2040:

- For the 2°C scenario, the most ambitious deployment scenario, an average capacity factor of 33% would result.

For the Paris Pledges Scenario, an average capacity factor of 32% would result. For the Business-as-usual Scenario, the average capacity factor would be 31%. Unfortunately, to date relatively little research exists on the remaining technological potential for improving capacity factors of wind turbines, especially for European wind conditions. However, studies by the U.S. Department of Energy (Zayas et al., 2015) and (IRENA, 2016b) expect further advancements with respect to energy production due to continued reductions in specific power and increased hub heights, and therefore also a further increases in capacity factors globally.

After assigning an average capacity factor based on the technology status year, the total lifetime electricity generated by a wind turbine was then calculated as follows, with C the rated power of the wind turbine in kW, CF the assigned capacity factor and $T_{lifetime}$ the lifetime of the turbine in years (cf. Steffen et al. 2018).

$$E_{lifetime} = C_{Wind\ turbine} * CF * 8760\ \frac{h}{y} * T_{lifetime} \qquad [kWh]$$
$$= C_{Wind\ turbine} * CF * 8760\ \frac{h}{y} * T_{lifetime} * 3.6\ \frac{MJ_{el}}{kWh} \qquad [MJ_{el}] \qquad (17)$$

The technical lifetime of a wind turbine was assumed to be 20 years and constant over time. Finally, the energy delivered in MJ of electrical energy per Watt of installed capacity is then given as:

$$E_{delivered} = \frac{E_{lifetime}}{C_{Wind\ turbine}} \qquad \left[\frac{MJ_{el}}{W}\right] \qquad (18)$$

Figure 37 illustrates the derived historical learning curve for the energy delivered by wind onshore turbines.

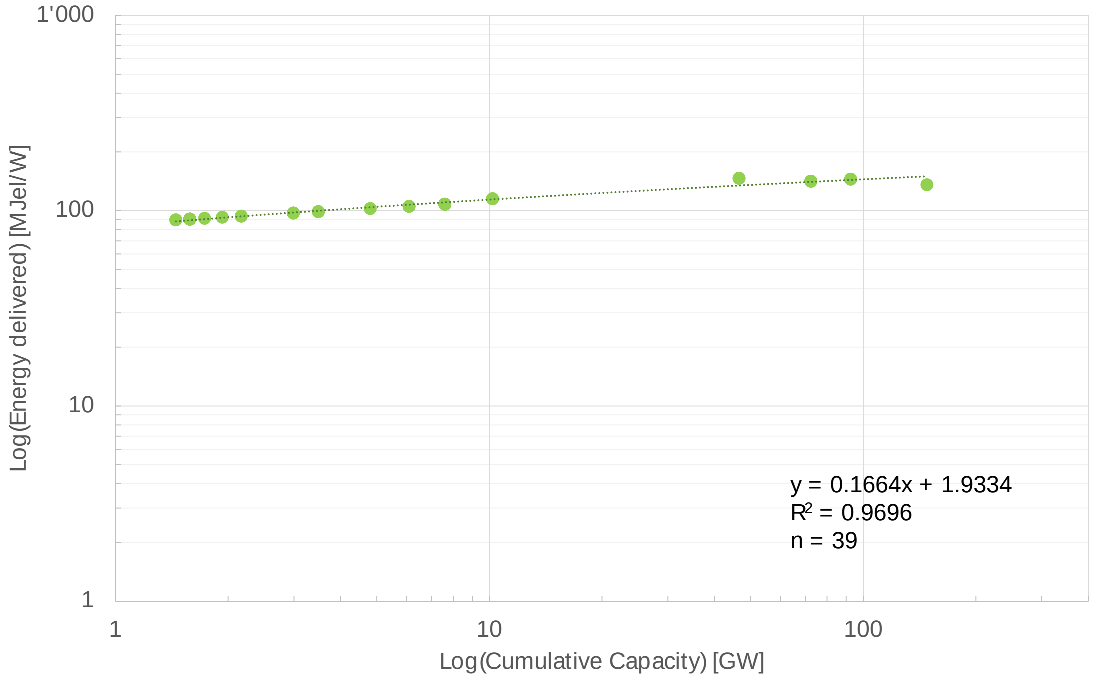

Figure 37: Historical learning curve for energy delivered of wind onshore.

4.3.5.5 Solar PV

Multi-crystalline silicon PV systems, which belong to the first-generation of PV technology, were chosen to be the subject of the analysis, due to their strong and continued dominance in today's photovoltaic industry (PV Magazine, 2013).

Cumulative installed capacity

Data on the historical cumulative installed capacity for solar has been compiled from two different sources as described in Steffen et al. (2018). Figure 38 shows the compiled time series for the global cumulative installed capacity for solar PV for the years 1980 to 2015.

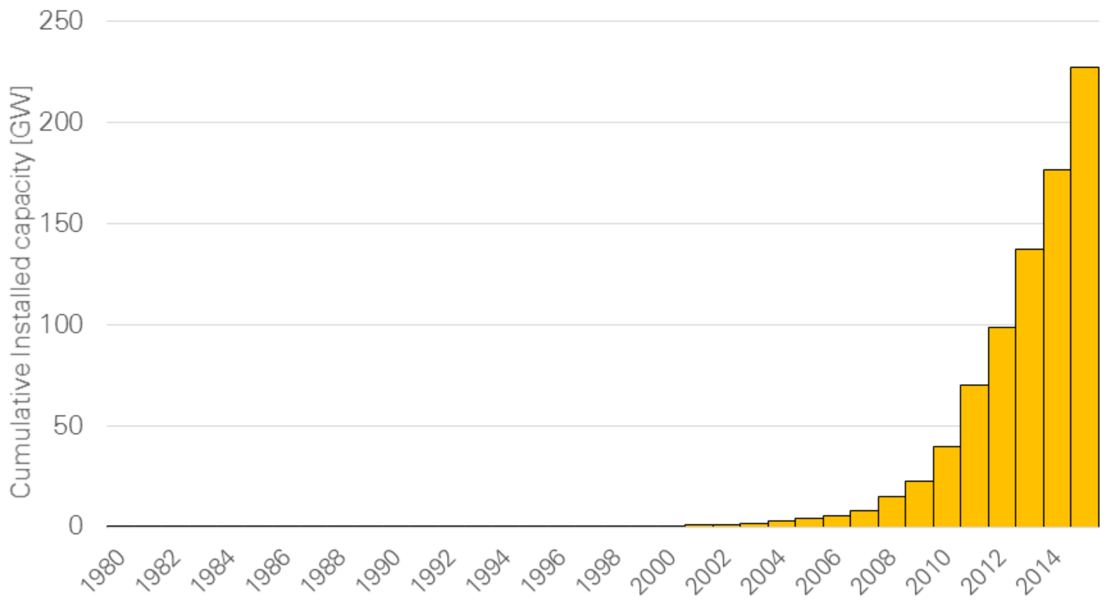

Figure 38: Cumulative installed capacity of solar PV 1980-2015.

