The Social Costs of Electricity Supply

Types of Costs, their Dynamics over Time and how Energy Models take these Costs into Account

Von der Carl von Ossietzky Universität Oldenburg – Fakultät II Informatik, Wirtschafts- und Rechtswissenschaften – zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaften (Dr. rer. pol.)

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List of abbreviations

°C	Degree Celsius
BAU	Business-as-usual
CCGT	Combined cycle gas turbine
CCS	Carbon dioxide capture and storage
CGE	Computable general equilibrium
CO_2	Carbon dioxide
CSP	Concentrating solar power
EJ	Exajoule
GDP	Gross domestic product
GHG	Greenhouse gas
Gt	Gigaton
GW	Gigawatt
IAM	Integrated assessment model
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
kW	Kilowatt
kWh	Kilowatt hour
LCOE	Levelised cost of electricity
LR	Learning rate
MW	Megawatt
MW_{el}	Megawatt electric
MWh	Megawatt hour
O&M	Operation and maintenance
PM	Particulate matter
PR	Progress ratio
PSA	Probabilistic safety assessment
PV	Photovoltaic
R&D	Research and development
R^2	Coefficient of determination
RD&D	Research, development and demonstration
SCC	Social cost of carbon
TWh	Terawatt hour
VRE	Variable renewable energy
W	Watt

1. Introduction

This introductory chapter provides the context for the four journal articles and the additional analysis on energy models that make up Chapters 2 to 6 of this thesis. It demonstrates how the four articles and the additional analysis combine to address a common research topic, namely to gain a better understanding of the current and future social costs of electricity supply.

The background, objectives and research questions of this thesis are outlined in Section 1.1, followed in Section 1.2 by an explanation of the methodological approach, as well as definitions of key terms used throughout the thesis. Section 1.3 explains how the four journal articles relate to one another and the common research topic, before an overview of the key results of each article is provided in Section 1.4. Finally, Section 1.5 describes the key findings of the thesis, the new insights it provides and its limitations, and concludes by identifying future research opportunities.

1.1. Background and research questions

This section explains the author's motivation for focusing his research on electricity supply costs and for deriving the three research questions that form the starting point of this thesis. The following Subsection 1.1.1 stresses the current and future relevance of electricity supply for social wellbeing and argues that good policy advice is essential for governments to create an appropriate regulatory environment for the power sector. Based on this understanding, Subsection 1.1.2 defines the key objective and the three main research questions of the thesis.

1.1.1. Background: The relevance of the power sector and the role of government

A decent standard of living depends to a great extent on a sufficient supply of electricity (Niu et al. 2013; Ouedraogo 2013; Pereira et al. 2011). Ensuring a sufficient and reliable electricity supply is, therefore, an important goal for governments around the world. The issue of how best to meet electricity demand is likely to remain high on the global political agenda in the coming years and decades. There are a variety of reasons for this.

For one, global population growth, as well as global per capita GDP growth, is expected to continue to rise in the coming decades, continuing to exert upward pressure on electricity demand (IEA 2016a; Karanfil and Li 2015; UN DESA 2017). The continuing trend towards digitisation and the associated spread of information and communication technology devices and services will be important drivers for additional electricity demand in the future (Gensch et al. 2017; Kishita et al. 2016; Røpke et al. 2010; Van Heddeghem et al. 2014). Furthermore, about 1.2 billion people globally (or around one in six) do not have access to electricity according to an estimate for the year 2014 (IEA 2016a). While progress has been made in the past in reducing this figure (IEA 2016a; The World Bank 2017), significant effort and investment will be necessary in the future to achieve the United Nation's Sustainable Development Goal of ensuring "universal access to affordable, reliable and modern energy services" by the year 2030 (UN 2015).

Finally, replacing fossil fuels with electricity and electricity-derived energy carriers (such as hydrogen) in final energy demand is widely regarded to be a key strategy for reducing and eventually eliminating energy-related CO_2 emissions (DDPP 2015; Lechtenböhmer and Samadi 2013; Williams et al. 2012). Therefore, a considerable volume of additional electricity generated by sources producing low greenhouse gas emissions is likely to be needed in the future for use in applications such as electric vehicles and heat pumps, if the internationally agreed target of limiting global warming to "well below 2 °C" compared to pre-industrial levels is to be achieved (UNFCCC 2015).

For these reasons, global electricity demand and, accordingly, global electricity generation are widely expected to continue to increase in the future, as Figure 1 highlights. The figure shows that all 12 scenarios from four different studies (IEA 2017a; Kitous et al. 2016; Teske et al. 2015; WEC 2016) expect global electricity production to increase considerably in the coming decades, despite assuming continued efficiency improvements in final energy use. These scenarios include both business-as-usual scenarios and climate change mitigation scenarios and, therefore, represent a broad range of potential futures. Dashed lines are used in the figure to indicate the more ambitious mitigation scenarios, describing an energy system transformation that would allow temperature change to be limited to 2 °C.[1] Although the exact scope and pattern of electricity generation growth differ between the scenarios, they all predict an increase in global electricity generation from about 23,800 TWh in 2014 to around at least 40,000 TWh in 2050. Six of the twelve scenarios expect electricity generation to more than double compared to 2014 levels, reaching over 48,000 TWh in 2050.

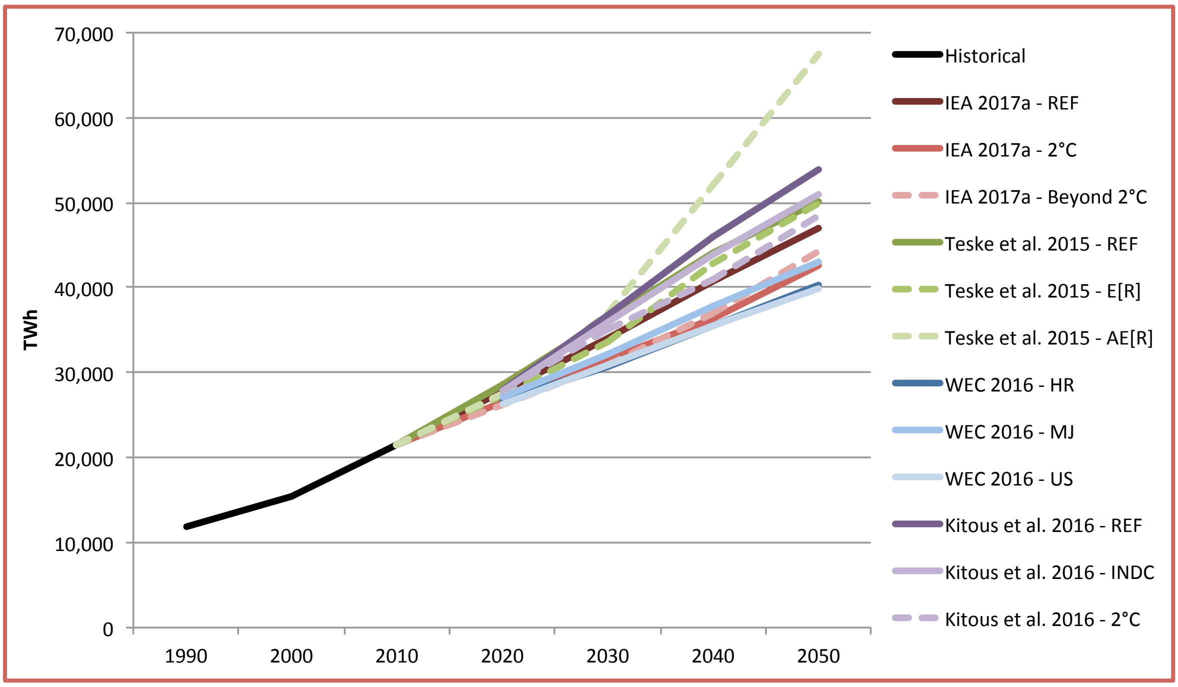

Figure 1: Global gross electricity generation up to 2050 as described by several recent global energy scenarios (in TWh, with historical data from 1990 to 2010)

Notes: "REF" stands for "Reference", "E[R]" for "Energy [R]evolution", "AE[R]" for "Advanced Energy [R]evolution", "HR" for "Hard Rock", "MJ" for "Modern Jazz" and "US" for "Unfinished Symphony". Data adapted from the studies cited in the figure and (for historical data) from IEA (2002, 2016a).

[1] Compared to their respective reference (business-as-usual) scenarios, most mitigation scenarios in the four studies exhibit lower electricity generation. This means that additional efforts in these scenarios to reduce electricity demand – particularly through greater efficiency improvements – overcompensate for increases in electricity demand associated with efforts to substitute fossil fuels by using more low-carbon electricity. However, the highly ambitious "Advanced Energy [R]evolution" scenario from Teske et al. (2015), which is based on a scientific study from the German Aerospace Center (DLR), is a notable exception. This scenario describes a global energy system that runs entirely on renewable energy by 2050, making it necessary to rely on large amounts of electricity generation from renewables, much of which is then converted to synthetic fuels.

Likewise, global power sector investments, which were an estimated 718 billion USD in 2016 (IEA 2017b), are expected to continue to grow in the coming decades (IEA 2017a; Teske et al. 2015; WEC 2016). These investment requirements, combined with the need to drastically transform the current prevailing electricity supply structures to achieve "deep decarbonisation", mean that important long-term power sector investment decisions will need to be made globally in the next few decades.

It is important for societies around the world that these investments enable key societal targets, such as climate change mitigation, access to electricity for all and air pollution reduction, to be reached. At the same time, societies are concerned about minimising market costs to prevent undue financial burden on consumers and industries.

It is widely believed that governments play a role in guiding future electricity sector investments in a socially desirable direction. From the standpoint of economic theory, there are two major reasons why government intervention in the electricity supply sector[2] can – to some extent – be justified (Jacobsson and Bergek 2011; Jaffe et al. 2005).

Firstly, various forms of electricity generation are associated with different types of external costs (Samadi 2017). These costs can be significant, particularly for fossil fuel-based electricity generation, requiring government regulation to internalise them. Secondly, there are considerable differences in the learning rates of electricity generation technologies (Samadi 2018), meaning that early investment in some technologies contributes significantly to lowering their costs in the future. Due to long time scales and enormous "learning investments" typically required before new technologies become competitive, this relationship between current investment and future costs is not likely to be fully taken into account by private investors. This, in turn, leads to positive externalities which should be internalised through appropriate government action.

Government intervention in the electricity supply sector to take such externalities into consideration can take many forms, including energy or emission taxes, emission caps, emission performance standards, public spending on research and development or financial support for individual technologies or specific infrastructure (Fischer and Preonas 2010; Sandén and Azar 2005). In order to properly design and fine tune these instruments – and decide which technologies should benefit – policymakers and regulators need knowledge about plausible and socially desirable future development pathways of the electricity system (Jacobsson and Bergek 2011; Söderholm et al. 2011).

An important tool used by researchers to help identify such pathways is electricity system or energy system modelling. Many examples of modelling exercises and efforts to inform policymakers about feasible or optimal development pathways of the electricity system exist. On the global scale, these examples include the IPCC's Fifth Assessment Report (Bruckner et al. 2014) and the Global Energy Assessment report coordinated by the International Institute for Applied Systems Analysis (Riahi et al. 2012). On the national and regional scale, examples include the power sector scenario study by the German Advisory Council on the Environment (SRU 2011) and the European Union's "Energy Roadmap 2050" study (European Commission 2011). Such scenario studies, as well as other policy advice on future power system developments, should be based on the best available science.

[2] On the demand side, market failures and barriers identified by researchers are also frequently cited to justify government intervention aiming to increase energy efficiency investments (Brown 2001; Gillingham et al. 2009; Linares and Labandeira 2010; Tietenberg 2009).

1.1.2. Key objectives and main research questions of the thesis

In the context of the background outlined above, the key objectives of this thesis are detailed in this subsection.

Key objectives:

The main objective of this thesis is to advance our knowledge of the current and likely future costs to society of electricity supply. A secondary related objective is to gain a better understanding of how these costs are taken into account in energy models typically used today. By advancing the knowledge in these areas, the thesis aims to contribute to the improvement of scientific advice on plausible and socially desirable future development pathways of the energy system.

More specifically, the thesis aims to:

- improve our understanding of what types of costs associated with electricity supply are relevant to society;
- identify and better understand the factors that influence the plant-level costs of electricity generation over time;
- evaluate to what extent energy models, which are frequently used to derive possible future pathways of the electricity system and are used for policy advice, take the various relevant types of social costs as well as the factors influencing costs over time into account.

An important motivation for pursuing these objectives is the fact that although the full social costs of electricity supply are made up of many different types of costs, the energy policy debate in the public arena often ignores certain types of costs when comparing different technologies. For example, advocates of coal-fired power generation tend to neglect the costs of climate change damage caused by greenhouse gas (GHG) emissions or the health-related costs caused by local air pollutants (Senate Republican Policy Committee 2012), while advocates of wind power tend to neglect the system costs caused by the variable nature of electricity generation from wind (Wind Europe 2016). The complexities associated with considering the full range of social costs, combined with the inclination of business and policy advocates to discuss these costs selectively, is likely to cause confusion among the public about the full social costs of electricity supply from different technologies. In addition, much of the available research on electricity supply costs focuses on comparing market costs, together with – in some cases – certain selected relatively easy-to-quantify types of external costs (e.g. Kost et al. 2013; Lazard 2016).

Consequently, it would seem to be pertinent for both the public and the scientific debate to provide an up-to-date and comprehensive overview of all the types of social costs of electricity generation and their respective relevance, and to discuss what factors are likely be the most important in driving future cost developments. This thesis aims to provide such an overview, with a view to enabling policymakers and the public to better understand and interpret existing cost studies and contributing to more comprehensive and more transparent future cost studies.

From these objectives, the following three main research questions were derived.

The three main research questions of this thesis:

1. What types of costs of electricity supply can be differentiated and are relevant to society and what are the uncertainties and limitations in quantifying these costs?
2. What are the main factors that affect plant-level electricity generation cost changes over time of different technologies and how well are these factors understood?
3. What relevant types of social costs of electricity generation and what factors affecting plant-level electricity generation costs over time are taken into account in different kinds of energy models?

Several studies are available that have addressed Research Question 1 (e.g. Alberici et al. 2014; Dalianis et al. 1997; ISIS 2009; Larsson et al. 2014). However, the most comprehensive of these, the NEEDS study (ISIS 2009), is almost a decade old. In recent years, no studies have been published that comprehensively address all relevant types of costs of electricity supply, attempt to quantify these costs and provide an up-to-date overview of the relevant literature. This thesis aims to fill this research gap by **providing a literature-based, up-to-date overview of all relevant types of social costs of electricity supply and, notably, by suggesting a framework for categorising these types of costs.**

Concerning Research Question 2, the author of this thesis is not aware of any study that has attempted to provide a comprehensive overview of the main factors that affect the electricity generation costs of various technologies over time. Gross et al. (2013) discuss important factors for cost changes for several technologies, but do not focus on this issue, nor do they deal with it using a comprehensive approach based on the sum of the available research. While many studies analyse key factors for *individual* technologies (see the literature review in Samadi 2016), these studies usually focus on only a few factors, often without discussing why other factors are ignored. This thesis aims to fill this gap by **providing a comprehensive, literature-based overview of the main factors that affect the plant-level electricity generation costs of various technologies over time and by suggesting a framework for categorising the relevant factors identified**.

To the author's knowledge, no previous analysis has focused on Research Question 3: how different types of social costs of electricity supply and the factors affecting electricity generation costs over time are taken into account in energy models. Many literature sources focus on how either individual models (e.g. Johnson et al. 2017; Leimbach and Baumstark 2010; Messner 1997; Popp 2004; Ueckerdt et al. 2015) or a range of models (e.g. Grubb et al. 2002; Kahouli-Brahmi 2008; Köhler et al. 2006; Löschel and Schymura 2013) incorporate *individual* types of costs or cost dynamics such as technological learning. This thesis intends to complement the existing literature by **providing a comprehensive overview of how different types of costs relevant to society and cost dynamics are represented in different types of energy models**. It should be noted, however, that the answer to Research Question 3 provided in this thesis is tentative, as a more complete answer would require additional research; research that could build on this thesis but is beyond its scope. Such additional research could include, for example, expert interviews, round table discussions with energy system modellers or large-scale model comparisons, such as those periodically conducted by the Energy Modelling Form since 1976 (Huntington et al. 1982).

The three main research questions are addressed in this thesis through four peer-reviewed articles, which make up Chapters 2 to 5, and in an additional analysis in Chapter 6 focusing on the treatment of electricity supply costs in energy models. Table 1 provides an overview of how the three main research questions are addressed in the following five chapters of this thesis.

Table 1: Overview of how the three research questions are addressed in Chapters 2 to 6 of this thesis

Research Question	Chapter	Article	Shortcut for article
1 (relevant types of social costs)	Chapter 2	Samadi et al. 2017: Sufficiency in Energy Scenario Studies: Taking the Potential Benefits of Lifestyle Changes into Account, in: *Technological Forecasting and Social Change* 124, 126-134.	Article 1
	Chapter 3	Samadi 2017: The Social Costs of Electricity Generation – Categorising Different Types of Costs and Evaluating their Respective Relevance, in: *Energies* 10, 3, 356.	Article 2
2 (factors determining cost changes)	Chapter 4	Samadi 2016: A Review of Factors Influencing the Cost Development of Electricity Generation Technologies, in: *Energies* 9, 11, 970.	Article 3
	Chapter 5	Samadi 2018: The Experience Curve Theory and its Application in the Field of Electricity Generation Technologies – A Literature Review, in: *Renewable and Sustainable Energy Reviews* 82 (3), 2346-2364.	Article 4
3 (treatment of costs in models)	Chapter 6	[Not published as an article]	

1.2. Methodological approach and definitions of key terms

The following Subsection 1.2.1 explains the general methodological approach of the thesis and the individual methods applied in the articles and the additional analysis on energy models. Subsection 1.2.2 provides definitions of the key terms used in this thesis.

1.2.1. Methodological approach

An extensive review of the available literature was undertaken as a basis for answering the first two research questions. This literature review was conducted to obtain a comprehensive understanding of the current scientific knowledge regarding the relevant types of social costs of electricity supply (Research Question 1) and of the main factors that affect electricity generation cost changes over time (Research Question 2).

As mentioned in Subsection 1.1.2 above, no literature sources could be identified which answer either one or both research questions comprehensively and with up-to-date data. For both research questions, therefore, the large number of individual pieces of information contained in all the identified literature sources were extracted and assessed. In a next step, all the relevant information was combined to comprehensively categorise the relevant types of social costs of electricity supply and the main factors that affect electricity generation cost changes over time.

Subsequently, this categorisation was used as the basis for answering Research Question 3. Specifically, it was the basis for constructing an online survey, which was sent to 66 energy modellers using 36 different models in April 2017. The modellers were asked to identify the types of socially relevant costs and the factors determining cost changes over time that are taken into account in the respective energy models they use.[3] The answers from this survey provided key input information for answering Research Question 3. In addition to the survey, a literature review was also performed, focusing on how energy models take the various types of social costs and cost dynamics into account. This review complemented the insights gained from the survey.

Apart from the identification and categorisation of relevant types of social costs of electricity generation, Article 2 also attempts to quantify these costs – as far as possible – for various electricity generation technologies. For the quantification of the plant-level costs, a spreadsheet tool by the Danish Energy Agency (2016) was applied to calculate both the current levelized costs of electricity generation and the predicted levelized costs for 2040. While plant-level cost estimates for several technologies are available from a number of publications, the decision was taken to make independent calculations. This enabled the most recent capital cost data to be used and, importantly, ensured a methodologically consistent choice of parameters, particularly with regard to the discount rate. A relatively low value was chosen for this rate, making it consistent with the social (as opposed to investor) perspective that is at the heart of this thesis.

Figure 2 summarises the methodology of this thesis, highlighting the methods used and the key categorisations developed to answer the three research questions.