Learning curve for energy invested

In order to derive a historical learning curve for the energy invested of multi-crystalline PV systems, data has been collected from the LCA and Net Energy Analysis literature by Steffen et al. (2018), with 13 studies meeting the general filter criteria (see section 4.3.2 for a description of the general filter criteria). Multiple studies had to be excluded because of an incomplete technological scope, meaning that they did not analyse the complete PV system, including the panel and the BOS[25]. The reported values were converted to uniform units of MJ of primary energy per Watt of installed capacity whenever needed.

In all studies from which the data was taken, the PCA method was applied, with the exception of the very first data point representing the technological status of 1986. Additional technology-specific

[25] The balance-of-system (BOS) includes components other than the PV modules (e.g. the inverter to convert DC into AC, the power control systems, cabling and the frame).

parameters which were collected from the studies for background information are the cell efficiency and module efficiency.

Figure 39 shows the derived historical learning curve for the energy invested of solar PV. It can be noted that the quality of the fit of the learning curve is considerably better than for the previously shown learning curves for energy invested.

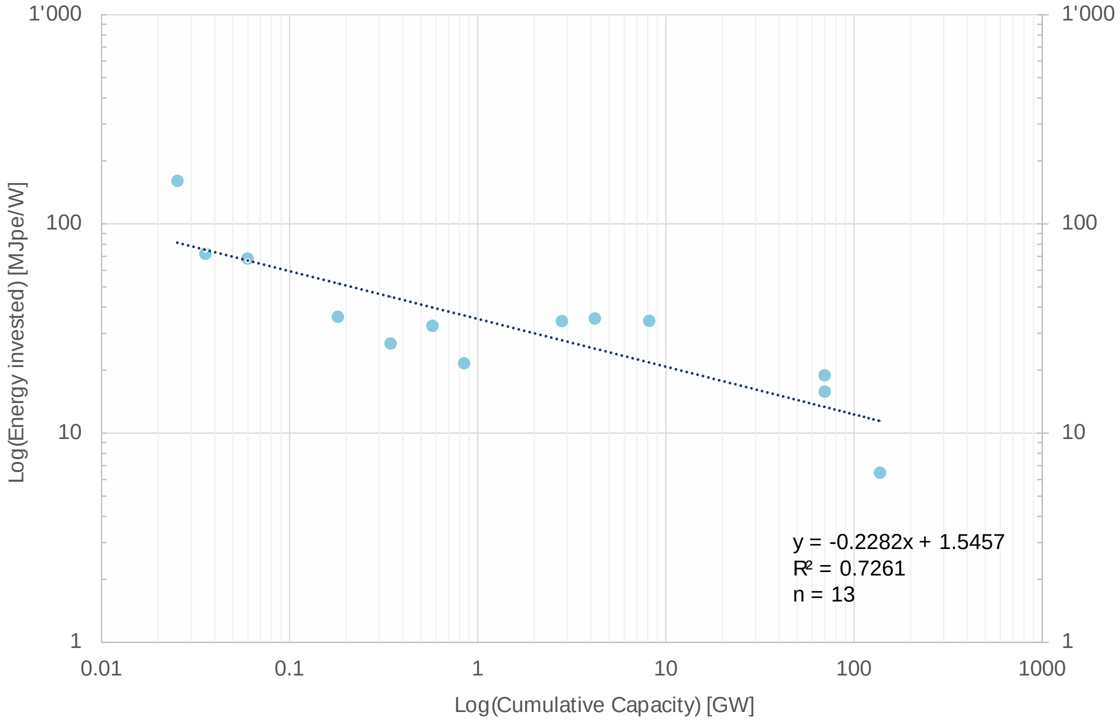

Figure 39: Historical learning curve for energy invested of solar PV.

Learning curve for energy delivered

Deriving a learning curve for the amount of electrical energy PV systems deliver over their entire lifetime is not trivial due to the location dependency of PV system performance. Local irradiance conditions have a strong influence on how much a PV system with a specific rated capacity can deliver. The collected data for deriving the energy invested learning curves sometimes indicates an annual energy yield of the PV systems under investigation (or would allow such a calculation from the data provided), however, the studies have been conducted for such diverse locations as China, Greece, Germany and the Netherlands. As this study aims at finding out how the energy delivered by PV systems has changed over time, as a function of increased cumulative capacity, this location dependency has to be removed. Therefore, similar to the approach for wind onshore, Steffen et al. (2018) propose taking an additional bottom-up perspective based on the performance ratio (PR) metric, holding irradiance conditions constant, to complement the analysis.

The *performance ratio* (PR) is a proxy for the system performance, since it compares the reference yield Y_r (the theoretical yield achievable by an ideal PV system operated under standard test conditions) with the final, actually achieved yield of the PV system Y_f (see Equation (19)). It therefore indicates the overall effect of losses on the PV performance, for example due to increased array temperatures[26], system component inefficiencies (e.g. inverter inefficiencies and cable losses) and failures, incomplete utilization of irradiance (due to shading, atmospheric dust composition etc.) (Van Sark et al., 2012). The PR is largely independent of the system size, the specific location and irradiance conditions, which allows for comparing different systems at different locations with regard to their performance. It varies over the course of a year, with measured values being typically higher in winter and lower in summer due to the influence of temperature.

$$PR = \frac{Y_f}{Y_r} \qquad [-] \tag{19}$$

The annual energy yield of a solar PV at a certain location is given by the following equation (Louwen et al., 2016), with PR denoting the performance ratio, H_{POA} the plane of array irradiance[27] (in kWh per year and m^2), G_{STC} the irradiance intensity at which the PV system capacity is determined (under standard test conditions, in W per m^2) and C_{PV} the rated capacity in W.

$$E_{annual} = PR * \frac{H_{POA}}{G_{STC}} * C_{PV} \qquad \left[\frac{kWh}{y}\right]$$
$$\text{with } G_{STC} = 1000\ \frac{W}{m^2} \tag{20}$$

The ratio H_{POA}/G_{STC} can be seen as the annual "sun full load hours": it defines the amount of hours, for which the sun would have to continuously shine on the panel at full power (1000 W/m^2) to generate the equivalent of the plane of array irradiance (Mertens, 2013).

In order to calculate the lifetime energy yield of a PV system, one has to correct for the *degradation* of performance over time due to age reasons, which can be approximated in the form of the equivalent lifetime (Louwen et al., 2016):

$$E_{lifetime} = E_{annual} * T_{equivalent\ lifetime} = E_{annual} * T_{lifetime} * \left(1 - r_{degradation} * \frac{T_{lifetime}}{2}\right) \quad [kWh] \tag{21}$$

All in all, the energy delivered by a PV system can be expressed as follows (in MJ of electrical energy per W of capacity):

[26] An increasing array temperature has a negative effect on the performance of the PV panel ("temperature effect"). The performance of a crystalline silicon panel decreases by about 0.4 to 0.5% per Kelvin (Mertens, 2013).

[27] Sum of incident irradiance on the array, depending for example on sun position, array orientation and ground surface reflectivity (PV Performance Modelling Collaborative, 2017)

$$E_{delivered} = \frac{E_{lifetime}}{C_{PV}} \qquad \left[\frac{MJ_{el}}{W}\right]$$

$$E_{delivered} = PR * \frac{H_{POA}}{G_{STC}} * T_{equivalent\ lifetime} * \frac{3.6\ MJ_{el}}{kWh}$$

$$= PR * \frac{H_{POA}}{G_{STC}} * T_{lifetime} * \left(1 - r_{degradation} * \frac{T_{lifetime}}{2}\right) * \frac{3.6\ MJ_{el}}{kWh} \qquad (22)$$

For a long time, the focus when evaluating PV system performance was on the cell or module efficiency of cells. However, the performance ratio as an indicator of overall PV system performance has recently been receiving increased attention, and a number of studies have investigated the development of the performance ratio over time. Those studies have found a clear tendency of improved performance for new PV installations, see for example Jahn & Nasse (2004); Van Sark et al. (2012); Reich et al. (2012); Jahn et al. (2004).

In the study by Reich et al. (2012), the performance ratios of about 100 German photovoltaic installations have been monitored since their commissioning, and the ranges of the measured PR over time are shown with regard to the installation year of the panels. For each installation year, a range of observed PR is reported, with a few panels performing very poorly (due to downtimes, sub-optimal orientation of the panels or incorporated outdated system components with below-average efficiencies), and others performing very well. The study indicates minima, maxima and the median PR values with respect to the installation year of the PV systems.

A second source providing data on the development of the performance ratio of PV panels over time is a study by Van Sark et al. (2012), which summarise the findings of Task 2 of the IEA Photovoltaic Power Systems Programme As part of this project, data for 170 PV systems from the IEA PVPS database was analysed, and the average PR with respect to the installation year reported. In general, this source found lower PR values than the study by Reich et al. (2012). A possible explanation for this is that this study indicates average PR values instead of median PR values: averages can be assumed to be more sensitive to outliers, which, in our case, are very badly performing PV panels.

In order to reflect these developments with regard to the energy delivered, measured data from Reich et al. (2012) has been taken to construct a learning curve for the performance ratio, as this data reports median values, which are considered less sensitive to outliers. The learning curve has been constructed by connecting the PR data to the historical global cumulative installed capacities of PV in a double logarithmic model. The data provided by Van Sark et al. (2012) was, however, used as part of a sensitivity analysis, for which an alternative PR learning curve based on this second data source was constructed. The learning rates based on both these PR learning curves were then used for the further calculations, the results of which can be found in Chapter 4.4.2.
Subsequently, the derived learning curve for the PR has then been used to assign a PR value to each "technology status year", and thus, to each data point which has already been collected for the energy

invested section[28]. Since Reich et al. only provide data for the installation years 2000 to 2009, an extrapolation had to be conducted for the years lying outside of these years. Figure 40 shows the PR values, which were assigned to PV systems representing the technological status of a specific year.

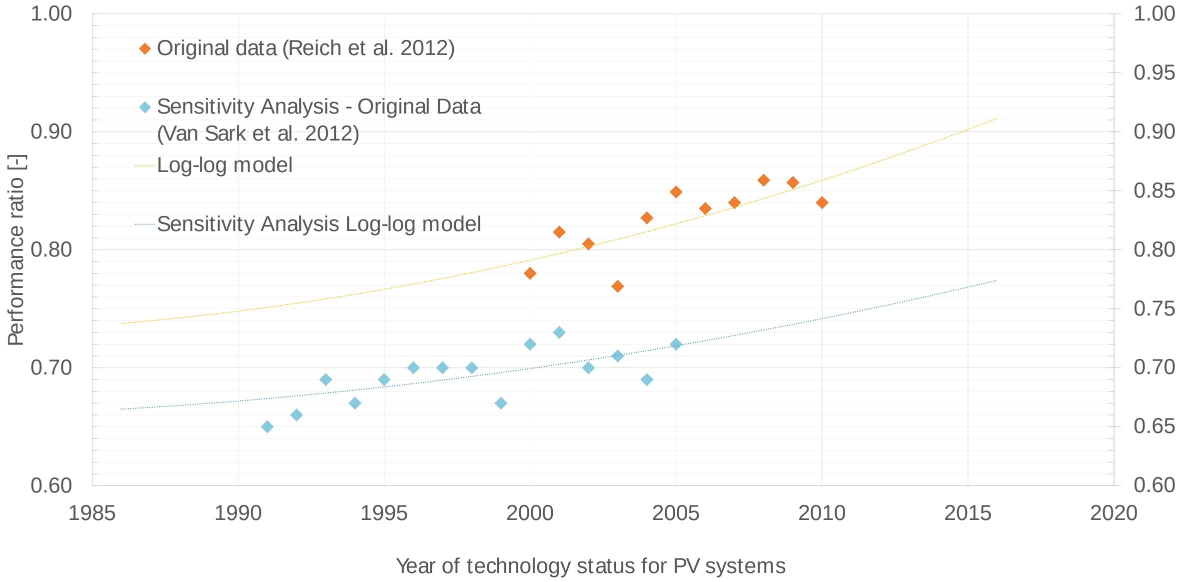

Figure 40: Performance ratio of PV systems over time (under German climate conditions).
Source: based on data from Reich et al. (2012) and Van Sark et al. (2012).

For a PV system representing the technology status of 2015, the present performance ratio curve would assign a PR of 0.9. A report by the Fraunhofer ISE (2017) on the status of PV technology in Germany states that today's newly installed PV plants can achieve PRs of 0.8 – 0.9, indicating that the modelled results are achievable, but probably represent rather an upper bound of performance, and refer to well performing modules. In order to further check the robustness of the curve, the PR values which would be assigned to PV systems in 2040 were calculated, and compared to what is considered to be the technical upper limit for future PRs today. Van Sark et al. (2012) estimate that modest increases of the performance ratio to 92% may be possible, and Reich et al. (2012) take the view that PRs above 90% are realistic and could already be achieved with components commercially available today. Based on the PV capacities projected by the three deployment scenarios from the prospective analysis (see Chapter 4.3.3 for further details), the following PR values result for the year 2040: for the 2°C scenario, the most ambitious deployment scenario, a PR of 0.94 would result, and a PR of 0.93 for the two other scenarios. In sum, the projected PR values seem to be ambitious, but probably achievable. Figure 41 shows the learning curve derived for the energy delivered, taking into account the assigned PR values.