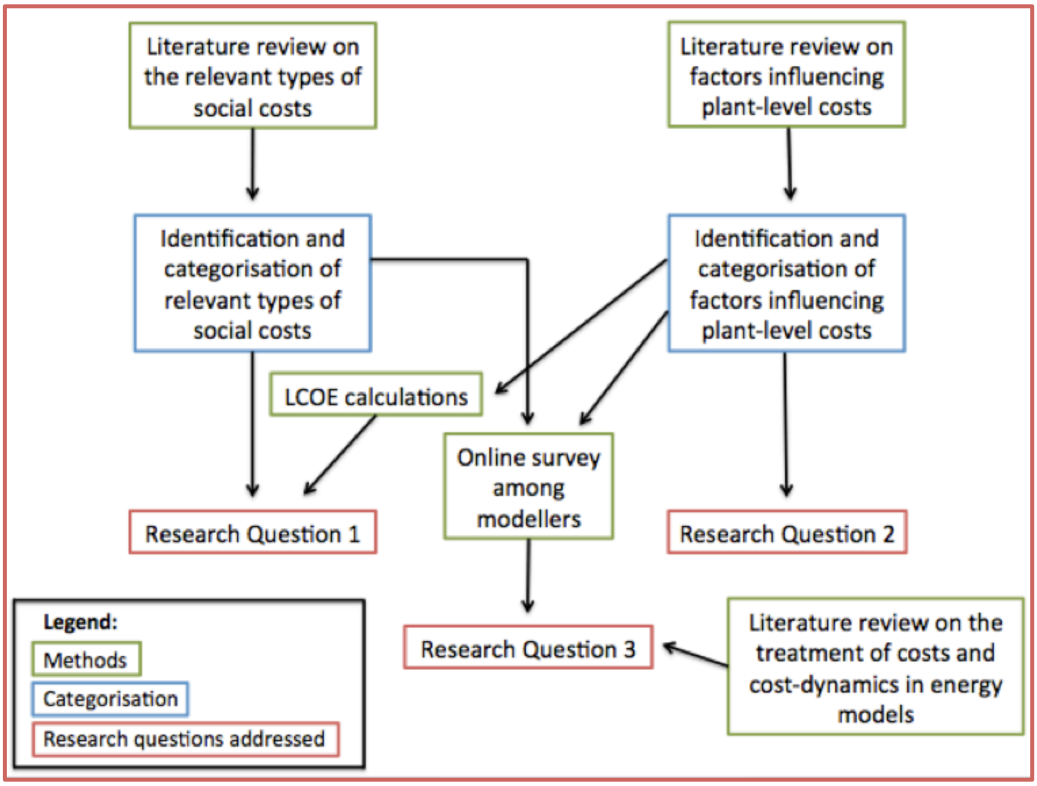

Figure 2: Overview of the methodological approach of this thesis

[3] Chapter 6 provides additional information on the survey, including its content, the energy modellers addressed, the response rate achieved and the key insights gained.

1.2.2. Definitions of key terms

In this subsection, key terms will be defined to ensure readers are familiar with the specific meaning of these terms as used in this thesis. These terms are also defined and discussed in more detail in the following two chapters (Chapter 2/Article 1 and Chapter 3/Article 2), but are introduced here as they are used throughout this first chapter.

Costs

In the field of economics, the cost of a good refers to the value of all the scarce resources that have been used to produce the good. This value, in turn, is measured in terms of the value of the next best good that could have been produced with the same resources, and is called opportunity cost (Christensen et al. 1998). In this thesis, the social opportunity cost of supplying electricity is referred to as the "social cost of electricity supply". Social costs are typically broken down into "private costs" and "external costs".

Private costs

The private costs of a good are those types of opportunity costs accrued by the market player who produces the good. These costs are taken into account by the producer when deciding on the production volume and the producer's aim is to minimise these costs. When analysing the total social costs of electricity generation, the argument is made in this thesis that it is useful to further differentiate private costs as "plant-level costs" or "system costs".

Plant-level costs

Plant-level costs encompass the private costs associated with electricity generation at the plant. These consist of capital (or investment) costs, fuel costs, non-fuel operation and maintenance (O&M) costs, and – if a carbon market is in place – carbon costs. These costs are frequently compared between different types of electricity generation technologies by calculating the "levelized cost of electricity" (LCOE).

System costs

System costs can be defined as all the costs associated with the reliable delivery, at the appropriate time, of the electricity generated at plant-level to the locations where the electricity is needed. These costs include the costs of transmission and distribution networks, of storage technologies and of a range of so-called ancillary services required for the stable operation of an electricity system. Following Hirth et al. (2015), we also include "profile costs" within the system costs (see below). As system costs are often difficult to ascribe unequivocally to individual power plants, some of these costs are typically apportioned to electricity suppliers and/or consumers by regulatory entities, for example through tariffs per unit of electricity produced or consumed.

Profile costs

Profile costs can be defined as the additional specific capital and operational costs that electricity generation from a new plant causes in the residual electricity system, as well as any overproduction costs of electricity generation from variable renewable energy sources (Hirth et al. 2015).

External costs

External costs can be defined as the costs arising from human activity that are not accounted for by the market player causing the externality (Christensen et al. 1998). For example, the particulate pollutants from a fossil fuel power plant that cause negative health effects for people living near the plant are external costs. The power plant "uses" the scarce resource of health, without the costs actually being accrued by the market player who caused it.

Sufficiency

Sufficiency can best be defined by contrasting it with efficiency and consistency. Efficiency is an option in which the input-output relation is improved. Fewer inputs of material or energy are needed per service unit, or more services are produced from the same amount of material or energy. Consistency aims at fundamental changes in production and consumption by substituting non-renewable resources with renewable resources. The option of sufficiency is linked to the level of demand for goods and services – in the context of this thesis specifically to the level of demand for electricity-intensive goods and services. Advocates of sufficiency call for this demand to be limited to a level which still allows for a "good life" (Muller 2009).

1.3. Role of the four articles as part of a common research topic

This section illustrates how the four peer-reviewed journal articles contained in this thesis relate to one another and how they address the common research topic – to better understand the current and future social costs of electricity supply. This section also discusses which aspects related to the social costs of electricity supply are outside the scope of this thesis.

Figure 3 provides a graphic overview of the key factors that determine the social costs of electricity supply. The figure shows which factors are discussed by which of the four articles in this thesis and clarifies how the articles relate to one another. The boxes indicate factors that influence the social costs of electricity supply – some directly, others indirectly. Boxes with solid red lines denote factors that have been analysed for this thesis. Factors that have not been analysed in detail for this thesis are indicated by boxes with dashed red lines.

It should be emphasised that the figure below is a reduced form representation of the complex interactions that determine the social costs of electricity supply. For the sake of simplicity and to focus on the most relevant elements, the figure does not attempt to include all factors and interdependencies.

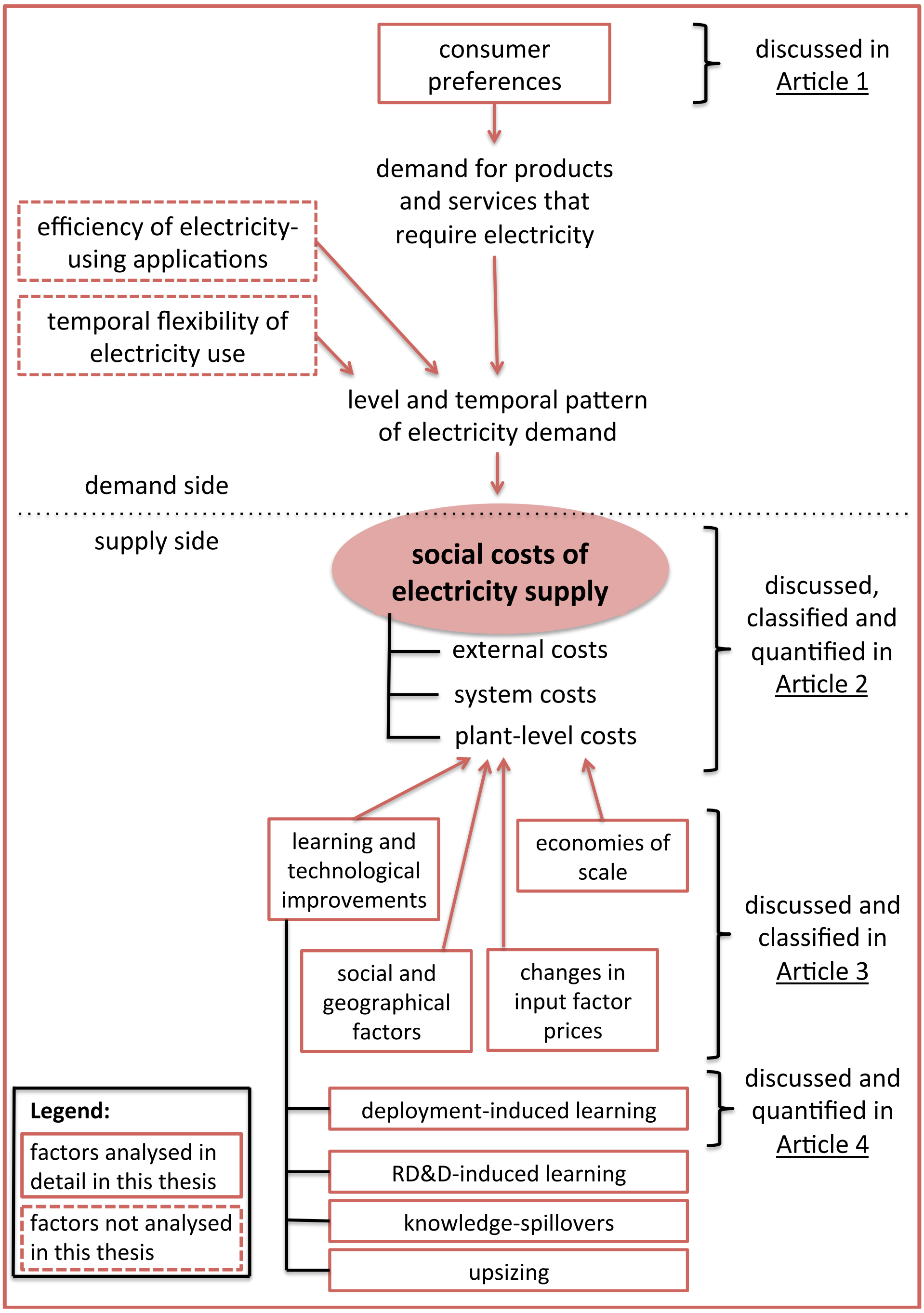

Figure 3: Reduced form representation of the interactions that determine the social costs of electricity supply and the role the four articles play in analysing these interactions

Consumer preferences, which determine the level of demand for energy-intensive services and products, are depicted at the top of the figure. This indicates that these preferences can be considered as the origin of energy demand and also, therefore, as the origin of electricity supply and related costs. **Article 1** addresses in a generic manner the question of how changes in consumer preferences can reduce energy demand and, accordingly, electricity supply costs.

As the figure indicates, **Article 2** can be seen to be at the centre of this thesis, as it defines the social costs of electricity supply as they are understood in this thesis. Specifically, the article suggests that the social costs of electricity generation should be differentiated in three categories, namely private costs, system costs and external costs.

Based on an extensive literature review, relevant types of costs are identified, assigned to one of the three categories and quantified (as far as possible) for key electricity generation technologies.

Article 3 focuses on one of the three cost categories identified in Article 2, namely the plant-level costs. Based on an extensive review of the empirical literature, ten key factors are identified that have been found to influence the plant-level costs of electricity generation technologies in the past. These ten factors are grouped into the four categories shown in Figure 3, namely "learning and technological improvements", "economies of scale", "changes in input factor prices" and "social and geographical factors". The article highlights the fact that a different combination of factors has influenced the past cost developments of each electricity generation technology. The article also discusses for each technology which cost-influencing factors could play a lesser or greater role in the future.

Finally, **Article 4** concentrates on one of the ten factors influencing plant-level costs identified in the previous article, namely deployment-induced learning, and explores this in further depth. Specifically, the closely related concept of experience curves is at the centre of this article. This concept is frequently used for explaining past cost changes and for forecasting future cost changes of electricity generation technologies. The different approaches to constructing experience curves found in the literature are examined and the various points of criticism raised against the concept and its application are discussed. Suggestions are provided on how researchers can avoid or reduce the problems associated with these points of criticism. An up-to-date review of the findings from the available literature on empirically observed experience curves is provided, allowing for a comparison of the extent to which deployment-induced learning can explain past cost changes of various electricity generation technologies.

Table 2 summarises the key elements associated with determining current and future social costs of electricity supply addressed as part of this thesis.

Table 2: Important elements associated with the social costs of electricity supply addressed as part of this thesis

	Article
Discussion and quantification of the social costs of electricity supply	
• Definition of the social costs of electricity supply, including identification of relevant types of costs	Article 2
• Quantification of current and possible future (year 2040) social costs of electricity supply for several technologies	Article 2
Demand-side factors influencing the social costs of electricity supply	
• Discussion of the potential of lifestyle changes in reducing electricity demand and thus the social costs of electricity supply	Article 1
Factors influencing the social costs of electricity supply over time	
• Identification and discussion of factors that have influenced plant-level costs of electricity generation in the past	Article 3
• Discussion of the experience curve concept as a way of depicting and quantifying deployment-induced learning	Article 4

In order to focus on the main research questions outlined in Subsection 1.1.2, a number of aspects relating to the social costs of electricity supply are not addressed in this thesis. Generally, and as Figure 3 makes clear, the focus of this thesis is on the supply side of the electricity system, with Articles 2, 3 and 4 dealing exclusively with supply-side factors that influence the social costs of electricity provision. Only Article 1 focuses on the demand side, by addressing in a generic manner the question of how changes in consumer preferences can reduce energy demand (and thus the costs associated with electricity supply). It should be noted that the supply side focus of this thesis is not intended to imply that demand-side factors are less relevant in determining the social costs of electricity supply. The choice was made for practical reasons; to limit the scope of the analysis and enable analysis of the supply side in sufficient detail.

On the demand side, two factors that are not analysed in this thesis but are particularly relevant for the costs of electricity supply are the efficiency of electrical applications and the flexibility of electricity use in production processes.[4] These two factors significantly influence the level and temporal pattern of electricity demand. Various studies are available on these topics (e.g. Arimura et al. 2012; Levy et al. 2016; O'Connell et al. 2014; Paulus and Borggrefe 2011), showing that (net) cost reductions can be achieved through energy efficiency improvements and increased temporal flexibility of electricity demand. Progress in both areas is generally considered to be essential for significantly reducing energy system CO_2 emissions in the coming decades, by limiting the growth in electricity demand and facilitating the system integration of renewable energy sources.

Regarding the definition, categorisation and quantification of the social costs of electricity supply, Article 2 points out that potential macroeconomic and geopolitical costs and benefits are not analysed, as it is extremely difficult to precisely quantify these or to determine how they differ between various electricity generation technologies.[5] Furthermore, due to the nature of the available literature, the identification of relevant types of costs and their quantification relies almost exclusively on findings from OECD countries. Article 2 stresses, therefore, that its findings are not necessarily representative of the social costs of electricity generation in developing countries. The article also points out that how social costs may differ between centralised/decentralised use of electricity generation technologies is not discussed in detail. This is perhaps most relevant for solar photovoltaic (PV) plants; large-scale plants are analysed in the paper for two reasons – better availability of cost data in the literature than for small-sale plants and to simplify comparisons with the other technologies typically used in large-scale form.

Of the three main categories of costs identified in Article 2, Articles 3 and 4 focus on plant-level costs. Specifically, this thesis does not examine in detail the factors that determine changes over time in external costs, such as improvements in pollution control technologies, or in system costs, such as changes in the flexibility of electricity demand. However, Article 2 briefly discusses the possible future evolution of system costs and stresses the importance of these costs in determining future electricity supply costs. The future evolution of system costs is an area where a particularly strong need for future research has been identified.

[4] Electricity demand at the site of final use can also be made more flexible in temporal terms. However, the potential of this flexibility is generally considered to be lower than at the production site, i.e. by industrial and commercial electricity users (O'Connell et al. 2014). The end-use flexibility interacts with consumer preferences. For reasons of simplicity, this interaction is not depicted in Figure 3.

[5] Such potential costs and benefits may, for example, stem from employment effects or changes in import dependency.

Finally, a further related aspect that this thesis does not focus on is potential government action to influence the factors identified as determining the social costs of electricity supply. For example, an interesting question – only briefly addressed in Article 1 – is whether political measures such as energy conservation campaigns (Tiefenbeck et al. 2013) or social initiatives such as the Transition Town movement (Barr and Pollard 2017) can induce changes in consumer preferences, potentially leading to lower demand for energy-intensive products and services (Capacci and Mazzocchi 2011; Mørkbak and Nordström 2009; White and Dahl 2006). Furthermore, this thesis does not discuss what policy instruments are best suited on the supply side to internalise and thereby reduce the external costs of electricity generation or whether – and if so how – governments should support the deployment of technologies for which relatively strong deployment-induced learning has been identified (Fischer and Sterner 2012; Lehmann and Gawel 2013; Nemet et al. 2010).

Table 3 summarises important elements associated with determining current and future social costs of electricity supply which are beyond the scope of this thesis. The table also identifies literature sources addressing each of these elements.

Table 3: Important elements associated with the social costs of electricity supply that are not dealt with, or not dealt with in detail, in this thesis

	Examples of literature sources that discuss these elements
Discussion and quantification of the social costs of electricity supply	
• Macroeconomic and geopolitical costs as potential additional types of social costs of electricity supply	Månsson 2014; Tourkolias and Mirasgedis 2011; Valentine 2011
• Differences in the social costs of electricity supply between centralised & decentralised forms of electricity generation	Cole et al. 2016; Tsuchida et al. 2015
Demand-side factors influencing the social costs of electricity supply	
• Efficiency of electrical applications	Arimura et al. 2012; Levy et al. 2016
• Flexibility of electricity use	Jonghe et al. 2012; O'Connell et al. 2014; Paulus and Borggrefe 2011
Factors and policies influencing the social costs of electricity supply over time	
• Factors determining changes over time in system costs	Hirth and Müller 2016; Scholz et al. 2017
• Factors determining changes over time in external costs	Ek and Persson 2014; Moore and Diaz 2015
• Specific government policies aimed at lowering the social costs of electricity supply	Dechezlepretre and Popp 2015; Fischer et al. 2017; Lehmann and Gawel 2013

1.4. Key results of the four articles

The following Subsections 1.4.1 to 1.4.4 provide the key results of each of the four articles.

1.4.1. Article 1: Sufficiency in energy scenario studies: taking the potential benefits of lifestyle changes into account

This article was published online in October 2016 in the journal "Technological Forecasting & Social Change". It was written in collaboration with five co-authors from the Wuppertal Institute; Marie-Christine Gröne, Uwe Schneidewind, Hans-Jochen Luhmann, Johannes Venjakob and Benjamin Best. The author of this thesis is the lead author of the article and wrote most of the text.[6] The complete article is provided in Chapter 2.

At the beginning of the article, a number of studies (Faber et al. 2012; Hallström et al. 2015; van Sluisveld et al. 2016; Stehfest et al. 2009) are referred to which indicate that lifestyles in which users consume relatively few energy-intensive goods and services have the potential to contribute considerably to public policy goals, including the reduction of energy-related CO_2 emissions. Such "energy-sufficient" lifestyles could thus complement climate and energy policy strategies aiming to increase efficiency and switch to renewable or carbon-free energy sources.

The article differentiates three different causes of shifts toward energy-sufficient lifestyles:

a) Changes in individual preferences towards less energy-intensive consumption patterns;
b) A government-induced increase in the relative prices of certain energy-intensive goods and services;
c) An outright ban by the government of certain energy-intensive goods and services.

Figure 4 (taken from the article) illustrates the microeconomic differences between these three types of sufficiency. For simplicity, the figure assumes that consumers choose between only two products: one is environmentally harmful while the other is environmentally benign. Consumers are restricted in their demand for these two products by their individual budgets and/or time constraints (indicated by the budget line b). Their preferences are depicted by the so-called indifference curves I. Each indifference curve represents those product combinations which lead to the same utility for a consumer. An indifference curve that is further down and to the left represents levels and combinations of goods that cause lower consumer utility, while a curve that is further up and to the right represents levels and combinations of goods that cause higher consumer utility.

[6] A declaration of co-authorship can be found in Annex B.