[28] Many of these data sources actually indicated performance ratios for the PV systems under investigation, however, these are often vague estimations or manufacturer's specifications, and do not represent measured values of actual PV performance.

The other parameters, which fed into the equation for the energy delivered, were assumed to be constant over time. The following table summarizes the assumptions.

Table 19: Assumptions for calculating the energy delivered by PV systems.

Parameter	Description	Assumption	Explanation
H_{POA}	Average plane of array irradiance [kWh/(m²y)]	1055	Average value for Germany taken from Fraunhofer ISE (2017). Somewhat conservative estimate, since the average plane of array irradiance of an ideally positioned module (south-facing, inclination of 30-40%) can be up to 15% higher.
$T_{lifetime}$	Lifetime [y]	30	Simbolotti & Taylor (2013) indicate for the year 2010 a lifetime of 25-30 years, and expect an increase to 30 to 35 years for the period 2015 to 2020. There is, however, little empirical evidence that the technical lifetime of PV panels really has improved over time. Another explanatory approach is that users and manufacturers have realised that panels are more durable than the initial conservative estimates, i.e. that it is not necessarily the technical lifetime but rather the "perceived" lifetime, which has increased over time, as experience from early PV installations accumulates.
r_{deg}	Degradation rate [%/y]	0.5	Taken from Jordan & Kurtz (2013); median degradation rate of silicon PV modules

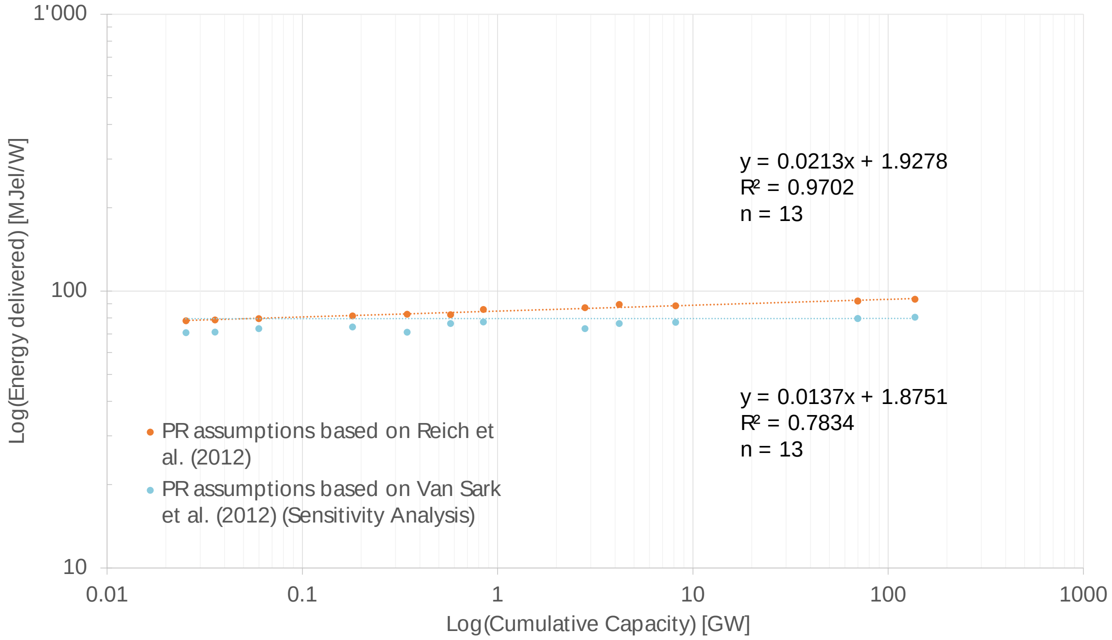

Figure 41: Historical learning curve for energy delivered of solar PV.

4.4 Results

This chapter presents the results of the study grouped in two sections: The first section reports on the results of the retrospective analysis, which analyses the past. The second section reports on the prospective analysis, which projects the historical learnings into the future, and assesses the resulting future EROI values.

4.4.1 Results of retrospective analysis

The results of the retrospective analysis are shown in a condensed version in Figure 42. For an easier interpretation, the slopes of the historical learning curves for energy delivered and energy invested are translated into learning rates in this graph. Thus, the figures indicate the rate at which the energy invested and delivered improve for each doubling of the cumulative installed capacity per technology.

It is important to note that for an improvement of the EROI, the energy invested is desired to decrease over time (i.e. a negative slope of the learning curve, which translates into a positive learning rate) while the energy delivered is desired to increase over time (i.e. a positive slope of the learning curve, which translates into a negative learning rate). The learning rates for energy invested and energy delivered should therefore have an opposite sign in order to leverage the maximum improvement potential of the EROI.

From the graph presenting the learning rates for energy invested and energy delivered, three rather different patterns can be observed across the analysed technologies:

1. For the technologies natural gas CCGT and Solar PV, high learning rates for energy invested (13 and 15%, respectively) can be observed (though the results for CCGT are subject to uncertainty given the limited data availability, see above). The observed learning rates for energy delivered are low.
2. Wind onshore shows the highest learning rate (8%) with respect to energy delivered among the technologies, while there is practically no learning with respect to the energy invested.
3. Hard coal shows a moderate learning with respect to energy invested (8%), but the opposite of learning can be observed for energy delivered (as a positive learning rate was found), which indicates that the energy delivered by hard coal power plants does not increase but rather decreases over time. Holding the energy invested constant, this would lead to a worsened EROI over time.

Figure 42 also gives an indication of the uncertainty which is associated with these results, with error bars indicating the 95% confidence interval of the derived learning rates. This confidence interval has been calculated based on the standard error of the slope when fitting a linear learning curve to the historical data, i.e. the “quality of the fit”. When looking at these error bars, it becomes evident that there is a relatively high uncertainty associated with the results. For natural gas and hard coal, the uncertainty is large with respect to the derived learning rate for energy invested. For wind onshore, the uncertainty in the learning rate for energy invested is considerably lower. For solar PV the indicated uncertainty for energy delivered seems to be very low. However, the learning curve for energy delivered hinges on a single data source for the development of the performance ratio over time. Additionally, this data has been extrapolated based on a log-log model to derive a continuous learning curve. In order to further explore the uncertainty with regards to the energy delivered learning rate, a sensitivity analysis has been conducted for PV, based on a learning rate for energy delivered using a second data source. Both of these learning rates have been fed into the prospective analysis, the results of which are presented in the next section.