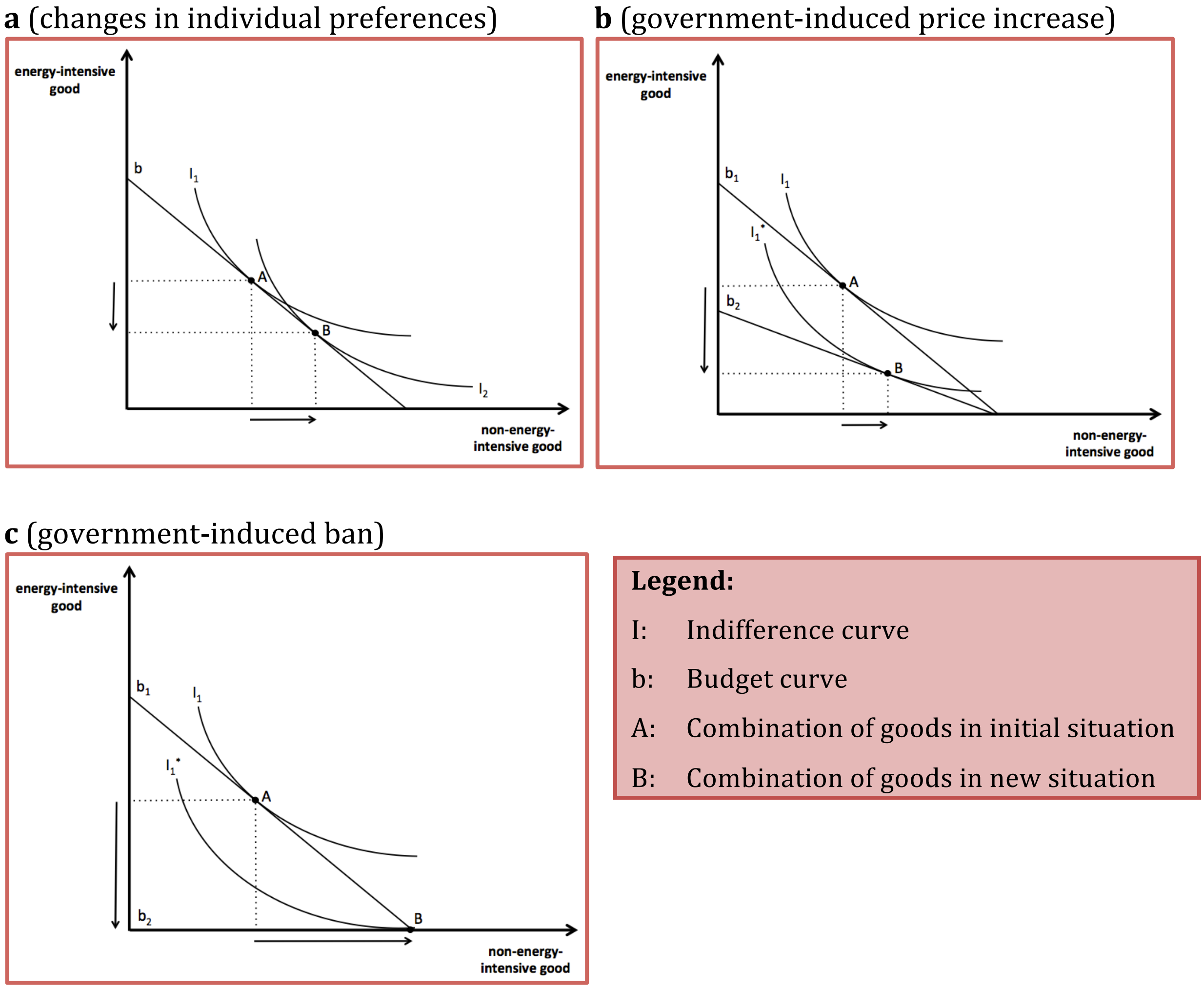

Figure 4: Illustrations of three different causes of shifts toward energy-sufficient lifestyles

The three different causes of shifts toward energy-sufficient lifestyles are associated with different costs or welfare effects, as the simplified two goods analysis in Figure 4 illustrates. In Figure 4a, the changes in preferences lead to a shift of all indifference curves, meaning that less energy-intensive lifestyles can be realised without any welfare losses. In the case of government intervention, however, the higher cost (Figure 4b) or outright ban (Figure 4c) of the energy-intensive good means that in these cases less energy-intensive lifestyles can only be realised through welfare losses; consumers end up on lower indifference curves since the price increase or the ban forces consumers to choose a level and combination of goods that they find inferior to the status quo.

Based on the literature findings that energy-sufficient lifestyles have the potential to contribute considerably to energy and climate policy objectives, an investigation is made to discover whether the potential benefits of sufficiency are examined in prominent recent energy scenario studies. The argument is made that these studies, which aim to advise policymakers, should present all the relevant options for achieving political goals such as climate change mitigation. It should then be up to political and societal debate to choose the preferred options to achieve these goals (Edenhofer and Kowarsch 2015).

The analysis of energy scenario studies in the article focuses on three well-known global studies, two by the International Energy Agency (IEA 2016a, 2016b) and one on behalf of Greenpeace International, the Global Wind Energy Council and SolarPower Europe

(Teske et al. 2015). All three publications are frequently referred to in scientific and political discussions on the future of the global energy system. The analysis of these three studies shows that even the most ambitious climate change mitigation scenarios in each study assume only very limited changes towards energy-sufficient lifestyles in the coming decades.

The article recommends that future scenario studies by the International Energy Agency (IEA) and other bodies should include scenarios which investigate more far-reaching shifts towards energy-sufficient lifestyles. To underline the fact that such analysis is possible, a number of other available global energy and emission scenarios, which explicitly take the potential of energy-sufficient lifestyles into account, are briefly discussed in the article (Berghof et al. 2005; Johansson et al. 2012; Sessa and Ricci 2014; UNEP 2002, 2007; WEC 2013). However, these studies are not as prominent in the energy debate and do not represent the global energy system in as much detail as the three analysed scenario studies by the IEA and Greenpeace et al.

Finally, the article's conclusion provides suggestions for energy scenario developers and the broader research community aimed at promoting the comprehensive consideration of sufficiency in future energy scenarios.

In relation to this thesis, the key aspect of the article is how shifts towards energy-sufficient lifestyles affect the cost of electricity supply. Assuming that energy-sufficient lifestyles do not only reduce overall energy use but also electricity demand, energy-sufficiency clearly reduces the total costs of supplying electricity, as less electricity needs to be generated and delivered to meet demand. However, whether shifting towards such lifestyles is economically beneficial depends on whether the assumed changes in lifestyles are associated with any costs themselves.

In a narrow definition of the term sufficiency, only changes in consumer preferences qualify as shifts toward energy-sufficient lifestyles. In these cases, no costs accrue, as the changes in preferences mean that individuals can achieve the same level of utility by using less energy or electricity. However, the article also discusses the possibility of changes towards energy-sufficient lifestyles that are "forced" upon individuals by government intervention. Such interventions can either increase the market prices of energy-intensive goods (e.g. through taxes), make them relatively less attractive (e.g. by improving public transportation) or ban these goods altogether. In these cases, individuals will shift towards energy-sufficient lifestyles, but these shifts can only be achieved at an economic cost, as economic theory predicts that welfare losses typically accrue when final consumption goods are taxed differently, meaning that lower electricity supply costs may be more than compensated by welfare losses due to a misallocation of goods (Mankiw et al. 2009).[7]

Regarding energy policy, this leads to the question of whether it is possible through governmental measures to shift individual preferences toward energy-sufficient lifestyles. A detailed discussion of this question is, however, beyond the scope of this thesis.

[7] This may be the case when in the initial situation no market externalities exist that can be internalised through the new tax. For this and other exceptions to the negative appraisal of differential commodity taxation, see Mankiw et al. 2009.

1.4.2. Article 2: The Social Costs of Electricity Generation – Categorising Different Types of Costs and Evaluating their Respective Relevance

This article was published online in March 2017 in the open access journal "Energies". The complete article is provided in Chapter 3. The article's Supplementary Materials can be found in Annex D.

The main objective of this article is to determine which types of costs associated with electricity generation are relevant to society and how these costs can be categorised. The article also attempts to quantify and compare for Europe and the USA the typical costs of electricity generation from onshore wind, offshore wind, solar PV, nuclear power, natural gas and hard coal. However, as the article stresses, the results of these cost comparisons need to be treated with care for several reasons. These reasons are discussed below.

The article relies on an extensive review of the available literature. Based on this review, several different types of costs of electricity generation are identified. The article suggests grouping these costs into three main categories: plant-level costs, system costs and external costs. Plant-level costs comprise the private costs associated with electricity generation at the plant, including investment, fuel and O&M costs. System costs can be defined as all the costs associated with the reliable delivery, at the right time, of the electricity generated at plant-level to the locations where the electricity is needed. Transmission and distribution costs are examples of this type of cost. Finally, external costs can be defined as the costs arising from electricity generation that are not accounted for by the generator who is causing the externalities. Examples are the health costs associated with local pollutants stemming from a coal power plant.

The following types of cost have been identified as relevant for society:

- Plant-level costs
  - Capital costs
  - Fuel costs
  - Market costs of GHG emissions
  - Non-fuel O&M costs
- System costs
  - Grid costs
  - Balancing costs
  - Profile costs
- External costs
  - Social costs of GHG emissions
  - Impacts of non-GHG pollution
  - Visual impacts and impacts of noise
  - Impacts on ecosystems & biodiversity (non-climate)
  - Costs associated with radionuclide emissions
  - Other potential external costs

Based on the literature review, the article also provides an assessment by the author of the current scientific understanding of the different types of costs of electricity generation. Not surprisingly, plant-level costs are generally well understood while understanding of the various types of external costs tends to be low. There are no markets on which the 'prices' of external effects can be observed and, in many cases, complex environmental interactions occur before a burden (e.g. emission of an air pollutant) has an impact and leads to damage (e.g. a respiratory illness). Therefore, in the article, for some of the potentially relevant external costs, the conclusion was drawn that current scientific knowledge is insufficient for deriving meaningful “typical values” for the different electricity generation technologies.

The findings from the comparison of technologies by total social costs, which, again, need to be interpreted with care, suggest that following decades of dramatically declining technology costs, the social costs of electricity generation from new onshore wind and solar PV plants are now lower than those of fossil fuel power plants. This is especially true in locations with good solar and/or wind resources. At the same time, it has proven conceptually difficult to compare the costs of nuclear power with other technologies, particularly renewable energy technologies. While the social costs of new nuclear power plants may be lower than for all other technologies analysed, this is only true if the assumption is made that nuclear power is not an inherently riskier investment than renewables and that the costs of potential large-scale nuclear accidents are negligible.

The challenge of properly dealing with differences in risks is one of the reasons why the article stresses the limitations of a technology-specific comparison of electricity generation costs. Another key limitation is the fact that, based on the current state of knowledge, not all types of costs can be quantified in monetary terms. In addition, costs for any type of electricity generation can differ considerably from one individual case to another, because the electricity system is a highly interconnected system in which the costs of supplying electricity from any one specific power plant depend on the specific characteristics of an electricity system. Consequently, the article suggests that policymakers not only rely on the results of technology-specific cost comparisons when making policy decisions, but also complement these results with insights gained through other methods, such as energy system cost modelling and/or multiple-criteria decision analysis (MCDA).

1.4.3. Article 3: A Review of Factors Influencing the Cost Development of Electricity Generation Technologies

This article was published online in November 2016 in the open access journal “Energies”. The complete article is provided in Chapter 4.

The objective of this article is to identify all the relevant factors which have influenced past changes in plant-level electricity generation costs of various technologies. The assumption is made that a comprehensive understanding of the reasons for past cost changes will help improve our understanding of future cost changes. Based on an extensive review of the empirical literature on past cost changes, ten different factors are identified and these factors are grouped into four categories: “learning and technological improvements”, “economies of scale”, “changes in input factor prices” and “social and geographical factors”. Figure 5 (taken from the article) provides an overview of the ten identified factors.

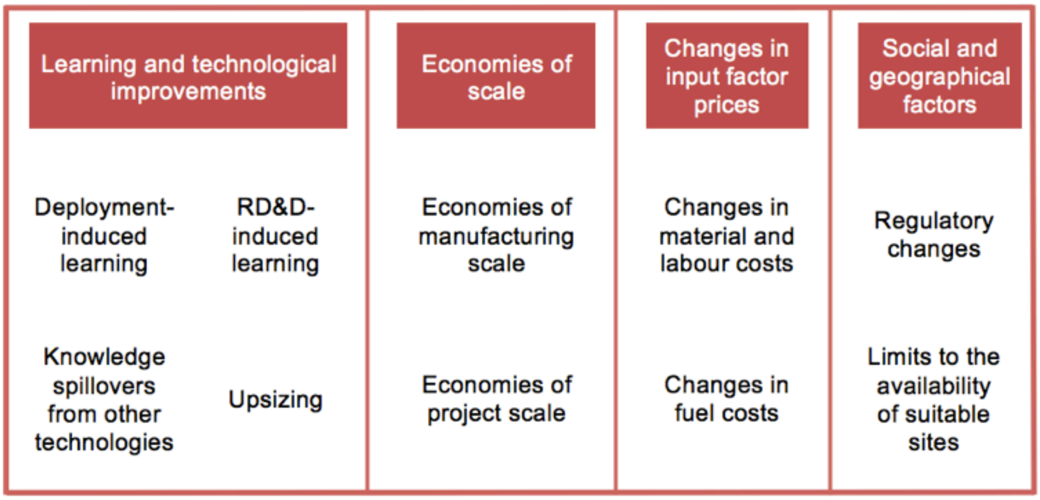

Figure 5: Factors influencing the market costs of electricity generation technologies as identified by the literature review

The article discusses which electricity generation technologies have been found to be influenced by each factor. The article focuses on onshore and offshore wind power plants, solar PV plants, concentrating solar power (CSP) plants, nuclear power plants, coal power plants and natural gas power plants, as the available literature analysing past cost changes mainly deals with these technologies.

The review underlines the fact that various factors tend to influence plant-level technology costs over time and that the most relevant factors differ from one technology to another. Generally, the six factors in the categories "learning and technological improvements" and "economies of scale" led to cost reductions, while the four factors in the categories "changes in input factor prices" and "social and geographical factors" led to cost increases over time.

The fact that each technology is affected by a different combination of factors influencing their plant-level costs helps explain the considerable differences in technology cost changes over past decades. For solar PV technology, which has seen drastic reductions in specific capacity costs (Mauleón 2016), several relevant factors have been identified that each had a cost decreasing effect, while no factors have been identified that unambiguously led to cost increases. For nuclear power, on the other hand, which has seen cost increases in past decades in most countries for which data is available (Lovering et al. 2016), several factors have been identified which have exerted upward pressure on costs, most notably changes in material and labour costs as well as regulatory changes.

Based on these findings, the article also briefly discusses, for each electricity generation technology, how the main factors influencing cost developments may change in the future. For solar PV, for example, the point is made that once manufacturing plants stop increasing in size – for example because the global market will eventually cease to grow – the technology will no longer benefit from economies of manufacturing scale. As this factor is thought to have contributed to PV cost reductions in the past (Nemet 2006; Yu et al. 2011), future cost reductions may slow down at some point in time. Nuclear energy, on the other hand, may see an end to continuous cost increases if small-scale nuclear power plants enter the market at some point in the future, as these smaller plants may offer an opportunity for producing a considerable number of identical plants, offering more potential for learning and for economies of manufacturing scale.[8]

1.4.4. Article 4: The Experience Curve Theory and its Application in the Field of Electricity Generation Technologies – A Literature Review

This article was published online in September 2017 in the journal "Renewable and Sustainable Energy Reviews". The complete article is provided in Chapter 5.

The objective of the article is to provide a thorough review of the experience curve theory and its application in the field of electricity generation technologies. To this end, the article first introduces the concept behind the experience curve: the idea that a technology's costs decline as experience with the technology (e.g. in the form of cumulative production) is gained. The article then provides a systematic overview of the different ways in which such experience curves can be constructed. The article subsequently provides a structured discussion of the limitations of the experience curve theory and its application. It derives suggestions about how to adequately address these limitations when constructing experience curves and when making use of the associated learning rates; i.e. the rate at which a technology's cost is found to decline as its experience doubles.

A key aspect of the article is the discussion of the findings of an extensive review of the available empirical literature on observed experience curves for electricity generation technologies. The findings are discussed separately for each technology for which literature is available, namely onshore and offshore wind power plants, solar PV plants, CSP plants, biomass power plants, nuclear power plants, coal power plants and natural gas power plants. Table 4 (taken from the article) provides an overview of the number of studies evaluated for each technology, the geographical domains used to determine a technology's experience and the time periods covered by the studies. As the table shows, by far the largest numbers of individual experience curve studies are available for onshore wind and solar PV power plants.

[8] On the other hand, considerably reducing the size of nuclear power plants might mean that they suffer from negative economies of scale effects. However, empirical studies of past cost developments do not conclusively show that the specific costs of electricity generation from nuclear power plants benefitted from economies of unit scale (or upsizing) effects, i.e. from the increasing size of nuclear power reactors.

Table 4: Overview of the experience curve studies reviewed and of the characteristics of their associated learning rates

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

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

For most technologies using renewable energy sources, and particularly for solar PV, the literature finds clear statistical support for a strong negative correlation between experience and costs. The limited number of literature sources establishing learning rates for fossil fuel technologies also find negative correlations for the most part, although these correlations tend to be weaker than for renewable energy technologies. For nuclear power plants, on the other hand, learning effects in the past seem to have been low and these have been negated in many countries by other factors influencing technology costs. As several authors have noted (e.g. Grubler 2010; Lovering et al. 2016), it is doubtful whether the experience curve theory is a useful tool for explaining the past cost developments of nuclear power plants or their anticipated future costs.

Based on the literature findings on past learning rates, as well as the insights gained from the analysis performed in Article 3 (Samadi 2016), this article eventually derives plausible ranges for future one-factor learning rates[9] of individual technologies. These ranges could be used, for example, by energy system modellers seeking to use plausible future cost assumptions in their models.

The article concludes by pointing out that the empirical and theoretical insights from the reviewed literature suggest that learning does indeed take place as experience is accumulated by a technology. However, it also stresses that it is important for researchers to bear in mind that additional factors may play a considerable role in influencing technology costs. More generally, the uncertainties associated with using observed learning rates to anticipate future cost developments need to be taken into account by researchers.

[9] Unlike "two-factor" or "multi-factor" learning rates, one-factor learning rates do not correct observed cost changes or expected future cost changes for cost-influencing factors other than experience, such as RD&D spending or input prices. While certainly a simplification, one-factor learning rates are used for practical reasons by many energy models.

1.5. Main findings and conclusions

The following Subsection 1.5.1 presents the main findings of this thesis by summarising the insights gained for each of the three guiding research questions. Subsection 1.5.2 then addresses the limitations of the thesis, specifically regarding the two main methods used – a literature review and an online survey of experts. Finally, Subsection 1.5.3 presents the conclusions based on the main findings of the thesis, deriving recommendations for policymakers and the energy modelling community, as well as suggesting future research opportunities.

1.5.1. Main findings of the thesis

Main findings in relation to Research Question 1:

Research Question 1:

What types of costs of electricity supply can be differentiated and are relevant to society and what are the uncertainties and limitations in quantifying these costs?

This research question was mainly answered through an extensive review of the available literature (Samadi 2017). The following seven key findings result from the analysis related to this research question.

Several types of costs are relevant in assessing the social costs of electricity supply
Twelve different types of electricity supply costs relevant to society were identified and these cost types were grouped into three categories: "plant-level costs", "system costs" and "external costs". Table 5 provides an overview of the twelve identified types of costs within the three categories, shows their relevance for social cost comparisons of different electricity generation technologies and also provides an assessment by the author of the current scientific understanding regarding each cost category.

Table 5: Types of costs found to be relevant for comparing the social costs of electricity generation technologies

Cost category	Relevance for comparing costs	Scientific understanding
Plant-level costs		
Capital costs	High	High
Fuel costs	High	Moderate/high
Market costs of GHG emissions	High	High
Non-fuel O&M costs (fixed and variable)	High	Moderate/high
System costs		
Grid costs	Low/medium	Moderate
Balancing costs	Low	Moderate/high
Profile costs	Medium/high	Moderate
External costs		
Social costs (minus market costs) of GHG emissions	Medium/high	Low
Impacts of non-GHG pollution	Medium	Low/medium
Landscape and noise impacts	Low/medium	Low/medium
Impacts on ecosystems & biodiversity (non-climate)	Unclear	Low
Costs associated with radionuclide emissions	Unclear	Low

The significance of individual types of costs differs from one technology to another

It was further shown that the significance of the individual types of costs (and cost categories) differs from one type of electricity generation technology to another. Generally, for fossil fuel plants, fuel costs and external costs are particularly relevant; while for nuclear power plants and many renewable energy technologies, capital costs and – at high penetration rates – system costs are most relevant.

There are considerable uncertainties in quantifying some types of costs

Another key finding of the analysis conducted to address Research Question 1 was that, despite several decades of research into the social costs of electricity supply, considerable uncertainties remain in quantifying some types of costs (see Table 5). This is particularly the case for external types of costs. Quantifying the costs of GHG emissions, for example, remains difficult and contentious, and large ranges are found in the literature. Similarly, the costs associated with air pollution from fossil fuel and biomass power plants are also difficult to quantify. Quantifying the costs associated with the impacts of electricity supply on ecosystems and biodiversity appears to be even more uncertain as there has been little research in this area, there are no widely accepted methodological approaches for quantification and ecosystem interdependencies are highly complex. Finally, determining and monetising the external costs of nuclear power, particularly those related to potential large-scale accidents at nuclear facilities, remains highly contentious and there is no consensus about appropriate methodologies.