Generally speaking, the results of the retrospective analysis have revealed that some of the derived learning rates are associated with a rather large uncertainty. When extrapolating these results into the future, it is therefore all the more important to consider these uncertainties. The results of the prospective analysis, which takes into account both the uncertainty in terms of future deployment, and the uncertainty with respect to the derived learning rates, are presented in the next section.

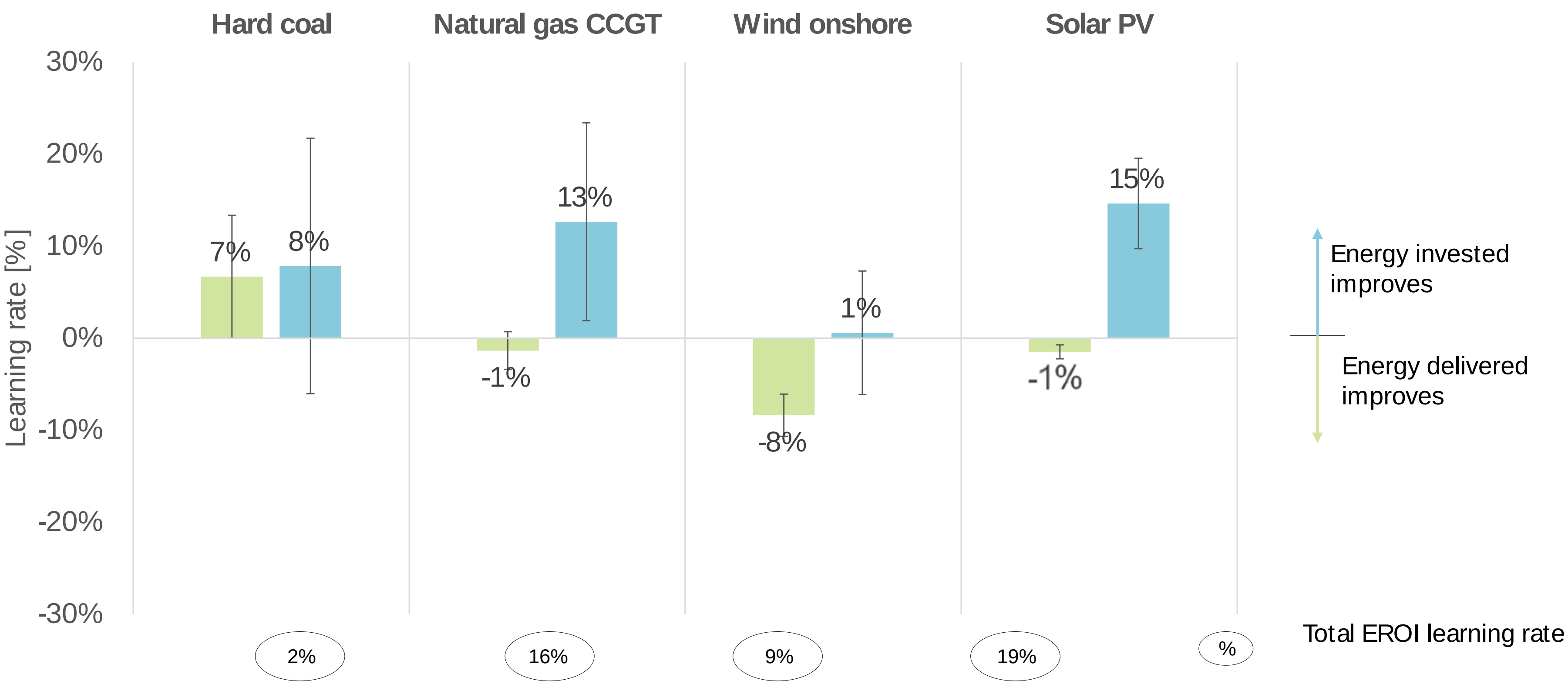

Figure 42: Historical learning rates for energy delivered and energy invested per technology.
Illustration of results from retrospective analysis. The slopes of the historical learning curves for energy delivered and energy invested have been converted to equivalent learning rates using Equation (10). The error bars indicate the 95% confidence interval of the learning rates and were calculated using the standard errors of the learning rates.

4.4.2 Results of prospective analysis

The previous section reported on the results from the retrospective analysis, that is, the energy learning rates observed from historical data. In the prospective analysis, the historical learning curves are projected forward, in order to investigate the EROI values which could then in the future.
An uncertainty analysis forms part of the prospective analysis, which analyses the two main sources of uncertainties of the analysis:

1. Uncertainty on *deployment* (i.e. how much additional capacity will be built per technology), which is addressed with a scenario analysis, which calculates the outcome for three alternative deployment scenarios
2. Uncertainty on the derived *learning rates*, which is simulated with a Monte Carlo Analysis.

Figure 43 presents the results of the Scenario Analysis. In order to put the prospective results into perspective, EROI values are also indicated for the time period 1990-2015, which base on the actual, historical cumulative installed capacities per technology. As of 2015, the cumulative installed capacities projected by three deployment scenarios form the basis for the calculations: the Business-as-usual Scenario, the Paris Pledges Scenario and the 2°C Scenario.

When comparing the resulting EROIs for the three deployment scenarios per technology, it becomes apparent that there is not much difference between the most and the least ambitious deployment scenario. For wind onshore, there is a difference of 2, for solar PV a difference of 2.5 EROI units between the Business-as-usual and the 2°C scenarios. For natural gas, the difference is minor (0.4 units) and for hard coal, the difference is even smaller (0.07 units).

When looking at the part of the graph, which relates to the time period prior to 2015, a significant development of the EROI of wind and solar PV over time is visible at first glance. Wind onshore starts with an EROI of about 12 in 1990, and doubles its EROI value until 2015. In 2040, an EROI between 28 and 30 is projected by the scenarios, which makes it the best performing technology among the four technologies.