Some types of costs are highly location and system-specific

Apart from the general difficulties in quantifying and monetising certain impacts of electricity supply, there is an additional obstacle to making universally-valid cost quantifications for individual technologies. This obstacle is the fact that some types of costs are highly location-specific and/or highly specific to the characteristics of the electricity system within which the technology operates. Such location and system-specific types of costs can be found in all three of the differentiated cost categories. For example, the specific per kWh capital costs of PV or onshore wind power plants differ significantly from one location to another depending on solar radiation or wind conditions. Profile costs of technologies are highly dependent on the characteristics of the rest of the electricity system, such as the share of electricity generated from variable sources and the flexibility of conventional power plants. Finally, the health-related costs of air-polluting power plants depend to a large extent on their location and the number of people living in the affected area.

A universally-valid ranking of generation technologies by costs is not possible

Due to the uncertainties and difficulties in quantifying several of the types of costs, as well as the highly location and system-specific nature of some of these costs, a universally-valid ranking of generation technologies by social cost cannot be established. Instead, the social costs of electricity supply from one technology will vary according to the location and electricity system. Furthermore, energy system interdependencies mean that system costs cannot be definitively allocated to individual technologies.

In some regions of the world, onshore wind and solar PV technologies exhibit lower social costs than competing technologies

Bearing the above-mentioned uncertainties and limitations of universally-valid assertions in mind, the analysis in this thesis suggests that at least in Europe and the USA and when assuming medium estimates for the social costs of carbon, the "new" renewable technologies of onshore wind and, in the USA, solar PV are more competitive than fossil fuel technologies in terms of the total social costs. Furthermore, in the USA, newly-built onshore wind and solar PV plants at typical sites exhibit not only lower quantifiable social costs than fossil fuel technologies, but also similar costs to nuclear power as a competing low-carbon technology, even if the higher investment risks of nuclear power and the risks associated with radionuclide release are ignored. In Europe, this is currently true for onshore wind plants at favourable sites.[10]

Changes in consumer preferences may contribute to limiting electricity supply costs in the future

While the work conducted as part of this thesis focused primarily on the supply side, the potential for reducing the costs of electricity supply by lowering demand through behavioural change was also discussed in a conceptual manner. It was argued that there is the potential for behavioural change to reduce electricity supply costs, but based on microeconomic reasoning such cost savings may be offset by welfare losses if behavioural change is forced upon consumers and is not the consequence of change in individual preferences. Currently, little research is available on the potential of measures or initiatives from policymakers or non-governmental actors to contribute to changes in individual preferences.

Main findings in relation to Research Question 2:

> **Research Question 2:**
>
> What are the main factors that affect plant-level electricity generation cost changes over time of different technologies and how well are these factors understood?

This research question was answered by an extensive review of the available literature (Samadi 2016). The following three key findings result from the analysis related to this research question.

A number of factors influence plant-level generation costs over time

Ten factors were identified from the available literature as having influenced plant-level electricity generation costs in the past. These ten factors were grouped into four categories: “learning and technological improvements”, “economies of scale”, “changes in input factor prices” and “social and geographical factors”. Table 6 provides an overview of the ten cost-influencing factors identified and the four categories. It also shows how the respective factors have influenced individual electricity generation technologies in the past.

[10] It should be noted that capital costs for solar PV systems, as well as for onshore and offshore wind turbines, have not only fallen rapidly in the past few years but are also widely expected to continue to do so in the future (Creutzig et al. 2017; Fraunhofer ISE 2015; IRENA 2016). Creutzig et al. (2017) have shown that recent and expected future cost declines in solar PV plants mean that the cost-optimal share of solar power in future electricity systems may be considerably higher than previously expected. Particularly in the longer term, however, the relative cost of low-carbon electricity generating technologies will not only depend on the development of plant-level costs, but also on the system costs caused by additional power generation from variable renewable energy sources and the allocation of these costs to individual technologies.

Table 6: Factors found to influence the plant-level costs of electricity generation technologies and their respective past impact on different technologies

	Learning and technological improvements				Economies of scale	
	Deployment-induced learning	RD&D-induced learning	Knowledge spillovers from other technologies	Upsizing	Economies of manuf. scale	Economies of project scale
Wind (on- & offshore)	↓	↓	↓	↓/o	↓	↓
Solar PV	↓	↓	↓	o	↓	↓
CSP	↓	↓	(↓)	(↓)		
Nuclear energy	↓	(↑)	(↓)	o	o	↓
Coal	↓	(↓)		↓/(o)	↓	↓
Natural gas	↓	(↓)	↓		(↓)	

	Changes in input factor prices		Social and geographical factors	
	Changes in material and labour costs	Changes in fuel costs	Regulatory changes	Limits to the availability of suitable sites
Wind (on- & offshore)	↑	o	↑	(↑)
Solar PV	↓/↑	o	(o)	(o)
CSP		o	(o)	(o)
Nuclear energy	↑	(o)	↑	↑
Coal	↑	o	↑	↑
Natural gas		↑	(↑)	

Notes: An arrow pointing downward indicates that there is clear evidence in the literature that a factor has led to cost reductions in the past, while an arrow pointing upward indicates that there is clear evidence that a factor has led to cost increases. Circles imply that the literature has found no effects or only minor effects. Two different signs indicate that a factor has had different effects on a technology's cost depending on the time period, with the dominant effect over the past one to two decades shown on the right-hand side. Brackets are added in cases where the literature is not entirely conclusive and where the author's assessment of the direction of cost changes is, therefore, based on limited empirical evidence in the literature. A blank box indicates that no information, or only insufficient information, is available to assess the effects of that particular factor on the cost of a particular technology.

The significance of individual factors in explaining past cost developments differs from one electricity generation technology to another

It has been shown that different factors have been relevant in explaining cost changes over past decades for different types of electricity generation technologies (see Table 6). While all technologies appear to have benefited from deployment-induced learning – although to different extents – other factors identified have exerted relevant influence on only some, but not all, of the technologies analysed. For example, it appears that solar PV technology has benefited in the past from economies of manufacturing scale, while nuclear power has not. Similarly, regulatory changes were found to have exerted cost-increasing effects on nuclear power and coal-fired power plants (countering learning-induced cost decreases), but not on solar PV.

Uncertainties remain about the relevance of some cost-influencing factors for certain technologies

Although a large number of empirical studies have been conducted in recent decades, improving our understanding of past cost changes of electricity generation technologies, considerable uncertainties remain about the relevance of some potentially important cost-influencing factors, such as research, development and demonstration (RD&D) expenses, economies of manufacturing scale and regulatory changes. The potential impact of RD&D expenses on electricity generation technologies is particularly contentious and difficult to determine. There are a number of reasons for this difficulty, including the lack of comprehensive data on private and government RD&D expenses, multicollinearity with other relevant cost-influencing factors and uncertainty regarding the precise impacts of RD&D expenses on technological improvements.

Main findings in relation to Research Question 3:

> **Research Question 3:**
>
> What relevant types of social costs of electricity generation and what factors affecting plant-level electricity generation costs over time are taken into account in different kinds of energy models?

This research question was answered mainly by conducting and evaluating an online survey among modellers. The survey questions were based on the findings from the research performed to answer Research Questions 1 and 2. The following two key findings result from the analysis related to this research question.

Energy models typically do not take all socially-relevant types of costs of electricity supply into account

The survey results indicate that energy models typically do not take all socially-relevant types of costs of electricity supply into account. In particular, many types of external costs and system costs are often not considered. The survey results further indicate that, to a great extent, the model type used dictates which costs are taken into account. For example, models intending to simulate the behaviour of market actors understandably do not take external (i.e. non-market) costs into account. However, many optimisation models, which aim to describe a socially-optimal evolution of the energy system, also neglect some relevant types of external costs – such as the health costs associated with air pollution, the visual and noise impacts of power plants or the costs associated with large-scale nuclear accidents. These types of costs are particularly uncertain or contentious and are also highly location-specific, which may explain why they are often not considered. Similarly, system costs are difficult to model, as an adequate representation is computationally demanding and requires models to possess high temporal and spatial resolutions.

Most models only account endogenously for a few cost-influencing factors

Regarding the factors found by empirical studies to influence the cost development of electricity generation, the survey results suggest that many of these factors are not endogenously represented in energy models. While most of the surveyed models can consider deployment-induced learning, changes in fuel costs and/or changes in the quality of available sites, other factors are typically not accounted for endogenously. These other factors include RD&D-induced learning, upsizing, economies of manufacturing scale and economies of project scale, which the empirical literature suggests are highly relevant in determining the development of some technologies' electricity generation costs over time. For some of the cost-influencing factors, a correlation between their endogenous representation and model types was observed. For example, global models are better suited to endogenously representing factors known to be shaped globally, such as deployment-induced learning and fossil fuel cost changes. Uncertainties related to the relevance and parameterisation of many of these factors, as well as the computational demands of endogenously representing them in energy models, are likely to be two key reasons why models typically only include an endogenous representation of a few of the relevant factors.[11]

Overview of main findings

Box 1 summarises the main findings of this thesis.

Box 1: Overview of the main findings of this thesis

- Several types of costs are relevant in assessing the social costs of electricity supply.
- The significance of individual types of costs differs from one technology to another.
- There are considerable uncertainties in quantifying some types of costs.
- Some types of costs are highly location and system-specific.
- A universally-valid ranking of generation technologies by costs is not possible.
- In some regions of the world, onshore wind and solar PV technologies exhibit lower social costs than competing technologies.
- Changes in consumer preferences may contribute to limiting electricity supply costs in the future.
- A number of factors influence plant-level generation costs over time.
- The significance of individual factors in explaining past cost developments differs from one electricity generation technology to another.
- Uncertainties remain about the relevance of some cost-influencing factors for certain technologies.
- Energy models typically do not take all socially-relevant types of costs of electricity supply into account.
- Most models only account endogenously for a few cost-influencing factors.

1.5.2. Limitations of this thesis

Before drawing conclusions in Subsection 1.5.3, the key limitations of this thesis will be discussed in this subsection.

The identification and categorisation of relevant types of social costs of electricity supply and the main factors that affect plant-level cost changes over time, as well as the analysis of how energy models treat these types of costs and cost-influencing factors, is based on a comprehensive review of the available literature. This literature, specifically

[11] According to the survey results, about two-thirds of the models endogenously account for only three or less of the factors identified.

the English language, peer-reviewed literature that this study focused on for practical reasons (language) and reasons of quality assurance (use of mainly peer-reviewed literature), has several limitations in respect to its contribution in answering the research questions posed by this thesis:

- The vast majority of the available literature in this field focuses on European countries and/or the USA. A limited number of studies are available for Japan and China, while very few studies are available for other countries, for example countries in Southeast Asia, Africa or South America. Consequently, the findings of this thesis in respect to socially-relevant types of costs and relevant cost-influencing factors apply first and foremost to Europe and the USA. While it is likely that many of the general findings also apply to other countries, the quantification and relative relevance of some types of costs and cost-influencing factors may differ systematically between Europe and the USA and other countries, particularly developing countries. For example, in all countries the quantifiable external costs of fossil fuel generation can be expected to be higher for electricity generation from fossil fuels, while profile costs can be expected to become highly relevant in all regions of the world when electricity generation from wind and/or solar PV reach high shares. On the other hand, current and future profile costs of electricity generation from wind and solar PV in countries in which conventional electricity generation is dominated by highly flexible hydropower dams and in which electricity demand is growing quickly, such as in Brazil, may be much lower than in Europe and the USA, where conventional power generation is dominated by thermal power plants and electricity demand is relatively stable (Hirth 2016; Tveten et al. 2016).
- For a number of potentially relevant external costs of electricity generation, no reliable estimates could be found in the literature. Potential external types of costs whose relevance could not, therefore, be assessed as part of this thesis include those related to energy supply disruption, non-renewable resource extraction, water withdrawal, consumption and contamination and the toxicity of materials used to build/manufacture plants. The effects associated with these potential externalities are complex and in many cases highly location or case-specific. Similarly, no peer-reviewed literature could be identified that attempts to quantify potential technology-specific differences in macro-economic or geopolitical effects. In this thesis, therefore, no attempts have been made to quantify external costs and benefits potentially associated with these effects; for example, regarding consequences on employment or good governance.
- Empirical studies evaluating the past relevance of cost-influencing factors on electricity generation costs face several challenges. These include data limitations, difficulties in operationalising some suspected cost-influencing factors and the multicollinearity of some factors. Consequently, the findings of these studies can be ambiguous and are associated with some uncertainties, for example in relation to the role that RD&D expenses play in shaping cost developments.

With regards to improving our understanding of past cost changes of electricity generation technologies, this thesis focused on *plant-level* costs. This can be regarded as an appropriate prioritisation, as plant-level costs tend to account for the majority of the total social costs of electricity generation (see Article 2) and as past changes in plant-level costs have generally been particularly dynamic. However, system costs and external costs are also relevant in determining the social costs of electricity generation, and changes in some types of external costs (e.g. costs associated with landscape and noise impacts) and system costs (e.g. profile costs) may become more relevant in the future. Therefore, additional research is recommended, particularly in relation to the possible future evolution of profile costs, as detailed in the following subsection.

The main method used in this thesis to gain insights into the treatment of electricity supply costs in energy models was an online survey of energy system modellers. This method allowed for a large number of modellers to be contacted and for responses to be gained for over twenty well-known energy models of different types. Consequently, this allowed for general insights into the treatment of electricity supply costs in currently-used energy models to be gained. However, due to the inherent limitations of a self-administered survey, detailed information on exactly how individual models treat specific types of costs, or how the methodological approaches applied in the models differ from one model to another, could not be obtained through this approach. This issue is revisited in the recommendations for further research in the following subsection.

1.5.3. Conclusions and future research opportunities

This thesis advances our understanding of the current and possible future costs to society of electricity supply. It specifically offers the following insights.

- It provides a comprehensive and up-to-date overview of our current knowledge about the types of costs associated with electricity supply and their respective relevance for individual electricity generation technologies. In this regard, the thesis updates previous studies (Alberici et al. 2014; ISIS 2009; Larsson et al. 2014) based on a comprehensive literature review, with a greater focus than past studies on the detailed analysis of the different types of "system costs" which will become more relevant in the future.
- It provides for the first time a comprehensive and technology-specific overview of the factors that have influenced plant-level electricity generation costs in the past. It also discusses how this knowledge about these factors may be used to improve our understanding of possible future cost changes.
- It offers a general overview of how electricity supply costs are taken into account in different types of energy models frequently used by researchers to describe possible future electricity and energy system pathways.

A key conclusion from this thesis is the need for researchers and policymakers to be aware that a number of different types of costs are relevant in determining the social costs of electricity supply. The relevant types of costs include not only plant-level costs, but also system costs and external costs. The findings of this thesis, therefore, support and substantiate the assertions made by a number of authors (e.g. Heuberger et al. 2017; Ueckerdt et al. 2013) that it is problematic to rely on traditional LCOE analysis to derive conclusive judgements about different electricity generation technologies. Such reliance on LCOE data is becoming increasingly problematic because the relevance of system costs tends to increase in electricity systems around the world as the penetration of electricity generation from variable energy sources increases.

As the relevance of the different types of costs varies between different types of electricity generation technologies, any attempt at cost ranking will be affected by the types of costs which are taken into consideration in such a comparison. For example, fossil fuel technologies tend to benefit in such rankings when external costs (such as those related to GHG emissions and local pollutants) are neglected, while wind and solar PV technologies tend to benefit when system costs (such as profile costs) are neglected.

Therefore, when making such cost comparisons, researchers should ideally strive to include all relevant and quantifiable types of costs.[12] Researchers should clearly and transparently communicate whether or not certain types of socially-relevant costs are included in their cost comparisons. In addition, the considerable uncertainties associated with the quantification of many types of costs, especially external types of costs, and the related limitations of such cost comparisons should also be emphasised.

Likewise, when researchers aim to provide model-based advice to policymakers and societies about optimal or cost-minimising future developments of the electricity or energy system, all relevant types of social costs should ideally be taken into account by the models used. However, as the analysis in Chapter 6 suggests, even optimisation models typically applied for that purpose omit several relevant types of social costs. While there may be good reasons for omitting some types of costs, it is nonetheless recommended that model developers check carefully whether model amendments can be made to further improve the scope of social costs that are taken into account. As gaps are likely to remain even in the most comprehensive models (due inter alia to computational limitations and considerable uncertainties in the parameterisation of some types of costs), missing cost types should be transparently communicated when model results are presented.

Another conclusion from the findings of this thesis is that it is likely to remain challenging to derive meaningful cost ranges for some types of social costs. This is the case when the quantification of costs involves making value judgements that are difficult or impossible to objectify. Examples include the difficulties in objectively valuing the risks associated with nuclear power or CO_2 storage for future generations, or the problem of how to value biodiversity losses. Modelling exercises can find ways to deal with types of costs that are difficult to quantify, as past studies have shown. For example, energy system modelling exercises currently typically adopt constraints on future temperature increases or define associated GHG emission limits (often making use of nationally or internationally set policy targets) instead of having to define the specific costs of CO_2 equivalent emissions. Another example are the studies that develop several scenarios with varying constraints for the future deployment of contentious technologies such as nuclear power or carbon capture and storage (CCS). The specific characteristics of – and differences between – these scenarios can then support societies and policymakers in deciding on the level of risk deemed acceptable.

In addition, methods that do not rely on the monetisation of these types of costs may offer additional support for societies aiming to understand how their future electricity supply should be configured. Multiple-criteria decision analysis (MCDA) is an example of a promising method when not all types of costs can be monetised, or when monetisation is highly uncertain (Kahraman and Kaya 2010; Mirasgedis and Diakoulaki 1997; Troldborg et al. 2014).

On the other hand, for some types of socially-relevant costs, further improvements in our understanding of their actual magnitude are possible through further research. Two types of costs for which this holds true are profile costs and the costs associated with landscape and noise impacts of individual technologies such as onshore wind power plants. For profile costs, a better understanding of current cost ranges depending on electricity system characteristics, shares of electricity generation from variable renewable energy sources and the specific design of a respective power plant would be

[12] The suggestion of a "system LCOE" approach is an example of a step in this direction (Ueckerdt et al. 2013).

enlightening. As profile costs are likely to become more relevant in the future, studies evaluating their potential future evolution are of particular interest. Such studies should take possible future changes in terms of technological advances (including in storage technologies), electricity demand flexibility and grid extensions into account. While in recent years, several studies have tried to describe future electricity and energy system characteristics that allow for a low-cost or cost optimal expansion of high shares of renewables (e.g. Brouwer et al. 2016; Jacobson et al. 2015; Palzer and Henning 2014; Pfenninger and Keirstead 2015), more studies of this nature – including studies for different countries and based on varying assumptions about future developments – would be useful. Specifically, it would be helpful for policymakers to gain information on how profile costs can be minimised in the future, through studies such as the one by Mills and Wiser (2015).

Although this thesis has focused mainly on the supply side of the electricity system, future research opportunities have also become apparent in relation to the demand side. For example, future research could support steps towards a future low-carbon energy system by further examining the future potential of demand-side flexibility, storage technologies and grid expansion by cost-effectively integrating large shares of variable renewable electricity generation. In terms of an improved understanding of our potential to limit future energy demand, researchers could examine if and in what manner changes in consumer preferences towards lower energy consumption can be induced by government measures or societal initiatives.

Regarding the costs associated with landscape and noise impacts, one possible approach for further research could be to conduct studies that use different methods – including both revealed and stated preference methods – for the same study area. Such an approach could help to better understand the differences observed in results between studies that use different methods. Studies could also attempt to confirm or contradict the limited evidence available to date which suggests that the costs associated with landscape and noise impacts for onshore wind power plants are higher in Europe than in the USA. If confirmed, the cause of these differences could be examined. Furthermore, it would be valuable for studies to evaluate how these costs can be minimised and whether young people who grow up accustomed to seeing a plethora of onshore wind power plants and are accepting of this technology can be expected to remain so as they grow older.

From the analysis of factors determining past cost changes of electricity generation technologies, it can be concluded that it is important for researchers to remember that a variety of factors influence electricity supply costs. Understanding the varying relevance of different cost-influencing factors for past cost changes of specific electricity generation technologies is helpful in projecting future cost developments for these – or even other – technologies. The likely or possible future influence of all potentially relevant factors should be considered when making such projections, as opposed to looking at only *one* of these factors, as for example in the case of projections based solely on single-value one-factor experience curves. Although making technology cost projections for years or even decades into the future is likely to remain challenging, taking all known and relevant cost-influencing factors into account should lead to a better understanding of the uncertainties involved in future cost developments of a technology, allowing for the derivation of plausible future cost ranges.