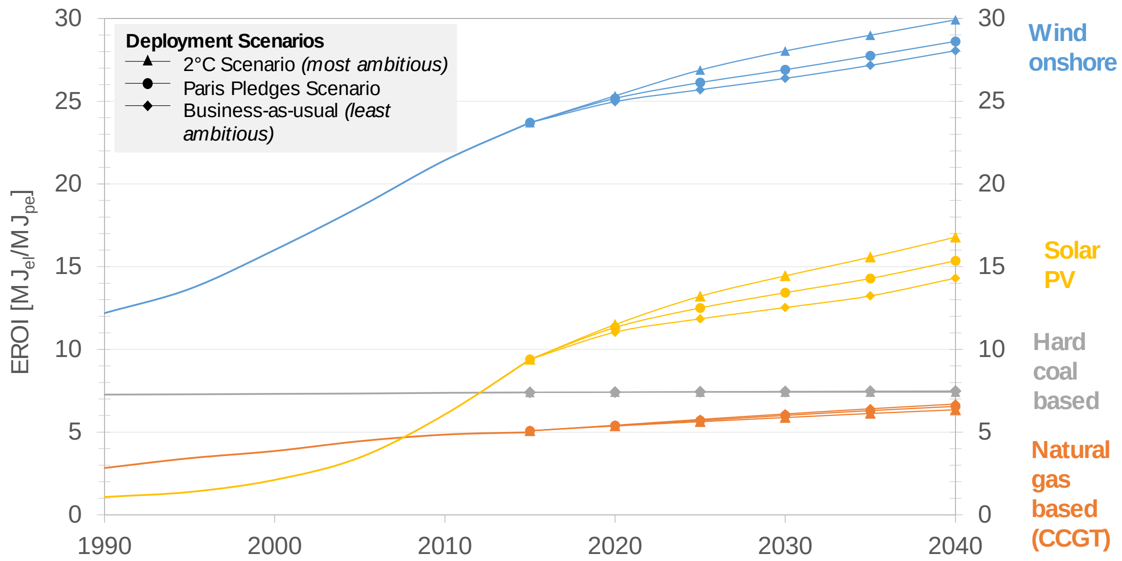

Figure 43: EROI over time for three alternative deployment scenarios.
For the time period 1990-2015, calculations are based on actual, historical cumulative installed capacities. For the time period beyond 2015, the calculations are based on the cumulative installed capacities calculated for each scenario, based on figures from the IEA.

Solar PV starts with an EROI around 1 in 1990, and improves to an EROI of 9 in 2015, catching up with both natural gas and hard coal within this period. In 2040, the analysis projects an EROI of 14.3 in the Business-as-usual scenario, an EROI of 15 in the Paris Pledges Scenario, and an EROI of 17 in the 2°C Scenario. This ranks Solar PV the second best technology among the four. For hard coal, not much development is visible in the graph. Starting with a comparatively high EROI of 7 in 1990, the EROI rises only slightly to 7.4 in 2015. In 2040, the best case (Business-as-usual Scenario) projects an EROI of 7.5, which is still higher than the projected values for natural gas. The graph shows a modest development over time for natural gas: the results suggest that the technology's EROI improved from around 3 in 1990 to 5 in 2015. By 2040, an EROI of around 6 is expected.

Figure 44 additionally shows the results for the sensitivity analysis of Solar PV, assuming a lower learning rate of 1.0% for energy delivered, which has been derived from a second data source. The results for the sensitivity analysis are slightly lower than the previous results, with the resulting EROI values ranging from 12.5 to 14.5, as compared to a range between 14.5 to about 17 for the results with the higher learning rate for energy delivered. However, the position of Solar PV among the four technologies remains unchanged, even with this lower learning rate.

The results shown so far have been calculated by taking the derived learning curves for granted, without taking into account the uncertainty inherent to them. In the Monte Carlo Simulation, those results were re-calculated with stochastically varying learning rates for energy invested and delivered, by picking them randomly from a distribution which takes into account the quality of the fit of the learning curve to the historical data.

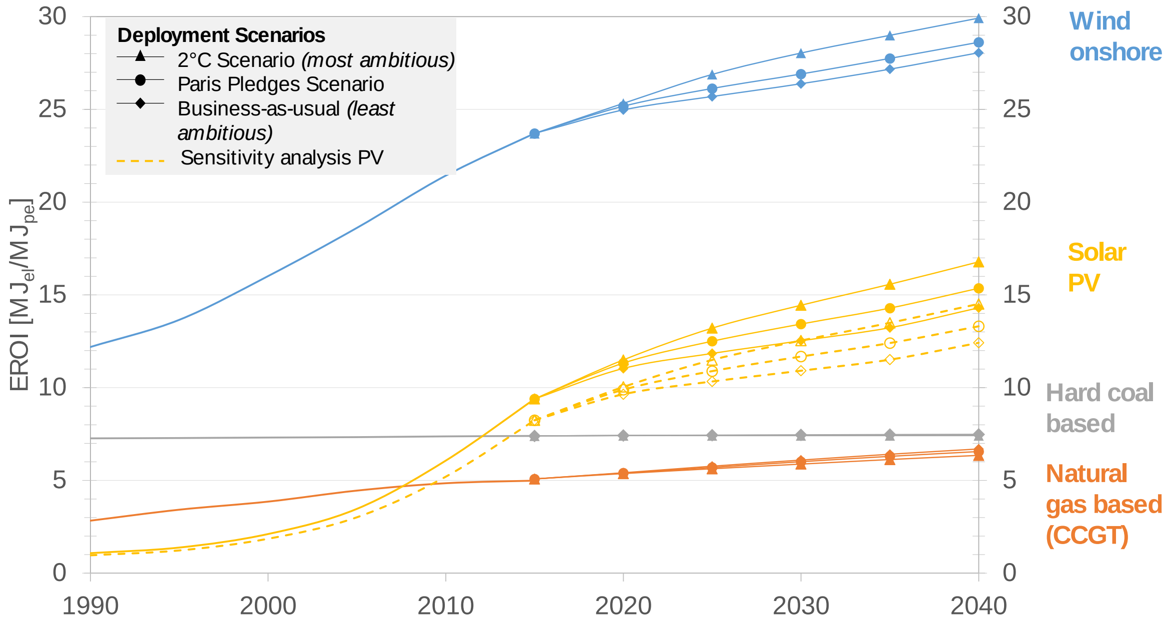

Figure 44: EROI over time for three alternative deployment scenarios, with sensitivity analysis for PV.

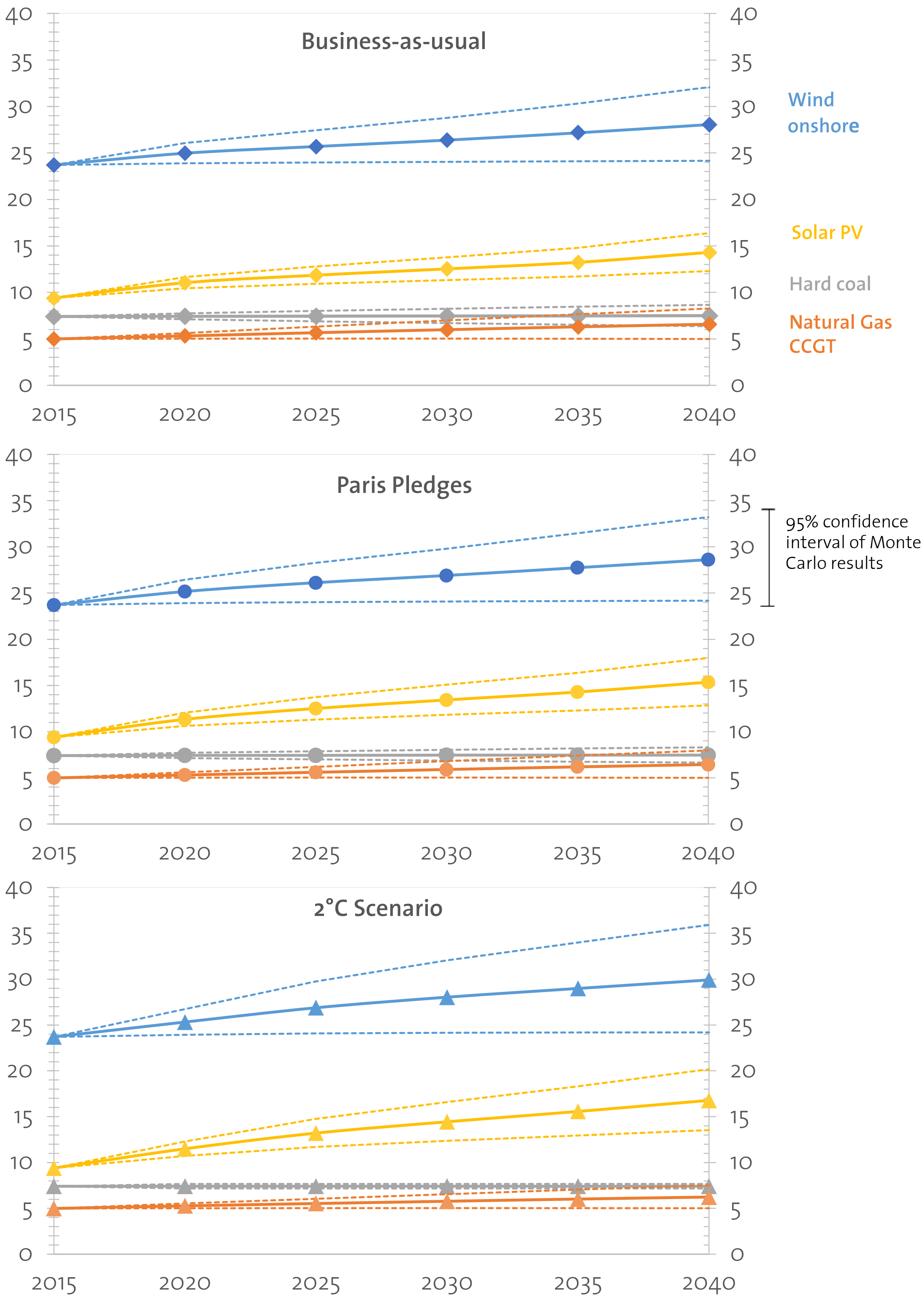

Figure 45: EROI over time with 95% confidence intervals from Monte Carlo Analysis. The results are shown for the deployment scenarios Business-as-usual, Paris Pledges and 2°C Scenario. The dashed lines represent the 95% confidence intervals from the Monte Carlo Analysis, reflecting the uncertainty with respect to future learning rates. The symbols represent the deterministic values from the previous Scenario analysis.

Figure 45 illustrates the results of the Monte Carlo Simulation. In addition to the deterministic results obtained by the previous Scenario analysis, the graphs illustrate the 95% confidence intervals of the results of the Monte Carlo Simulation. The graphs highlight that, even when considering the uncertainty which is associated with the future learning rates, the ranking of solar and wind within the ranking doesn't change. In all deployment scenarios, wind remains the best technology, followed by solar with the second best performance. What might change, however, is the relative position of natural gas and hard coal: taking into account the uncertainty in the learning rate, it is possible that natural gas could outperform hard coal between 2030 and 2035.

Figure 46 now takes into account both sources of uncertainty – the uncertainty with regards to the deployment, addressed by the three deployment scenarios, and the uncertainty with regards to the learning rate, addressed by the Monte Carlo Analysis. For the Monte Carlo Analysis, the uncertainty bands (or the 95% confidence intervals of the Monte Carlo Analysis) of the scenarios with the outermost limits were chosen, which encompass the confidence intervals of all other scenarios. In this way, the results presented in the graph indicate the greatest possible range of EROI values in line with this analysis.

Interestingly, the ranking of the technologies remains almost unchanged, even when taking into account these considerable uncertainties. Only the relative position of natural gas as compared to hard coal cannot be determined with certainty. However, it can be noted that the range of possible values for wind onshore and solar in 2040 becomes significantly larger than in the Scenario Analysis. When following the outer limits of the uncertainty range, for wind onshore, EROI values of 36 – in the best case - or of 24 – in the worst case – seem to be possible. For solar PV, the uncertainty range approximately encompasses values from 12 to 20. However, the indicated range of EROI values needs to be understood as a probability distribution, with extremely high or extremely low values having a lower probability than values which lie in between.