As considerable uncertainties remain about the precise influence of various factors on past cost developments of different electricity generation technologies, more research into this area would also be useful. While additional and more comprehensive quantitative studies may help to advance our understanding in this field, qualitative research focusing on individual technologies and the channels through which specific technological improvements arose in the past might be able to deliver important complementary insights. One research question that future quantitative and qualitative research in this area could focus on is the question of interrelationships between the individual factors identified in this thesis, for example the possibility that increased deployment leads to higher RD&D expenses and to greater opportunities for technology upsizing.

While for various reasons it may not be possible for energy models to include an endogenous representation of *all* or even most of the identified cost-influencing factors, model developers should examine for each of these factors whether it is possible and reasonable to include an appropriate endogenous representation in their respective models. At the same time, model users should be aware of any limitations in the endogenous representation of long-term changes in electricity generation costs. Model users can mitigate such limitations by reflecting key cost-influencing factors exogenously. They may do so for example by deriving a range of plausible future one-factor experience curves for individual technologies, with the ranges reflecting uncertainties about the future relevance of several cost-influencing factors. These ranges could be used in multiple or stochastic model runs to evaluate different outcomes (Bosetti et al. 2015; Chen and Ma 2014; Shittu 2014). When presenting model results, model users should be transparent in making clear what types of cost dynamics are/are not taken into account by the model and in what ways.

Future research may also focus on gaining a deeper understanding of the different ways in which costs dynamics are represented in different types of energy models. The survey conducted as part of this thesis offers a general overview of the treatment of cost dynamics in energy models and of apparent differences between different types of models, but expert interviews with modellers and/or more model comparisons could certainly contribute to a much deeper understanding of the way cost dynamics are taken into account in energy models. Such an improved understanding would enable a better interpretation of differences in model results, e.g. in relation to optimal system development under certain GHG emission constraints, and could offer opportunities for model developers to improve their respective models based on experiences from other models.

Finally, a more systematic evaluation than was possible within the scope of this thesis of how general technology characteristics determine the factors that are most relevant in influencing cost developments is recommended. Insights into this area may make it easier to make cost projections for new and emerging technologies; not only for electricity generation technologies but also for others, such as storage technologies.

Box 2 summarises the suggestions for future research derived from this thesis.

Box 2: Overview of the suggestions for future research derived from this thesis

- Researchers should transparently communicate uncertainties and types of costs that have been omitted when presenting the results of cost-optimising energy model runs.
- Researchers should check whether it is possible to develop several scenarios with varying constraints for the future deployment of contentious technologies.
- Methods that do not rely on the monetisation of different types of costs should complement cost-optimisation studies.
- Research should aim for a better understanding of current and future profile costs and, specifically, of how these costs can be minimised in the future.
- Potential characteristics of future energy systems able to cost-effectively integrate large shares of variable renewable electricity generation should be studied further.
- The extent to which government or society can bring about changes in consumer preferences that result in lower energy consumption, and how this can be achieved, should be studied.
- Different methods could be used within individual studies to further examine the costs associated with landscape and noise impacts of different technologies.
- Studies could evaluate how landscape and noise impacts of different technologies can be minimised.
- The likely or possible future influence of all potentially relevant factors should be considered when making cost projections.
- Qualitative studies focusing on the channels through which specific technological improvements arose in the past can complement quantitative research.
- The interrelationships between individual factors influencing generation costs could be investigated more closely by quantitative and qualitative studies.
- Model developers should examine whether it is possible to improve the endogenous representation of cost changes in their respective models.
- Model users can mitigate model limitations by reflecting key cost-influencing factors exogenously.
- Future research could focus on gaining a deeper understanding of the different ways in which costs dynamics are represented in different types of models.
- A systematic evaluation of how the general characteristics of a technology determine the factors that are most relevant in influencing cost developments is recommended.

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2. Sufficiency in Energy Scenario Studies: Taking the Potential Benefits of Lifestyle Changes into Account

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Sufficiency in energy scenario studies: Taking the potential benefits of lifestyle changes into account

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ABSTRACT

In recent years, a number of energy scenario studies which aim to advise policy makers on appropriate energy policy measures have been developed. These studies highlight changes required to achieve a future energy system that is in line with public policy goals such as reduced greenhouse gas emissions and an affordable energy supply. We argue that behavioural changes towards energy-sufficient lifestyles have considerable potential to contribute to public policy goals and may even be indispensable for achieving some of these goals. This potential should, therefore, be reflected in scenario studies aiming to provide comprehensive advice to policy makers. We analyse the role that energy-sufficient lifestyles play in prominent recent global energy scenario studies and find that these studies largely ignore the potential of possible behavioural changes towards energy-sufficient lifestyles. We also describe how such changes have been considered in several other scenario studies, in order to derive recommendations for the future development of global energy scenarios. We conclude that the inclusion of lifestyle changes in energy scenarios is both possible and useful. Based on our findings, we present some general advice for energy scenario developers on how to better integrate sufficiency into future energy scenario studies in a quantitative manner.

1. Introduction

In recent years, a number of global, regional and country-level scenario studies which aim to advise policy makers on appropriate energy policy measures have been developed (e.g. European Commission, 2011; IEA, 2015a, 2015b; Jeffries et al., 2011; Nagl et al., 2011; Teske et al., 2015). These studies highlight the changes that are needed to achieve a future energy system in line with public policy goals such as reduced greenhouse gas (GHG) emissions, reduced import dependency and/or an affordable and reliable energy supply. Ideally, such scenario studies should highlight the full range of credible options for achieving these public policy goals available to policy makers and societies, who should then choose the options they deem to be preferable or the most promising (Edenhofer and Kowarsch, 2015).

Lifestyles in which users consume less goods and services, have the potential to make a considerable contribution to achieving public policy goals associated with the energy system (Faber et al., 2012; Hallström et al., 2015; Stehfest et al., 2009; van Sluisveld et al., 2016). Consequently, it might be expected that available scenario studies investigate to what extent and under what conditions energy-sufficient lifestyles can contribute to these goals. This article analyses whether this potential is actually discussed in prominent global energy scenario studies published by the International Energy Agency (IEA) and others. We contrast our findings from these studies with selected energy and emission scenario studies which explicitly include the role played by energy-sufficient lifestyles in their respective scenarios. This article aims to contribute to the theory and practice of energy scenario development by outlining the advantages of including future lifestyle changes in scenarios in a manner that is conducive to providing good energy policy advice.

In the next section (Section 2), we explain how we define the term "sufficiency" for the purpose of this article. We do so by differentiating sufficiency from efficiency and consistency and describing three types of sufficiency. In Section 3, we discuss key characteristics of energy scenarios and demonstrate why it is important for energy scenario studies to include scenarios highlighting the potential of future changes towards more sustainable lifestyles. In Section 4, we analyse to what extent prominent global energy scenario studies published recently by the IEA and Greenpeace et al. take the potential of sufficiency into account. We contrast the findings of this analysis by describing a number of scenario studies that have assumed considerable future changes towards energy-sufficient lifestyles. Finally, in Section 5, we draw upon

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the findings and arguments presented in the article to derive some general advice for energy scenario developers and the broader research community on how to better integrate sufficiency into future energy scenario studies in a quantitative manner.

2. Defining sufficiency

Depending on the scope of an analysis and the question to be answered, different aspects and boundaries are highlighted in the definition of sufficiency. The scientific discussion on sufficiency as a strategy was, among others, coined by Wolfgang Sachs. He developed the idea that the two strategies of efficiency and sufficiency should be combined. "While efficiency is about doing things right, sufficiency is about doing the right things" (Sachs, 1999).

Two authors who place the ethical dimension of sufficiency at the centre of their research are Princen (2003) and Muller (2009). Both point out that consumption limits should be defined not only on an individual level, but also on a societal one. Princen (2003) argues that "there can be enough and there can be too much." Defining limits of resource- and energy-intensive behaviour is one of the most difficult and debated aspects of sufficiency. Even though there might be a broad consensus in the literature of the existence of certain thresholds, determining these thresholds is highly contested. Muller (2009) holds the view that energy sufficiency is a duty of all liberal societies to ensure social justice and to avoid external impacts from energy consumption which are harmful to other people.

There is a consensus among supporters of sufficiency that it can result in wellbeing and satisfaction. "Sustainable sufficiency is defined as achieving economic objectives consistent with the principle of right livelihood, ensuring the preservation of the natural environment and the welfare of each individual and society at large. […] The concept of sustainable sufficiency focuses attention on unsustainable consumption patterns within a society obsessed with maximizing short term economic growth whilst ignoring the reality of limits resulting from a finite supply of natural resources" (Lamberton, 2005). This quote indicates that the concept of sufficiency is closely connected to the degrowth paradigm.[1] If widely adopted, sufficiency can be expected to affect economic growth, as it calls for a reduction in consumption levels. There is a debate among researchers whether or not economic activity in affluent societies needs to be reduced in the future in order for human activities to remain within planetary boundaries (Bergh and Kallis, 2012; Jakob and Edenhofer, 2015; Loske, 2015).

For the purpose of this article, sufficiency is especially relevant in regard to its potential to reduce *energy* consumption. It can be seen as an option to reduce GHG emissions from the energy sector. In the following, we develop a specific definition of sufficiency, bearing in mind how sufficiency can be relevant in the development of energy scenarios. In energy scenarios, political choices for achieving sustainability goals are among the main drivers of the energy system. At the highest level of aggregation, these options can be divided into three pillars: efficiency, consistency and sufficiency. Based on a literature review, these are the three main categories of options for achieving sustainability goals (e.g. Huber, 2000; Linz and Scherhorn, 2011; Mundaca, 2010).

Therefore, sufficiency can best be defined by contrasting it with efficiency and consistency. Efficiency is an option in which the input-output relation is improved (*better*). Fewer inputs of material or energy are needed per service unit, or more services are produced from the same amount of material or energy. Consistency aims at fundamental changes in production and consumption by substituting non-renewable resources with renewable resources (*different from today*). A prominent example is the use of renewable energy sources instead of fossil fuels. The option of sufficiency is linked to the level of demand for goods and services – in this context specifically to the level of demand for energy-intensive goods and services. This demand should be limited to a level which still allows for a "good life". In industrialised countries, fulfilling this requirement would certainly lead to a reduction in demand for such goods and services (*less/enough*) (Muller, 2009).

Regarding the implementation of behavioural changes towards energy-sufficient lifestyles, two general leverage points can be identified. On the one hand, there is the purchase, rental and investment phase (e.g. the purchase of a refrigerator, an apartment or a car). In this phase, sufficiency policies target a reduction in the equipment rate and size, or they promote the shared use of goods ("sharing economy", as opposed to individual ownership). On the other hand, reductions can be made in the usage phase; for example by aiming to reduce journey frequency or length, or by moderating room temperature choice in winter.

In terms of energy scenarios, sufficiency can be categorised by the drivers that foster its implementation. Sufficiency in the context of energy-intensive goods and services can be achieved by:

A) Modification of individual preferences
A change in the preference structure of individuals, leading to lower levels of consumption or more sustainable consumption patterns, constitutes one type of sufficiency. In this type of sufficiency, changes in consumption are made voluntarily by individuals and are not associated with any kind of sacrifice. The associated preference changes can be the result of cultural changes or changing societal ideas about what constitutes wellbeing and a "good life" (Schneidewind and Zahrnt, 2014). These changes may be triggered by a pioneer group causing others to follow (Linz, 2012). Policy can try to induce preference changes, e.g. through information campaigns or educational initiatives (Jackson, 2005). An example of the modification of individual preferences is a change in vacation patterns, when destinations that can be reached by bicycle or public transport are preferred over destinations that can only be reached by plane.

B) Modification of relative prices
Consumer demand for goods and services can also be altered by external incentives without the premise of changes in preference structures. Policies can achieve desired changes in the demand for goods and services by changing their relative prices.[2] An example is an increase in taxation levels for energy or emission-intensive goods and services. It should be noted that political measures taken to influence the relative costs of goods and services should ideally result in market prices that mirror their actual societal costs, as only then do markets lead to a socially optimal allocation of goods and services, according to economic theory (Dahlman, 1979). In other words, any political modification of relative prices should be limited to the internalisation of external effects, such as the health costs associated with air pollution or the climate change damages caused by burning fossil fuels.

C) Politically imposed bans or limits
It is also possible to bring about a reduction in the demand for energy-intensive goods and services by banning or limiting their sale or use. From a microeconomic point of view, such political measures lead to "forced sufficiency" and have cost impacts by cutting off certain options within consumers' individual preference structures.[3] This third type of sufficiency is, therefore,

[1] Degrowth can be defined as "the intentional limiting and downscaling of the economy to make it consistent with biophysical boundaries", (Bergh and Kallis, 2012).

[2] Another way for policy makers to reduce the demand for an environmentally harmful product without restricting its sale is to make an alternative and less environmentally harmful product more attractive. For example, public transport could be improved by increasing its comfort level, its frequency and/or its reliability, ideally leading to a reduction in car use. We consider such changes in goods or services to be a special case within our sufficiency type B.

[3] However, it may be justifiable to challenge the typical assumption in economic theory that consumer preferences are formed in a sovereign way and that forced changes necessarily lead to reductions in welfare (e.g. Norton et al., 1998; Penz, 1986; Schubert and Chai, 2012). Furthermore, looking at society as a whole, orders and restrictions may result in positive net effects if they lead to reductions in adverse ecological impacts and if the saved resources are used, for example, to alleviate poverty.

structurally different from types A and B discussed above and, in narrow definitions of the term, is not considered to constitute sufficiency. An example of this type of sufficiency is the ban of the use of private cars in city centers.

Fig. 1a to c illustrates the microeconomic differences between these three types of sufficiency. For simplicity, each figure assumes that consumers choose between only two products: one is environmentally harmful while the other is environmentally benign. It should be noted that the environmentally benign option does not necessarily need to be a type of consumer product in the traditional sense; it could, for example, be a walk in the park or another form of (non-material) activity. Consumers are restricted in their demand for these two products by their individual budgets and/or time constraints (indicated by the budget line b). Their preferences are depicted by the so-called indifference curves I. Each indifference curve represents those product combinations which lead to the same utility for a consumer.

3. The need for energy scenarios to consider sufficiency

Scenario building is a method for anticipating possible future developments. Scenarios represent causal relationships between diverse input parameters and describe, as output, possible futures within a vast range of plausible future development trajectories. As policy is essentially about choosing between different policy options which result in different future outcomes, policy makers need to be informed about the likely nature of these outcomes. The more complex the system is that is addressed by policy makers and the more far-reaching their decisions are, the more knowledge they need about the likely outcomes of their decisions. The scenario method offers a way to analyse and compare the future consequences of different political decisions in a consistent and transparent manner. The method is frequently used in the energy policy domain, as this domain is characterised by long planning horizons (e.g. in regard to power plants and energy infrastructure) and complex technological, economic and social interactions. The scenario method is therefore of special relevance for providing advice to energy policy makers (Nielsen and Karlsson, 2007).

Scenario developers need to define external elements, i.e. elements which they assume the scenario actors either cannot modify or do not wish to modify. These elements, once specified (and possibly quantified), can be referred to as a scenario's boundary conditions. Embedding the interactions of a scenario's internal elements into a wider environment (the boundary conditions) is a crucial characteristic of scenarios (Hamrin et al., 2007; Kahn and Wiener, 1967; Nielsen and Karlsson, 2007; Opaschowski, 2009; Reibnitz, 1987). Alternative human behavioural options are represented in scenarios by varying the parameters of their internal elements, allowing for an analysis of the interrelationships between internal and external elements. This concept demonstrates two different explanations of the unpredictability of the future:

a) The inability to predict the future development of factors that are within the control of human beings, as the precise choices that human beings will make cannot be anticipated[4]
b) The uncertainty of the status or evolution of the factors that human beings either cannot control or do not wish to control (i.e. uncertainty about the boundary conditions)

Consequently, the combination of these two types of uncertainty leads to the unpredictability of the future. In scenario studies, the boundary conditions are usually described in so-called *storylines*. The distinction between factors that are within the control of human beings on the one hand and boundary conditions on the other is important

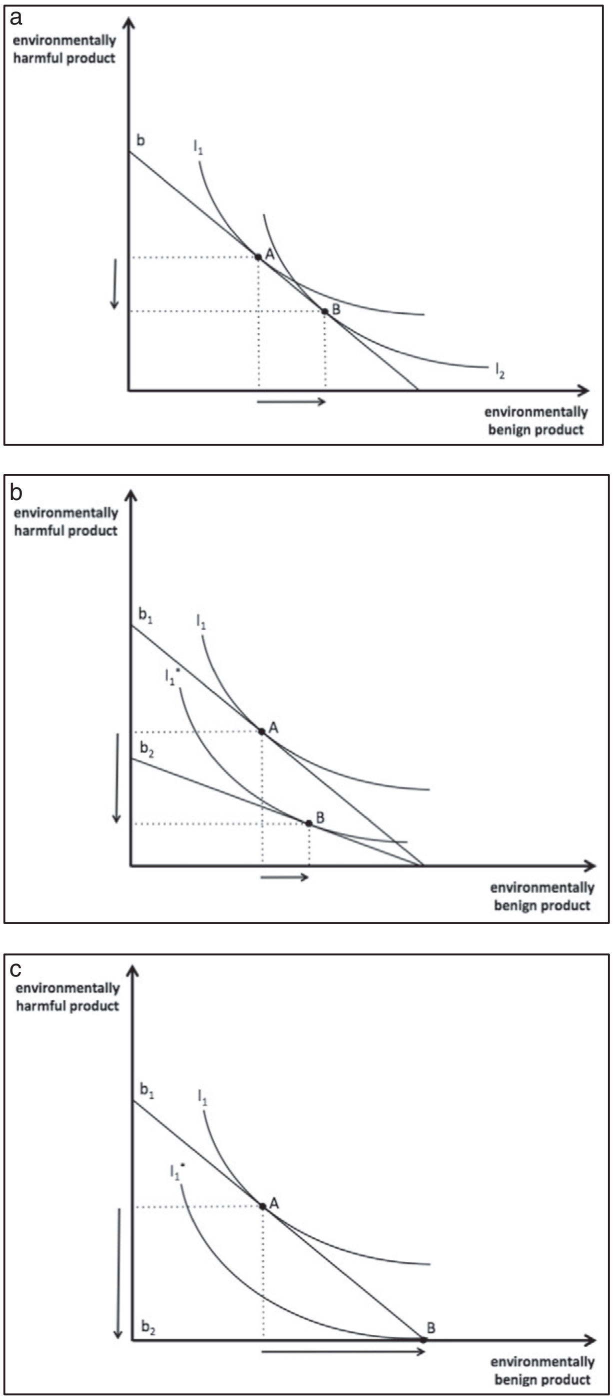

Fig. 1. Illustrations of our three types of sufficiency. a: In sufficiency type A, the location of the indifference curve changes from I_1 to I_2 as a result of changing preferences in favour of the environmentally benign product. This change in preferences leads to a reduction in the demand for the environmentally harmful product and an increase in the consumption of the alternative product, even though the relative prices of both products remain unchanged. b: In sufficiency type B, the environmentally harmful product becomes more expensive, for example due to higher taxation. Consumers can now afford less of this product, which is reflected by the shift in the budget line from b_1 to b_2. As a consequence of the change in relative prices, consumer demand for the environmentally harmful product reduces, even though consumer preferences have not changed. Consumers fall to the lower indifference curve I_1^* because they can no longer afford the combination of products on the indifference curve I_1. c: Finally, in sufficiency type C, the government prohibits the sale of the environmentally harmful product, resulting in the new budget curve b_2 running on the x-axis. Clearly, in this case, the demand for the environmentally harmful product is reduced to zero (assuming the government is able to fully enforce the ban), while demand for the alternative product increases.

[4] The term "human being" here refers to individuals as well as to the collective (i.e. politics).

when considering how to integrate sufficiency into scenario analysis. This is due to the fact that it leads to the question of whether sufficiency should be introduced in scenarios through the storyline or through the specific actions and measures of scenario actors such as policy makers or societal groups.

While it is obvious that individuals and societies have significant choice about the type and volume of goods and services that they consume, in most cases scenario developers treat consumption patterns as an external element. If sufficiency is taken into account at all in a study's scenarios, it is usually assumed to simply emerge – with no detailed discussion on how the accompanying lifestyle changes are initiated (see Section 4). Fig. 2 depicts schematically a number of elements that influence energy system development and how these are typically classified within energy scenarios. Some elements clearly have to be treated as external (e.g. fossil fuel resources), while others clearly have to be treated as internal (e.g. taxation rates for different energy sources). Additionally, there are a number of elements for which classification is less clear and these include sufficiency or consumption patterns.

Scenario developers intending to integrate sufficiency into their scenarios need to decide whether to treat sufficiency as an internal or an external element. We argue that it is preferable to treat sufficiency as an internal element, i.e. a human behavioural option. Only by treating sufficiency in this way can scenarios illustrate which political measures or social dynamics need to be implemented or initiated in order to induce energy-sufficient lifestyles. Treating sufficiency as an external element that may simply emerge in the future has a key disadvantage: it may lead the readers of the scenarios, including policy makers, to believe that no measures need to be taken to promote energy-sufficient lifestyles.

Regarding energy scenarios, we see a particular need for these to take into account the possibility of a future with lifestyles that are based on sufficiency. Over the past two decades, there has been growing concern among policy makers around the globe about the need to significantly reduce energy-related CO_2 emissions in order to prevent the worst possible consequences of global warming. National, regional and global energy scenarios have, therefore, increasingly focused on illustrating how significant reductions in these emissions can be achieved. Good policy advice should highlight all the possible options for achieving political goals and leave it to political and societal debate to choose the preferred options (Edenhofer and Kowarsch, 2015). We argue that sufficiency is an important option for achieving GHG emission reductions and should, therefore, be reflected in energy scenario studies. However, as the following section (Section 4) will show, today's prominent global energy scenario studies largely neglect the potential of sufficiency.

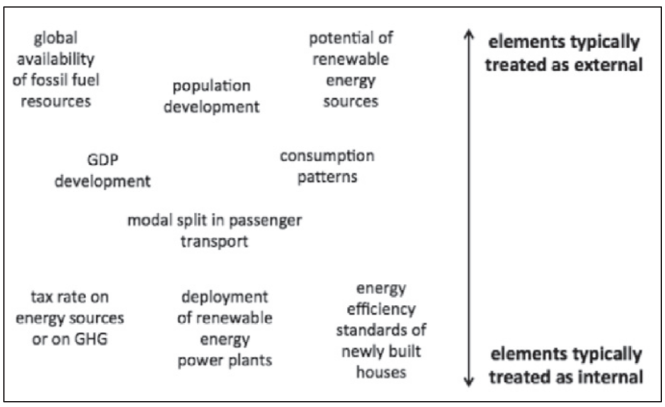

Fig. 2. Schematic illustration of the differentiation between internal and external elements in the energy scenario literature.

Instead, these studies typically illustrate that ambitious CO_2 mitigation is feasible by means of technological solutions requiring only minor lifestyle changes (or no changes at all), despite the assumption of further economic growth in all regions of the world. We argue that a detailed look at the results and assumptions of the scenarios calls this view into question. Specifically, we point out the following four aspects that we believe indicate the significant risk of relying solely on technology to achieve the desired major reductions in energy-related CO_2 emissions:

- Uncertainty about whether efficiency improvements can actually be achieved
  All mitigation scenarios assume much greater improvements in energy efficiency in the future than in the past. While in principle such improvements are technologically feasible, it is unclear whether society will actually be able to achieve these potential efficiency improvements and whether all the cultural, political and economic barriers to greater efficiency can really be overcome. Furthermore, it can be argued that energy scenarios tend to overestimate the overall impact of efficiency measures on energy reduction by neglecting possible rebound effects.[5]
- Uncertainty about whether the supply side can be transformed as quickly as envisioned
  On the supply side, the sustained introduction of new low-carbon energy technologies would be required on a massive global scale. For example, in the IEA's 2DS scenario (IEA, 2015b), 21 GW of new nuclear power plants are built every year on average in the period from 2026 to 2050, while in the recent past (2008–2012) there was an annual increase of less than 3 GW. Likewise, new Concentrated Solar Power (CSP) plants in the scenario are assumed to be installed at an annual rate of 27 GW between 2026 and 2050, while annual installation in the recent past was less than 0.5 GW. While there may be no actual technological barrier to increasing the use of each technology on the scale envisioned in the scenarios, it is likely be a considerable challenge from a system perspective to achieve the proposed increase and parallel implementation of *all* the different technologies. This challenge is further complicated by the fact that, simultaneously, the energy system's infrastructure needs to be adjusted in order to ensure a stable supply of energy.
- **Mass implementation of low-carbon technologies may violate non-climate related sustainability criteria**
  Relying heavily on supply side low-carbon technologies risks neglecting sustainability criteria other than CO_2 mitigation. For example, the use of Carbon Capture and Storage (CCS) in combination with either fossil fuels or bioenergy is associated with a number of negative effects on the environment and on human health, caused among other things by airborne emissions (Corsten et al., 2013; Siirila et al., 2012). Nuclear power, on the other hand, continues to provoke debate regarding long-term waste disposal, its role in the proliferation of nuclear weapons and the risks associated with potential large-scale accidents or terrorist attacks (Ahearne, 2011). Even the use of renewable energy technologies can lead to undesired impacts e.g. on biodiversity or resource requirements (Kleijn et al., 2011; Viebahn et al., 2015) if the implementation of these technologies is not carefully managed. The level of risk associated with neglecting social and/or ecological needs obviously increases relative to the scale of the implementation of these low-carbon technologies.
- **The broad societal support required for successful transformation cannot be guaranteed**
  Scenario studies show that achieving ambitious CO_2 mitigation targets will require higher energy system investments than in a business-as-

[5] The rebound effect describes the phenomenon in which improvements in energy efficiency can lead to an increase in demand for goods or services. This increased demand leads to additional energy consumption which can (partially) negate the original energy savings.

usual scenario (IEA, 2015b; Teske et al., 2015). During the initial phase of the transformation, these higher investments will not be offset by lower fuel expenses. Accepting higher costs is likely to require broad societal support for the transformation of the energy system. From today's perspective it is unclear whether this support will be adequate, especially given that stakeholders with vested interests are likely to use these upfront costs to try to persuade the public to demand a slow-down of the transformation process.

Similar arguments against focusing solely on technological solutions in climate change mitigation are also put forward by other authors, including Franceschini and Pansera (2015), van den Bergh (2013) and van Sluisveld et al. (2016).

The doubts raised above about the prospects of attaining mitigation pathways as described in published decarbonisation scenarios should not be misunderstood. We wholly support efforts to significantly increase energy efficiency and to rapidly grow the share of renewable energy sources in energy supply. However, simply hoping for the flawless development of energy efficiency and energy supply decarbonisation to materialise is, in our view, an over-optimistic assumption given the highly complex nature of society and its energy system – and the considerable risks associated with unmitigated or inadequately mitigated climate change.

4. Sufficiency in global energy and emission scenarios – a literature review

In this section we consider the role that sufficiency plays in the literature on global energy and emission scenarios. The first part of the section reviews three recently released global energy scenario studies that are frequently referred to in scientific and political discussions on the future of the global energy system. We find that these studies' scenarios do not take sufficiency into account or do so only marginally. In the second part of this section we contrast this finding by discussing selected global energy and emission scenario studies that include scenarios which assume changes towards energy-sufficient lifestyles. These latter studies are not as frequently cited in global energy and energy policy discussions. Most of these studies also do not describe the global energy system in detail, but instead either focus on certain types of energy consumption (e.g. aviation) or investigate more generally all relevant human-induced changes to the global environment. This two-step approach aims to highlight that on the one hand much of the prominent literature on global energy scenarios lacks consideration of sufficiency, while on the other hand energy and emission scenario studies released in the past have shown that it is possible and useful to integrate sufficiency into energy and emission scenarios.

4.1. Examples of prominent recent global energy scenario studies

We initially consider three global energy scenario studies from two different organisations to evaluate the role that sufficiency plays in some recently released, prominent global energy scenario studies (IEA, 2015a, 2015b; Teske et al., 2015). Two of the studies were published by the International Energy Agency (IEA) and the other one was published by Greenpeace and two renewable energy industry associations. Scenarios from these three studies were selected for this review for the following reasons:

- All three studies include detailed descriptions of their scenarios, including information about energy service demand.
- All three studies include ambitious mitigation scenarios (see Table 1), meaning that potential emission reductions through lifestyle changes would be especially valuable.
- The two IEA studies are part of two prominent series of scenario studies. Results from these series have been cited frequently by researchers (e.g. Haley, 2012; Islam et al., 2013; van der Zwaan et al., 2016) and policy makers (European Commission, 2011; G7 Energy Ministerial Meeting, 2016).
- The study commissioned by Greenpeace, GWEC and SolarPower Europe is also part of a series of publications that has been cited by many researchers, including the IPCC (e.g. Esteban and Leary, 2012; Fischedick et al., 2011; Haley, 2012).

The following table provides an overview of the three scenario studies analysed and the energy system CO_2 emission reductions achieved in each study's most ambitious mitigation scenario.[6]

Our analysis established that none of the mitigation scenarios in these three global energy scenario studies explicitly assume that people will significantly modify their consumption patterns over the next decades compared to a business-as-usual (BAU) scenario.[7] In all the studies' mitigation scenarios, behavioural changes are only assumed to take place in the transport sector compared to a BAU scenario. All three studies explicitly assume in their most ambitious mitigation scenarios that there will be a shift towards more energy efficient modes of transportation compared to BAU (higher shares of travel by rail, bus, cycling and/or walking and smaller shares of travel by car and/or plane). As changing the mode of transport requires users to make significant behavioural changes, the modal shift towards less energy and carbon-intensive modes is here considered to be a mitigation option that can be classed under sufficiency.[8]

In addition to this modal shift, two of the three studies (with IEA, 2015a being the exception) assume in their most ambitious mitigations scenarios that transportation volumes are reduced to some extent in comparison to the respective BAU scenarios. In its most ambitious mitigation scenario the study by Greenpeace et al. (Teske et al., 2015) also explicitly assumes the future purchase of smaller cars than in its BAU scenario. Similarly, in their policy recommendations, the authors of the Energy Technology Perspectives 2015 study (IEA, 2015b) suggest that one way to make passenger road transport more efficient is to switch "towards smaller and/or less powerful vehicles".

This indicates that in the transport sector some (limited) form of sufficiency is taken into account in all of the scenario studies analysed. The limited information provided by the studies indicates that this is mostly assumed to be a collective form of sufficiency (our "type B" sufficiency); for example, "massive policy intervention" (Teske et al., 2015) and "travel demand management" (IEA, 2015b) are mentioned as prerequisites for achieving modal shift in the transport sector. The study by Greenpeace et al. (Teske et al., 2015) states that in its mitigation scenarios "transport pathways do not rely on the very few idealists who always do 'the right thing'. Among the policy measures proposed by the study to reduce transport demand are "charge and tax policies that increase transport costs for individual transport". Furthermore, according to the authors, cities particularly need to change "so that making the 'right choice' will be also the 'easiest choice'".

However, at the same time, the authors of the Greenpeace et al. study (Teske et al., 2015) appear to suggest that some changes in

[6] However, in the BAU scenarios of the analysed studies, consumptions patterns are expected to change in the future, as average income continues to increase. As in the past, per capita demand for many products and services is expected to increase, including for energy-intensive amenities like air travel, residential floor area or air conditioning.

[7] We recognise that a case can be made to classify modal shift as efficiency rather than sufficiency. After all, the overall volume of passenger transport does not change in the case of modal shift, but merely becomes less energy-intensive. However, our view emphasises the fact that people typically not only wish to travel from one point to another but also wish to do so within a short time or with a certain level of comfort and flexibility. Taking these additional demands into account, it becomes clear that switching, for example, from car to bus or from airplane to high-speed train may be interpreted as switching to a service which has other characteristics, some of which are likely to be judged as less favourable by a number of travellers.

[8] It should be noted that both IEA studies include not only energy-related but also process-related CO2 emissions from the industrial sector, while the study by Greenpeace et al. does not account for process-related CO2 emissions.

Table 1
Overview of the analysed global energy scenario studies.
Sources: IEA, 2015a, 2015b; Teske et al., 2015.

Name of the study	Organisation	Publication date	Change in energy system CO_2 emissions compared to 2010 in each study's most ambitious mitigation scenario	
			by 2030	by 2050
energy [*r*]evolution – A Sustainable World Energy Outlook 2015	Greenpeace/GWEC/ SolarPower Europe	September 2015	−32%	−100%
Energy Technology Perspectives 2015	IEA	May 2015	−16%	−55%
World Energy Outlook 2015	IEA	November 2015	−18%	–

individual preferences leading towards energy-sufficient lifestyles (our "type A" sufficiency) will be required in the coming decades. "The transport sector requires sufficiency especially in regard to usage of individual cars and aviation." No specific reference to sufficiency or similar remarks about the need for changes in individual preferences can be found in the other scenarios analysed. Nor do we find statements in any of the three scenarios arguing that behavioural changes can or should also be triggered by strict policy mandates (our "type C" sufficiency).

While none of the analysed scenarios seem to include in their quantitative modelling more dramatic changes towards sufficient lifestyles (e.g. a reduction in demand for consumer goods), the potential for behavioural changes to contribute to sustainable development is recognised as a central principle in the Greenpeace et al. study (Teske et al., 2015). It stresses that "alongside technology driven solutions, lifestyle changes […] have a huge potential to reduce greenhouse gas emissions". At the same time, the study states that "[n]o behavioural changes or loss in comfort levels" are assumed for the quantitative scenarios.

Table 2 provides an overview of the types of lifestyle changes considered in the most ambitious mitigation scenario of each of the three global energy scenario studies analysed. The table also contrasts the types of lifestyle changes included in the scenarios with examples of lifestyle changes that, according to the literature, can significantly reduce energy demand and CO_2 emissions.

Table 2 suggests that, currently, many scenario developers are cautious in quantitatively implementing assumptions about far-reaching lifestyle changes. The analysed scenario studies assume limited behavioural changes in the transport sector only, mostly in the form of modal shift. The effect of these changes on total energy sector CO_2 emissions are limited. For example, in the Energy Technology Perspectives 2015 study (IEA, 2015b), modal shift and transport reductions combined result in annual CO_2 emission reductions in the 2DS scenario of about 2.5 Gt by 2050 compared to the baseline scenario. This represents only 6% of the overall energy sector emission reductions (41 Gt) by 2050. In contrast, technological solutions in the transport sector (more efficient vehicles and low-carbon fuels) are assumed to result in almost three times this reduction in annual emissions (about 7 Gt).

Table 2
Overview of the types of lifestyle changes considered in the analysed scenario studies and examples of additional types of lifestyle changes.
Sources: Faber et al., 2012; Hallström et al., 2015; IEA, 2015a, 2015b; Teske et al., 2015; Tom et al., 2015; van Sluisveld et al., 2016.

Lifestyle changes explicitly (and mostly moderately) taken into account in each analysed study's most ambitious mitigation scenario	
energy [*r*]evolution – A Sustainable World Energy Outlook 2015	• Shift towards more energy efficient modes of transportation • Reduction in transportation volumes • Use of smaller cars
Energy Technology Perspectives 2015	• Shift towards more energy efficient modes of transportation • Reduction in transportation volumes • Use of smaller cars (mentioned as *one* way to increase efficiency)
World Energy Outlook 2015	• Shift towards more energy efficient modes of transportation
Examples of additional lifestyle changes that can significantly reduce energy demand and CO_2 emissions, according to the literature	
• Reduction in room temperatures in winter • Reduction in floor area per person • Reduction in the number and sizes of household appliances and their use • Reduction in the purchase of consumer goods (incl. sharing consumer durables with other people) • Reduction in average meat consumption	

4.2. Global energy and emission scenario studies taking sufficiency into account

The fact that the prominent global energy scenario studies analysed in the previous sub-section only take marginal account of the potential for lifestyle changes to reduce energy demand and GHG emissions may come as a surprise. After all, other global energy and emission scenario studies have, in the past, explicitly included scenarios assuming significant changes towards energy-sufficient lifestyles. Some of these studies are discussed in the following. While we limit our discussion to *global* scenario studies, it should be noted that there are also some *country-specific* scenario studies that have included scenarios assuming energy-sufficient lifestyles (e.g. Emelianoff et al., 2013; Prime Minister's Office, 2009; Skea et al., 2011). Furthermore, while our focus is on studies released since 2000, some older energy scenario studies have considered the future potential for lifestyle changes (e.g. Carlson et al., 1980).

Among the most prominent international studies examining lifestyle changes within scenarios are two publications by the United Nations Environment Programme (UNEP). The *Global Environment Outlook 3* (Bakkes et al., 2004; UNEP, 2002) and *Global Environment Outlook 4* (UNEP, 2007) both include one scenario that explicitly assumes lifestyle changes compared to today and compared to a future BAU scenario. The reports develop distinct scenarios to gain a better understanding of possible future developments in various parts of the global environment up to the year 2032 (UNEP, 2002) and 2050 (UNEP, 2007). In the "Sustainability First" scenario, people increasingly emphasise the values of solidarity, reciprocity, sufficiency and stewardship. This shift in values is assumed to be driven mostly from the bottom up by individuals and grassroots organisations, which become increasingly involved in setting the policy agenda. Specifically, the authors note that "as the limits of a top-down, policy-driven approach are realized, the shift toward sustainability is increasingly accomplished through lifestyle changes" (Bakkes et al., 2004). Not surprisingly, various indicators of environmental damage are lower in the "Sustainability First" scenario for the coming decades than in the three other scenarios presented by each report.

The 2013 study *World Energy Scenarios* by the World Energy Council (World Energy Council, 2013) developed two different global energy scenarios to 2050. These scenarios differ, among other things, in regard to lifestyle assumptions. In the Symphony scenario, global final energy demand in 2050 is 20% lower than in the Jazz scenario due to environmentally-conscious citizens. Lower consumption levels are one reason for energy-related CO_2 emissions in the Symphony scenario peaking by 2020, while they peak 20 years later in the Jazz scenario. By 2050, energy-related CO_2 emissions in the Symphony scenario are less than half the level of those in the Jazz scenario (19 Gt CO_2 compared to 44 Gt CO_2). However, the two scenarios also vary in the use of energy supply technologies, with all the low-carbon electricity generation options (renewables, nuclear, CCS) being more aggressively supported in the Symphony scenario compared to the Jazz scenario.

Of the four global scenarios developed within the European research project *PASHMINA* (Sessa and Ricci, 2014), one scenario assumes that consumption and travel needs will be considerably reduced by 2050 in comparison with the other three scenarios, as a result of pervasive lifestyle changes. People in this "New Welfare" scenario are assumed to become more concerned about wellbeing and quality of life than about economic wealth. Instead of material consumption, education and research are assumed to become central social values. Global GHG emissions in the New Welfare scenario see a greater reduction by 2050 than in the other three scenarios, due mainly to lifestyle changes but also supported by "radical changes of urban infrastructure, working life and goods and services delivery schemes".

Another European research project (Berghof et al., 2005) examined the consequences of future developments in air travel up to the year 2050. One of the four scenarios developed in the *CONSAVE 2050* project is the "Down to Earth" scenario, in which changing values, regional lifestyles and high levels of environmental consciousness among the general public are assumed. In this scenario, the increase in global demand for air passenger transport between 2000 and 2050 is limited to an average annual rate of 0.5%, while the increase is considerably greater (average annual rates of 1.5% to 3.8%) in the three other scenarios.

Finally, the *Global Energy Assessment* study, developed under the lead of the International Institute for Applied Systems Analysis (Johansson et al., 2012), presents a large number of mitigation pathways for the global energy system based on three distinct pathway groups. One of these groups, the GEA-Efficiency group, emphasises demand side efficiency improvements and also assumes some behavioural changes compared to today and in contrast to the other two pathway groups (GEA-Mix and GEA-Supply). These changes are largely limited to the transport sector, where shifts towards public transport and reduced car ownership are assumed. While energy demand is lowest in the GEA-Efficiency pathways, cumulative emissions are similar in all three pathway groups as GEA-Mix and GEA-Supply compensate for higher energy demand by the greater use of low-carbon energy supply.

These studies differ in regard to the detail they provide in explaining the assumed shifts in values and lifestyles and how these shifts are assumed to be triggered. In the World Energy Council study (World Energy Council, 2013), the PASHMINA project (Sessa and Ricci, 2014) and the two Global Environment Outlooks (UNEP, 2007, 2002), changes in values and/or in environmental consciousness are described and are apparently assumed to emanate from within society, but little or no information is provided to explain what triggers these changes. The CONSAVE 2050 study (Berghof et al., 2005) is more explicit, noting that "heightened environmental consciousness might be brought about by clear evidence that impacts of natural resource use, such as deforestation, soil depletion, over-fishing, acidification, and climate change pose a serious threat to the continuation of human life on Earth."

In the studies mentioned in the previous paragraph, policy changes are not described as key triggers for more sustainable lifestyles, although the two UNEP studies (UNEP, 2007, 2002) and the World Energy Council study (World Energy Council, 2013) suggest that policy makers are expected to *react* to the new social norms by enacting policies that foster more sustainable lifestyles. In contrast, the Global Energy Assessment (Johansson et al., 2012) specifically focuses on policy measures that can lead to or support lifestyle changes. It devotes several pages to a discussion of the potential role and possible limitations of government policies to promote more sustainable lifestyles.

None of the analysed scenario studies suggest that policies banning certain goods and services are required, viable or desirable.