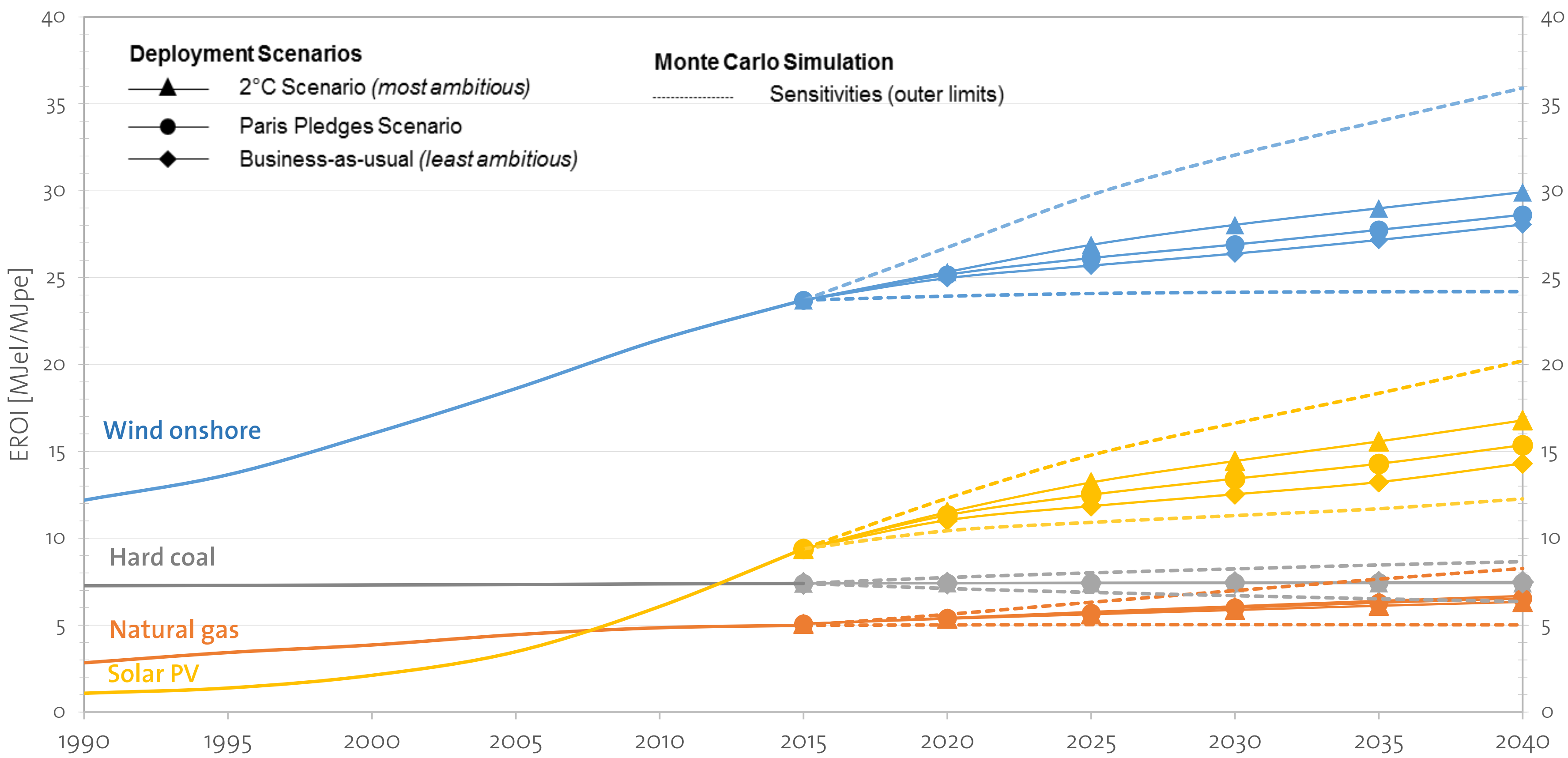

Figure 46: EROI over time for three deployment scenarios and with uncertainty bands from Monte Carlo Analysis.
Represented is a synthesis of the uncertainty analysis, with the depoyment scenarios addressing the uncertainty on future deployment, and the uncertainty bands from the Monte Carlo analysis representing the uncertainty with respect to future learning rates. For the uncertainty bands from the Monte Carlo Analysis, the scenario with the outermost limits was chosen for each technology, to show the maximum range of uncertainty, and thus the maximum range of EROI values in line with the analysis.

5 Implications and conclusion

The following section discusses some implications for policy makers, researchers and further stakeholders in Switzerland and Europe.

First, on a technological level, the static analysis has shown the merits of hydro power technologies from an energy performance perspective. Hydro power technologies, such as hydro run-of-river and hydro storage plants, have an outstanding energy performance. While the finding that these technologies have a very favourable performance might not seem surprising, it is however remarkable to which extent they outperform all other analysed technologies: Hydro run-of-river power plants, for example, have a more than twenty times higher EROI than geothermal and natural gas based power plants. With hydro power technologies being at the core of the present electricity mix, this can be interpreted as a very encouraging result from a Swiss perspective. This study therefore provides further arguments in favour of Switzerland’s most important domestic energy source, suggesting that it should retain its important position within the Swiss energy system in the future. The situation is similar for energy storage technologies, where pumped-hydro storage plants outperform all other analysed technologies by far in terms of ESOI.

Second, nuclear power shows a relatively good performance in the static analysis with respect to EROI, but a low performance with respect to nr-CED. At the same time, the analysis has shown that the new renewable energy technologies wind and solar PV are already viable options in Switzerland today, taking into account Swiss solar radiation and wind conditions. The Swiss nuclear phase-out is therefore unlikely to have substantial negative impacts on the energy performance of the Swiss electricity system, and concerns regarding the availability of useable energy for the Swiss society seem unjustified. The results of this study are also in line with the general strategic direction of the Swiss Energy Strategy 2050, which foresees a strong expansion of domestic renewable energy capacities (UVEK, 2011), and also makes a case for Switzerland’s plans to support the expansion of renewables abroad as part of its carbon mitigation commitments (UNFCCC, 2016b). Thus, the energy performance perspective on renewable power generation technologies taken in this study complements the cost and environmental impact perspectives offered by other studies (Bauer et al., 2017), agreeing with them on the viability of these technologies.

Third, the dynamic analysis reveals that wind power (onshore) and solar PV have significantly improved their energy performance over the past years, and that further performance improvements can be expected in the future. In contrast, for more mature technologies like hard coal and natural gas, energy performance has remained relatively constant over time, and few future improvements are to be expected. Thus, the relative attractiveness from an energy performance point of view of renewable energy technologies is likely to further increase in the future. There is significant potential for Swiss industrial firms active in the manufacturing of solar PV and wind energy equipment (Ziegler and Bättig, 2010)to benefit from these developments, and they are well positioned to do so.

Fourth, it has been shown that the significant increase in deployment of wind and solar PV, fostered by support policies in many countries, has not only improved financial performance but also energy performance of these technologies. Deployment – and not just efforts in the domain of R&D – is thus crucial for technological development, and accumulating experience can have a substantial impact on emerging energy technologies (Schmidt and Sewerin, 2017). This also suggests that other emerging technologies, such as battery storage, may see similar performance improvements, and should not be prematurely excluded as technology options for the future.

Fifth and on a more abstracted level, the analysis has demonstrated that the energy performance of power generation technologies, especially of emerging technologies, can be subject to major changes over time. Static energy performance indicators, which provide information on present-day technological performance and do not adopt a forward-looking perspective, provide only a snapshot of performance rather than the full picture. Basing policy decisions on such static indicators can be misleading and could lead to "lock-ins" of suboptimal technology options. If dynamic indicators are not available, policy makers should at least make sure that they use "up-to-date" static indicators referring to the latest technological status.

To conclude, this study set out to assess the current energy performance of power generation technologies for the Swiss context, and to provide an outlook for the future performance of selected power generation technologies. The study has shown that from an energy performance perspective, renewable energy technologies are well suited to meet much of Switzerland's future energy demand, and its results give rise to optimism that Switzerland, with its Energy Strategy, is on the right track to a low-carbon energy system without putting at stake the energetic basis of society's prosperity.

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