5. Conclusion and advice for energy scenario developers

As indicated, recently released prominent global energy scenario studies analysed in this paper barely take lifestyle sufficiency into account when presenting policy options. We have argued that this lack of analysis of the potential of sufficiency to contribute to a reduction in energy demand and GHG emissions is a weakness in energy scenario studies which aim to provide advice to policy makers. We suggest that future scenario studies should quantitatively assess the potential of sufficiency. The quantitative potential of lifestyle and behavioural changes should be highlighted more prominently in these scenarios and should not be blurred by combining differences in lifestyle assumptions with unrelated differences in energy efficiency and/or energy supply – as is the case in some of the scenario studies discussed in the previous section (Johansson et al., 2012; World Energy Council, 2013). Sufficiency and changes in lifestyle should rather be embedded, discussed and quantified independently of technology decisions. Ideally, studies should also discuss and – as far as possible – model the impact on economic activity of energy-sufficient lifestyles.

Based on our analysis, we make five general suggestions to energy scenario developers and the broader research community aimed at promoting the comprehensive consideration of sufficiency in future energy scenarios:

- With energy scenario studies typically comprising several diverse scenarios, sufficiency should be integrated in at least one scenario. It should be integrated either in terms of an alternative storyline or – ideally – in terms of a political and societal course of action.
- Narratives underlying the quantitative assumptions for sufficiency potentials can help to illustrate the plausibility of the envisaged development. Narratives can create a picture depicting sufficiency-oriented lifestyles, can indicate how fulfilling they may be and can highlight the central issues that policy makers and society need to manage. A participative development of these narratives can enhance their acceptance and their strength.
- In recent years, a number of studies have attempted to quantify the potential of sufficiency measures (Faber et al., 2012; Hallström et al., 2015; Stehfest et al., 2009; van Sluisveld et al., 2016). Future scenario studies could draw on these studies when devising scenarios that take into account lifestyle changes.
- Scenario studies dealing with lifestyle changes should also describe the triggers for sufficiency. Scenario authors can learn from the European research project SPREAD – Sustainable Lifestyles 2050 (see Neuvonen et al., 2014), which considers, among other things, potential triggers that may lead to lifestyles that are more sustainable.
- Further advances in the following research areas may help to better integrate sufficiency in future energy scenarios:
  (1) Understanding the potential of sufficiency to help reduce energy demand and respective emissions
  (2) Identifying promising (political) strategies to support energy-sufficient lifestyles
  (3) Understanding the dynamics and transformational potential of bottom-up sufficiency initiatives
  (4) Advancing methods to properly integrate sufficiency into existing energy models

If these general suggestions are taken into consideration, energy policy advice will be improved by outlining energy scenarios which highlight the full range of available GHG mitigation strategies. Such scenarios may be able to show policy makers and the public how ambitious climate change mitigation targets can be achieved without relying on excessively optimistic technological assumptions, and may possibly increase public support for changes to the lifestyles of the more affluent of the world's population.

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3. The Social Costs of Electricity Generation—Categorising Different Types of Costs and Evaluating their Respective Relevance

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Review

The Social Costs of Electricity Generation—Categorising Different Types of Costs and Evaluating Their Respective Relevance

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Abstract: Various electricity generation technologies using different primary energy sources are available. Many published studies compare the costs of these technologies. However, most of those studies only consider plant-level costs and do not fully take into account additional costs that societies may face in using these technologies. This article reviews the literature on the costs of electricity generation technologies, aiming to determine which types of costs are relevant from a societal point of view when comparing generation technologies. The paper categorises the relevant types of costs, differentiating between plant-level, system and external costs as the main categories. It discusses the relevance of each type of cost for each generation technology. The findings suggest that several low-carbon electricity generation technologies exhibit lower social costs per kWh than the currently dominant technologies using fossil fuels. More generally, the findings emphasise the importance of taking not only plant-level costs, but also system and external costs, into account when comparing electricity generation technologies from a societal point of view. The article intends to inform both policymakers and energy system modellers, the latter who may strive to include all relevant types of costs in their models.

Keywords: electricity generation technologies; social costs; plant-level costs; system costs; external costs; literature review

1. Introduction

Access to electricity is widely regarded as a prerequisite for an appropriate standard of living and social integration [1], yet in 2014 almost 1.2 billion people still lacked this access [2]. At the same time, electrical appliances continue to grow in importance in the daily lives of billions of people. Consequently, the share of electricity in final energy demand has steadily grown over the past decades [3]. This trend is expected to continue in future decades as climate change mitigation strategies involve replacing fossil fuels with electricity in end-use applications [4–6]. Ensuring the sufficient provision of electricity generated by economically, environmentally and socially acceptable means will, therefore, continue to be an important objective for policymakers around the world.

Currently a large number of electricity and energy system models exist that aim to inform policymakers about the lowest cost solutions for meeting future electricity demand [7,8]. Policymakers may be interested in such analyses to "back the right horse" when deciding, for example, on public research, development and demonstration (RD&D) expenses, energy infrastructure priorities or the level of financial support given to specific technologies. Models explicitly aiming to inform policymakers about the lowest cost evolution of electricity supply from a societal perspective should obviously strive to consider all types of electricity generation costs that are relevant to society (as opposed to taking into account, for example, only those types of costs that are relevant to investors).

Based on an extensive literature review, this article seeks to provide a comprehensive overview of the current knowledge on the social costs of electricity generation. It identifies the relevant types of costs and makes suggestions about how to categorise these. More specifically, the article aims to emphasise the fact that not only plant-level costs, but also system and external costs, are relevant when assessing the costs of various types of electricity generation technologies from a societal perspective. Energy system modellers may be able to use the findings from this article to complement their models and to better understand the capabilities and limitations of their respective models in considering the total social costs of electricity generation.

For practical reasons, this article focuses on the social costs of electricity generation in Europe and the USA, as very little literature is available on social costs (especially system costs and external costs) in other world regions. It should, therefore, be kept in mind that some of the findings in this study are likely to be specific to electricity systems in industrialised countries and are not necessarily representative of the social costs of electricity generation in developing countries. Furthermore, due to the availability of the literature and to simplify inter-technology comparisons, this study focuses on medium to large-scale (i.e., utility-scale) applications of electricity generation technologies. The social costs of small-scale, decentralised electricity generation will differ to some extent. For example, while plant-level costs for decentralised systems tend to be higher than for centralised ones (due to economies of scale), transmission costs tend to be lower and local generators may put special emphasis on minimising external costs, such as air pollution and noise.

It should also be noted that this article does not discuss specific instruments that society or policymakers can use to ensure that the full social costs are taken into account by market actors. Such instruments include taxation, emission trading systems, subsidies and corporate social responsibility [9–12].

This article is structured as follows: Section 2 defines the term "social cost of electricity generation", which is the sum of the various types of costs grouped into the three main cost categories of plant-level costs, system costs and external costs. Section 3, the main section of this article, discusses the qualitative and quantitative findings from the literature for each type of differentiated cost. Based on these literature findings. Section 4 summarises the typical estimates of the various types of social costs for several electricity generation technologies. Finally, Section 5 concludes and suggests further areas of research.

2. Defining and Categorising the Social Costs of Electricity Generation

This article evaluates the cost to society of generating electricity using various technologies. In the field of economics, the cost of a good refers to the value of all the scarce resources that have been used to produce the good. This value, in turn, is measured in terms of the value of the next best good that could have been produced with the same resources, and is called opportunity cost [13]. In the remainder of this article, the social opportunity cost of generating electricity is being referred to when the terms "cost" or "social cost" are used.

Social costs are typically broken down into "private costs" and "external costs". The private costs of a good are those types of opportunity costs that are accrued by the market player who produces the good. These costs are taken into account by the producer when deciding on the production volume, and the producer's aim is to minimise these costs. External costs, on the other hand, can be defined as the costs arising from human activity that are not accounted for by the market player causing the externality [13]. For example, the particulate pollutants from a fossil fuel power plant causing negative health effects for people living near the plant are external costs. The power plant "uses" the scarce resource of health, without the costs being accrued by the market player who caused it.

It is argued here that when analysing the total social costs of electricity generation, it is useful to further differentiate private costs into the two categories of "plant-level costs" and "system costs". Plant-level costs encompass the private costs associated with electricity generation at the plant. These consist of capital costs, fuel costs, non-fuel operation and maintenance (O&M) costs, and—if a carbon market is in place—carbon costs. These costs are frequently compared between different types of electricity generation technologies by calculating the "levelized cost of electricity" (LCOE).

System costs can be defined as all the costs associated with the reliable delivery, at the right time, of the electricity generated at plant-level to the locations where the electricity is needed. These costs include the costs of transmission and distribution networks, of storage technologies and of a range of so-called ancillary services required for the stable operation of an electricity system. Following [14], we also include "profile costs" within the system costs. Profile costs can be defined as the additional specific capital and operational costs that electricity generation from a new plant causes in the residual electricity system, as well as any overproduction costs of electricity generation from variable renewable energy (VRE) sources.

As system costs are often difficult to ascribe unequivocally to individual power plants, some of these costs are typically apportioned to electricity suppliers and/or consumers by regulatory entities, for example through tariffs per unit of electricity produced or consumed.

It could be argued that the sum of plant-level costs, system costs and external costs as defined in this article still does not encompass the total social costs of electricity generation. This is because the macroeconomic and geopolitical effects stemming from changes in the electricity system may have welfare effects beyond those reflected in the plant-level, system and external costs. For example, some electricity generation technologies may lead to greater levels of employment than others (on a per-kWh basis) and the creation of employment may be valued by society beyond the value attributed by the employer and the employee (and thus reflected in the employee's wage). Apart from employment effects, terms of trade effects and effects on the competitiveness of an economy are also discussed as possible relevant macroeconomic costs and benefits when comparing the total social costs of different electricity generation technologies. Finally, the choice of a primary energy source may also have geopolitical impacts, such as increased dependence on key natural gas or oil exporting countries.

While it is true that these potential macroeconomic and geopolitical effects are often relevant in energy policy discussions, it is extremely difficult to precisely quantify them or to determine how they differ between various electricity generation technologies. Due to these difficulties, and to focus more on the plant-level, system and external costs, it was decided not to include a discussion of macroeconomic and geopolitical costs and benefits in this literature review.

Figure 1 provides an overview of the cost categories that can be differentiated when determining the total social costs of electricity generation. It suggests that the definition of social costs as used in this article can be regarded as a definition in a narrower sense, as potential macroeconomic and geopolitical costs (and benefits) are not taken into account.

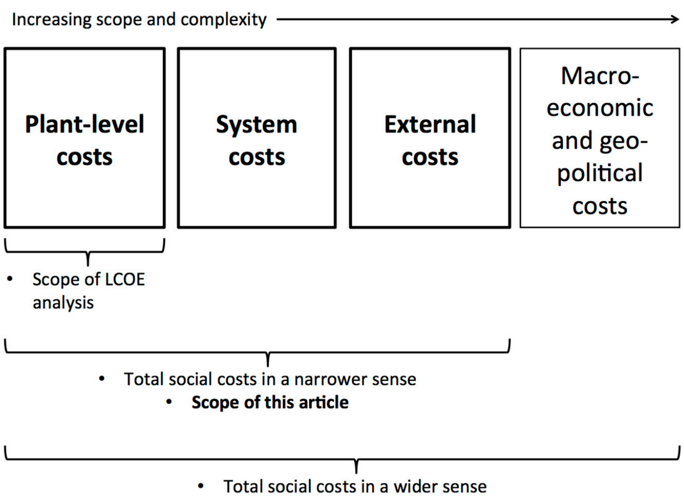

Figure 1. Overview of the main cost categories that can be differentiated when determining the total social costs of electricity generation.

It should be noted that while this article only deals with the social costs of electricity generation, it is important to bear in mind that energy efficiency improvements can, in many cases, reduce electricity demand at very low social costs per kWh [15–17].

3. Discussing the Individual Types of Social Costs of Electricity Generation

As explained in the previous section, the three main categories of the social cost of electricity generation differentiated in this article are plant-level costs, system costs and market costs. Within each of these main cost categories, additional sub-categories of costs are distinguished. These sub-categories of costs have been identified based on an extensive review of the available literature on the plant-level, system and external costs of electricity generation. Table 1 provides an overview of the types of costs that have been found to be relevant for some, or all, electricity generation technologies. Based on the literature review, the following three subsections will discuss and evaluate the current state of knowledge on the plant-level costs (3.1), system costs (3.2) and external costs (3.3) of electricity generation technologies.

Table 1. Overview of the sub-categories of costs found to be relevant for comparing the social costs of electricity generation technologies.

Plant-Level Costs
• Capital costs • Fuel costs • Market costs of greenhouse gas (GHG) emissions • Non-fuel operation and maintenance costs (fixed and variable)
System Costs
• Grid costs • Balancing costs • Profile costs
External Costs [1]
• Social costs of GHG emissions (minus market costs of GHG emissions) • Impacts of non-GHG pollution • Landscape and noise impacts • Impacts on ecosystems and biodiversity (beyond those related to climate change) • External costs associated with radionuclide emissions

[1] There may be additional relevant types of external costs, but this is difficult to determine. See Section 3.3.6.

3.1. Plant-Level Costs

This section introduces and discusses the types of costs of electricity generation that accrue at plant-level and are reflected in the various markets. These types of costs are:

- Capital costs;
- Fuel costs;
- Market costs of greenhouse gas (GHG) emissions;
- Non-fuel operation and maintenance costs (fixed and variable).

3.1.1. Capital Costs

Capital costs comprise investment costs (including grid connection costs), refurbishment and decommissioning costs, as well as financing costs. As there are competitive markets for most energy technologies and their respective components, it can be assumed that market prices are a good indicator for the actual macroeconomic costs that accrue from manufacturing and installing these technologies (apart from external costs, which will be discussed in Section 3.3).

The costs of connecting a power plant to the existing grid are usually included in capital costs, as a power plant developer usually needs to bear these costs [18,19]. In relation to the total capital costs (including connection costs), grid connection costs are usually low for fossil fuel and nuclear power plants, as well as for biomass and solar photovoltaic (PV) plants, with shares typically lower than 5% [20,21]. However, connection costs can be more relevant for other types of plants, such as onshore and offshore wind power plants, as these are often built further away from existing grids and their locations can be difficult to access. According to [22], grid connection costs typically make up 10% to 12% of the capital costs for onshore plants and 21% to 23% for offshore plants.

Decommissioning costs are typically included in capital costs. Even though at the time of decommissioning these costs may be significant, especially for nuclear power plants, they only accrue at the very end of a plant's lifetime. In the LCOE methodology these decommissioning costs become negligible (around 1% or less) once discounted at any commonly used rate: "For an investor [. . .] contemplating an investment today, decommissioning costs are too far in the future and not a decisive criterion from a financial perspective" [23].

Capital costs are an important type of cost for every energy technology. Their share in total LCOE is around or above 60% for renewable, nuclear and coal carbon capture and storage (CCS) power plants. For conventional coal and natural gas power plants, fuel and CO_2 costs are more important, especially at low discount rates [24].

3.1.2. Fuel Costs

It is difficult to determine to what extent the market costs for various fuels reflect their actual cost to society. For many of the fossil fuels produced globally, production costs are significantly lower than market prices, although the difference between production costs and prices is more pronounced for oil than for natural gas and coal (which are both more relevant in terms of electricity generation) [25]. These rents—captured by governments in taxes and royalties and by oil companies in profits—may be interpreted as an indication that market prices overestimate the global costs to society of using fossil fuels. On the other hand, these fuels are exhaustible resources, which means that the costs that accrue by using them include not only the extraction costs but also the opportunity cost of not being able to use the fuels at a later point in time [26]. However, this opportunity cost cannot be precisely quantified and it is unclear if, or to what extent, it is included in market prices.

For nuclear power, the waste management costs can be included within the fuel costs [24]. It should be mentioned that, like the decommissioning costs, there is also considerable uncertainty about the waste management costs of nuclear power plants.

The share of fuel costs in total plant-level costs varies considerably from technology to technology. While for many technologies using renewable energy sources no fuel costs accrue, the fuel cost share of natural gas power plants can be as high as around 70% [24].

3.1.3. Market Costs of GHG Emissions

A number of regional, national and sub-national carbon pricing systems are currently in place, and these covered about 13% of global GHG emissions in 2016 [27]. Although there are considerable differences between the various schemes, notably whether an emissions trading system or a carbon tax is used, they all share the key objective of reducing GHG emissions by assigning costs to them. This follows the insight from economic theory that internalising the costs of harmful emissions can efficiently reduce emissions to an acceptable level.

However, the existence of an emissions trading system or a carbon tax does not mean that the *total* costs accrued by society due to GHG emissions are actually internalised. While the social costs associated with GHG emissions are very difficult to determine for various reasons (see Section 3.3.1), they are widely assumed to be considerably higher than the current emissions costs in most carbon pricing schemes around the world. With the exception of a few schemes in Switzerland and Scandinavia, CO_2-equivalent prices in carbon pricing schemes around the world are currently below

€25/ton [27], although price increases beyond this level are expected in some regions in the early or mid-2020s [28,29]. In other words, the current costs of emitting CO_2 in most regions of the world are too low to fully reflect the damage caused by these emissions.

For fossil fuel electricity generation technologies, CO_2 prices can be decisive in determining their competitiveness. This is especially true for non-CCS coal power plants. At hypothetical CO_2 costs of €50/ton, plant-level costs of hard coal power generation would be about 90% higher compared to a situation in which no carbon pricing was in place.

3.1.4. Non-Fuel Operation and Maintenance Costs

Non-fuel O&M costs include fixed costs such as wages for the permanent plant staff and insurance costs, as well as routine equipment maintenance costs and variable costs for e.g., water, lubricants and energy used in auxiliaries.

The share of non-fuel O&M costs varies from one technology to another. It is relatively low (around or below 10%) for natural gas combined cycle gas turbine (CCGT) plants and conventional coal power plants and relatively high (around 25%) for onshore and offshore wind plants [24]. It is assumed in this article that markets for O&M services are generally operating normally and market prices for these services therefore reflect the full macroeconomic costs of their provision.

3.1.5. Sum of Plant-Level Costs in the Form of Levelized Cost of Electricity (LCOE)

Figure 2 provides an overview of the ranges of plant-level LCOE for selected types of newly-built power plants in Europe and the USA. For reasons of brevity, this subsection, as well as the social cost overview in Section 4, only discusses the three most prevalent types of conventional power plants (hard coal, natural gas CCGT and nuclear power plants) as well as onshore wind, offshore wind and solar PV. Wind and solar PV technologies are expected to play key roles in Europe and the USA in the coming decades [4,6,30]. The technological characteristics and LCOE ranges of other renewable generation technologies, such as hydropower, biomass, geothermal and solar thermal power plants, vary considerably and are therefore difficult to adequately discuss within the limited scope available here. For a detailed discussion of global and regional LCOE and their ranges, including for additional renewable energy technologies, readers are referred to [21,24,31,32].

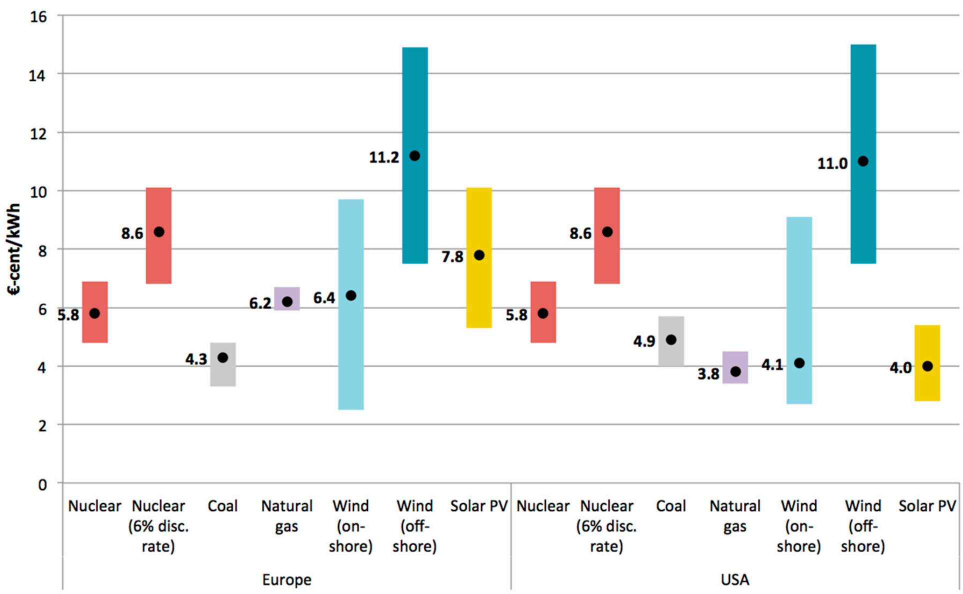

Figure 2. Plant-level LCOE ranges and central values (black dots) for selected types of newly-built power plants in Europe and the USA (w/o transmission costs and w/o costs of CO_2 emissions) using a discount rate of 3%. Sources: See detailed descriptions of LCOE calculations in the Supplementary Materials.

Data from a number of recent studies and documents [6,24,31,33–44] were used as input to calculate the LCOE. CO_2 costs and transmission costs are not included, as in this article these types of costs are treated as "external costs" (CO_2 costs, see Section 3.3.1) and "system costs" (grid costs, see Section 3.2.1), respectively. The LCOE presented also exclude the effect of subsidies, as subsidies only affect private costs, not societal costs. The central values represent plants with average costs, while the ranges were derived by varying capital costs (for all technologies), full load hours (for onshore wind, offshore wind and solar PV), fuel cost developments (for coal and natural gas) and technical lifetime (for nuclear power) within the range of values typically observed or expected. The Supplementary Materials provide details on the LCOE calculations, listing all the relevant input parameters, as well as their respective sources.

For coal, natural gas and nuclear power plants, it is assumed they can operate in baseload mode (with a capacity factor of 85%, following [24]). While such a capacity factor represents a value typically observed in electricity systems today, the expected further growth in electricity generation from variable renewable energy sources is likely to reduce the average capacity factors of conventional power plants in the future. As a sensitivity analysis, the International Energy Agency (IEA) [24] calculates the LCOE of baseload power plants at capacity factors of 50%. It finds that, compared to a capacity factor of 85%, the LCOE of natural gas-fired generation increases by 11%, the LCOE of coal-fired generation by 23% and the LCOE of nuclear power generation by 54%. However, higher LCOE costs from lower full load hours are regarded as "system costs" rather than "plant-level costs" in this article.

The LCOE calculations presented here are generally based on a discount rate of 3%, which is considerably lower than the typical cost of capital to private investors who face the risks associated with individual projects. It is typically argued that from a social or system-planner perspective (as adopted in this article), low discount rates of around 3% are more appropriate than market-observed discount rates. This is because society as a whole can effectively reduce the non-systematic risk that individual investors bear to zero by pooling risks across the entire population [45,46]. Lower discount rates lead to lower LCOE, with this effect being more pronounced for capital-intensive technologies, especially nuclear power plants, compared to plants with higher operational costs, such as natural gas [47].

However, society as a whole still faces specific risks with every investment made and it can be argued that these risks systematically differ from one type of electricity generation technology to another. Specifically, the risk of investing in small-scale technologies, such as wind and solar PV, with no fuel cost uncertainty and the opportunity to increase capacity in small steps is less risky than investing in large-scale power plants, such as large fossil fuel and nuclear power plants [48]. Natural gas power plants, in particular, exhibit fuel cost uncertainty, while nuclear and coal power plants need to achieve high full load hours over several decades to become worthwhile investments. Unexpectedly low future electricity demand or unexpectedly high future investments in power plants with lower variable costs, such as wind turbines and solar PV plants, could impede such high full load hours, which would significantly increase the LCOE of nuclear and/or coal power plants.

Concerning nuclear power, there is the additional risk that in the decades following a power plant investment, a society may put greater emphasis on the inherent risks associated with this technology; for example, because of a large-scale nuclear accident elsewhere or because of a change in the perceived threats faced from terrorism or warfare. This may result in a society deciding to stop operating these plants, possibly well ahead of the end of their technical lifetime, again leading to higher LCOE.

A detailed quantitative reflection of these uncertainties is difficult and beyond the scope of this article. Instead, the higher investment risks associated with large-scale power plants are assumed to be captured by applying a higher discount rate of 6% for these plants. As the differences in investment risks may, in the future, be most relevant when comparing the low-carbon options of renewable energy technologies on the one hand with nuclear power plants on the other hand, the LCOE calculations in Figure 2 include a separate cost range for nuclear power plants using a discount rate of 6% instead of 3%. (For reasons of brevity, the respective ranges for the fossil fuel plants are not shown.)

The ranges in Figure 2 show that, even within Europe and the USA, the LCOE can vary considerably, especially for renewable energy technologies. This is due, among other things, to differences in the location of plants, their sizes and their technological characteristics. The considerable differences between Europe and the USA in the central LCOE values for onshore wind, solar PV and natural gas CCGT plants are mainly explained by the generally stronger wind, higher solar irradiation and the lower cost of natural gas in the USA.

In Europe, typical plant-level LCOE is lowest for coal power plants at 4.3 €-cent/kWh, although onshore wind can be less expensive at good locations. The central LCOE estimates for nuclear power (at a 3% discount rate, i.e., not reflecting higher risks), natural gas and onshore wind are similar, around 6 €-cent/kWh. In the USA, typical current plant-level costs are lowest for natural gas, solar PV and onshore wind, all at similar costs of around 4 €-cent/kWh. The plant-level costs of offshore wind power plants are typically considerably higher than for all the other analysed technologies in both Europe and the USA. However, the results of several auctions held in 2016 in Europe for constructing offshore wind farms suggest that the combined effect of, among other things, technological and operational advances, increased competition, larger turbines and larger wind farms has recently led to typical offshore wind power costs being closer to the lower end of the offshore wind cost ranges shown in Figure 2 [49].

3.2. System Costs

System costs comprise the costs of integrating an individual power plant into an existing electricity system. Based on the available literature, Figure 3 provides an overview of a possible differentiation between three components of system costs.

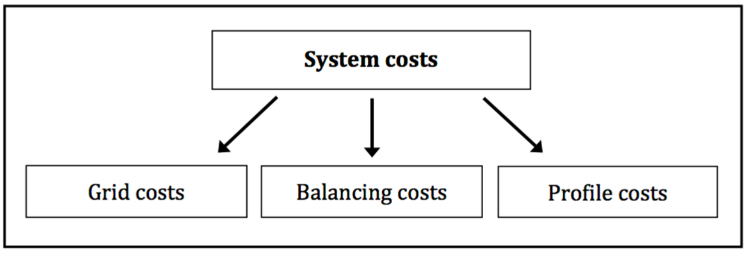

Figure 3. Three components of system costs. Sources: Based on [50,51].

While in recent years a growing body of literature has emerged discussing the various elements of system costs as depicted in Figure 3, there is currently no consensus on the precise definition of the term "system costs" and on the terms to be used for its individual components. This is particularly relevant for the cost component referred to in this article as "profile costs". These costs (or parts thereof) are also referred to in the literature as "backup costs", "adequacy costs", or (costs of the) "utilization effect". In this article, the definition of profile costs as provided by [14,51] is applied.

A plant's system costs vary considerably from case to case, depending not only on the type of plant, but also on the plant's location and on various characteristics of the electricity system into which it is to be integrated [52]. Therefore, only approximate figures or ranges for specific system costs can be assigned to the various types of generation technologies. Furthermore, available studies attempting to quantify system costs (or individual components of these costs) deal with electricity systems in either Europe or North America. There is currently a lack of analysis of system costs in other regions of the world, especially in developing countries, "where integration issues may be very different from in OECD countries" [50].

Studies quantifying system costs deal almost exclusively with VRE plants as, in general, their system costs can be expected to be much more relevant than the respective costs of non-variable sources. As Hirth [53] notes, this is due to the intrinsic technological properties of VRE technologies.

3.2.1. Grid Costs

Grid costs, or more precisely "grid reinforcement and extension costs", can be defined as the extra costs in the transmission and distribution system when power generation from a new plant is integrated into that system [54]. It can be argued that only a part of the extra costs should be allocated to the new plant, as other electricity producers may also benefit from the required grid reinforcements and extensions, for example through increased grid stability [50,55,56].

The specific grid costs of a new power plant—despite being difficult to establish precisely—may vary considerably from one case to another, with several factors determining these costs. Among these factors are the proximity of a new plant to the existing transmission grid, its distance to load centres, its capacity factor, the extent and quality of the existing grid and the lifetime of the transmission investments [50].

Research on grid reinforcement and extension costs in recent years has focused on costs associated with the expanded use of renewable energy sources, especially wind. Table 2 provides an overview of the specific grid costs of different electricity generation technologies at varying penetration rates as provided by several studies.

Table 2. Additional specific grid costs of different electricity generation technologies at varying penetration rates according to several studies.

Source	Country or Region	Technology	Penetration Rate (Share of Total Electricity Generation)	Grid Costs (in €-cent/kWh)	Comments
[57] [1] (meta-study)	USA	Wind (onshore and offshore)	Not provided (varying)	1.4	Median; full range: 0–7.2
[54] (meta-study)	Six European countries	Wind (onshore and offshore)	≈10%–60%	≈0.4	Median; full range: ≈0.2–1.1 Original data in €/kW; conversion assumes 2000 full load hours per year, a discount rate of 7% and a grid lifetime of 40 years No clear correlation between specific grid costs and penetration level
[58] [1]	Six OECD countries	Wind (onshore)	10% 30%	0.2 0.3	Median; full range: <0.1–0.3 Median; full range: 0.2–2.0
		Wind (offshore)	10% 30%	0.1 0.2	Median; full range: <0.1–0.2 Median; full range: <0.1–1.1
		Solar PV	10% 30%	0.4 0.5	Median; full range: <0.1–0.5 Median; full range: 0.2–4.3
		Nuclear, coal, gas	10% and 30%	0	-
[59]	Eleven European countries	Solar PV	15% to 18%	1.2	Maximum; lower in some countries; only distribution grid and cross-country transmission lines taken into account
[60]	Australia	CSP [2] (with storage) Geothermal Biomass Coal CCS	18%–23%	0.2 0.3 <0.1 <0.1	-

[1] Cost data in these studies is provided in USD. The costs were converted to EUR by using a conversion rate of 1 EUR = 1.1 USD; [2] Concentrating solar thermal power.

3.2.2. Balancing Costs

The stable operation of an electricity system requires electricity demand and electricity supply to be equal at all times. Electricity systems therefore require a central system operator who ensures that unplanned (and thus unpredictable) short-term fluctuations in both electricity demand and supply can be compensated by contracting sufficient reserves ahead of time. These reserves are used if needed to provide balancing power [61].

The need to hold such reserves has cost implications as, overall, this requires greater capacity compared to a hypothetical system in which demand and supply are perfectly predictable and any kind of system failure can be ruled out. Additional fuel costs (and the related emissions costs) also accrue, as plant efficiency is typically lower when a plant—to provide reserve capacity—is running below its full capacity and/or needs to ramp up and down frequently. Furthermore, frequent ramping may also negatively affect a plant's reliability and reduce its lifetime [62].

All types of power plants experience both planned and unplanned outages, so to a certain extent balancing costs can be attributed to all types of power plants. However, using VRE sources to generate electricity, as in the case of wind and solar PV power plants, generally leads to higher balancing requirements. As power generation from these sources is considerably more variable, less predictable and less controllable than power generation from other sources, these sources force other power plants in the system to change their output more rapidly and/or more frequently to maintain the balance between demand and supply [50,58]. Table 3 provides an overview of the specific balancing costs of different electricity generation technologies at varying penetration rates as provided by various studies.

Table 3. Additional specific balancing costs of different electricity generation technologies at varying penetration rates according to several studies.

Source	Country or Region	Technology	Penetration Rate (Share of Total Electricity Generation)	Balancing Costs (in €-cent/kWh)	Comment
[58]	Six OECD countries	Nuclear	10% 30%	<0.1 <0.1	-
		Wind (onshore and offshore) and solar PV	10% 30%	0.3 0.5	Median; full range: 0.2–0.7 Median; full range: 0.5–1.3
[63] [1]	Arizona, USA	Solar PV	8%	0.2	Median, full range: 0.2–0.3
[64] (meta-study)	USA and several European countries	Wind (onshore and offshore)	≈10% ≈20% ≈30%	0.3 0.3 0.4	Median; full range: <0.1–0.4 Median; full range: <0.1–0.5 Median; full range: 0.1—0.6
[59]	Eleven European countries	Solar PV	15%	0.1	-
[14] (meta-study)	Several European countries and several regions of the USA	Wind (onshore and offshore)	≈1% to 40%	≈0.3	Median, full range: <0.1–1.3 No clear correlation between specific balancing costs and penetration level

[1] Cost data in this study is provided in USD. The costs were converted to EUR by using a conversion rate of 1 EUR = 1.1 USD.

There is little information in the literature on the balancing costs of dispatchable electricity generation. However, these costs can be expected to be considerably lower than the respective costs of VRE power plants. Keppler and Cometto [58] estimate the balancing costs of nuclear power plants to be less than 0.1 €-cent/kWh.

3.2.3. Profile Costs

Largely following [14,51], profile costs can be defined as the additional specific capital and operational costs that electricity generation from a new plant may cause in the residual electricity system, plus overproduction costs of VRE electricity generation (see Figure 4).

Integrating new power plants into an existing system typically leads to increases in the specific costs of the residual power generation, i.e., the power generation of the existing plants still required after the integration of the new power plants. Any additional electricity generation, all other things being equal, leads to lower average full load hours of the existing plants, which in turn leads to higher specific generation costs. However, for conventional baseload, mid-merit or peak load plants, these costs do not or no longer accrue if or once corresponding old power plant capacities are decommissioned. Therefore, the literature typically focuses on new VRE power generation when discussing profile costs.

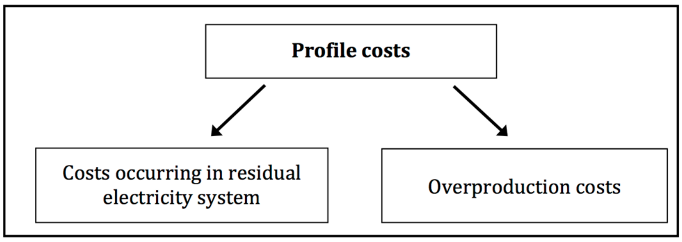

Figure 4. Two components of profile costs. Sources: Based on [14,51].

Higher specific *capital* costs typically accrue when adding VRE technologies, as these are unable, or only marginally able, to reliably contribute to covering peak electricity demand. Consequently, the conventional generating capacity needed to reliably cover peak demand at all times remains (almost) unchanged as VRE technologies are added [50]. At the same time, these dispatchable plants become utilised for fewer hours per year, so their specific capital costs are higher than they would be without the VRE electricity generation [65].

Higher specific *operational* costs, due to the higher use of mid-merit and the lower use of baseload power plants, typically accrue as an increase in electricity generation from new VRE power plants leads to changes in the cost-optimal mix of the remaining power generation. The reason for this is the fluctuating nature of VRE power generation. Due to this fluctuation, fewer residual power plants can generate electricity "around the clock" and these power plants are typically the ones with lower operational costs [65]. Hirth et al. [14] point out that the steeper gradients of residual load resulting from VRE power generation also leads to higher operational costs of thermal power plants, as their output needs to follow steeper gradients. This causes additional ramping and cycling costs. Note that these costs only refer to *scheduled* ramping and cycling, while the costs of *uncertainty-related* ramping and cycling are reflected in balancing costs.

It should be noted that in certain circumstances, additional electricity generation from VRE sources may *decrease* the average capital and/or operational costs of the remaining electricity generation. A prominent example is the expansion of power generation from solar PV plants in regions in which there is a high correlation between solar PV output and peak electricity demand. In such cases, the need to operate expensive peaking plants is reduced as solar PV output increases, up to the point a certain solar PV penetration rate is reached [66]. Another example is the deployment of a certain amount of wind turbines in electricity systems with high shares of hydropower and seasonal complementarity between wind and hydrological resources [67,68]. Furthermore, the IEA [50] notes that in cases of small electricity systems needing additional capacity because of growing peak demand, small, optimally-sized VRE power plants may incur smaller capacity costs than conventional power plants. This can occur when there is a mismatch between the additional capacity needed and the smallest conventional plant that can be operated efficiently.

For any given amount of new VRE electricity generation, profile costs are lower in the long term than in the short term as, over time, the residual power plant structure adapts to the requirements brought about by the new VRE power generation, leading to a higher share of peak-load power plants which exhibit lower costs at low capacity factors. Furthermore, electricity demand can also be expected to adjust in the longer term. For example, if over several decades the combined share of solar PV and wind electricity generation increases from an insignificant value to 50% or 70%, market forces—possibly supported by government regulations—are likely to lead to greater flexibility in electricity demand (aided by new and flexible demand sources such as electric vehicles and heat pumps). Such shifts can reduce peak demand and help balance the residual electricity demand, thus mitigating profile costs.

While there is general agreement that additional VRE electricity generation typically leads to additional costs in the residual electricity system, there is no consensus on whether these costs should be attributed partially or wholly to the new VRE power plants. It could be argued, for example, that the real problem is the inflexibility of the existing power plants or, more generally, "that system adaptation inherently occurs in power systems and thus cannot be attributed directly to specific new technologies" [69].

According to [14,51], profile costs consist not only of the additional costs accrued in the residual electricity system but also include the costs of VRE overproduction. Overproduction costs—typically only relevant at higher VRE shares—are the opportunity costs of not being able to use all the electricity that could, in principle, be generated at zero marginal cost by a VRE plant, because demand and/or transmission capacity at any given point in time is insufficient.

Table 4 lists the findings of three studies examining the long-term profile costs caused by adding wind and/or solar PV power generation. It should be noted that [14,65] do not include overproduction costs in their estimates. As specific profile costs generally increase when the share of VRE generation increases, average and marginal profile costs usually differ for specific VRE shares. Table 4 therefore differentiates between average and marginal specific profile costs. Some studies report only the former, while others report only the latter. The two studies in Table 4 reporting marginal costs also allow for an estimate of the average profile costs, so both values are provided.

Table 4. Average and marginal specific profile costs from wind and solar PV electricity generation according to several studies.

Source	Method Used	VRE Technology	Penetration Rate (Share of Total Electricity Generation)	Profile Costs (in €-cent/kWh$_{VRE}$)		Comment
				Average	Marginal	
[51] [1]	Generic modelling (typical for European countries with mainly thermal power plants)	Wind	10% 20% 40%	1.5 1.9 2.5	1.9 2.5 4.6	VRE curtailment costs included
		Solar PV	10% 15% 25%	1.5 2.1 3.3	2.7 3.3 9.8	
[65] [2]	Generic modelling (based on load data, wind power and solar PV data for Germany)	Wind	10% 20% 40%	1.0 1.3 1.5	n.s. n.s. n.s.	No VRE curtailment or related costs assumed
		Solar PV	10% 20% 40%	0.8 1.3 2.0	n.s. n.s. n.s.	
		Wind (2/3) and solar PV (1/3)	10% 20% 40%	0.3 0.7 1.1	n.s. n.s. n.s.	
[14] [1]	Meta-study (literature sources used cover several European countries and several regions of the USA)	Wind	10% 20% 40%	0.5 0.8 1.3	0.8 1.2 2.2	No VRE curtailment costs included; based on best-fit curve for values of studies using long-term models

[1] References [14,51] report marginal profile costs. Average costs are derived based on the marginal cost curves depicted in the studies and should be seen as approximate values; [2] Costs in this study are provided in USD. These costs were converted to EUR by using a conversion rate of 1 EUR = 1.1 USD.

It should be noted that, particularly at high penetration rates of VRE technologies, profile costs differ considerably depending on how flexible the overall system is or is assumed to be in the future. Various studies show that the profile costs of VRE technologies can be reduced significantly through, among other things, consumer demand response (including temporal flexibility in charging electric vehicles), grid and storage capacity extensions, combining wind and solar PV with the use of dispatchable renewable energy technologies and also through system-friendly design, location or orientation/tilt of wind and solar PV plants [52,70–72]. Findings in studies indicating extremely high marginal profile costs for certain VRE shares (such as in [51] for solar PV shares exceeding about 15% and wind shares exceeding about 25%) should therefore be interpreted with care if they do not assume that electricity demand will be able to adjust or that low-cost supply-side flexibility options can be achieved.

3.3. External Costs

This section introduces and discusses types of costs of electricity generation technologies that are not, or not fully, taken into account by the markets [73–75]. These so-called external costs are generally more difficult to identify and quantify than private costs because there are no markets on which their 'prices' can be observed and because, in many cases, complex environmental interactions occur before a burden (e.g., emission of an air pollutant) has an impact and leads to damage (e.g., a respiratory illness). Furthermore, many of the negative impacts are uncertain, locally removed to some degree from the actual source of the burden and/or occur with a significant time delay.

3.3.1. Social Costs of Greenhouse Gas Emissions

GHG emissions released by the combustion of fossil fuels contribute to global warming and ocean acidification and thus lead to damage and related costs. As will be discussed in the following, there are various difficulties in determining the Social Cost of Carbon (SCC), i.e., the monetized estimate of the change in expected social welfare resulting from a marginal change in CO_2 emissions.

Integrated Assessment Models (IAMs) are typically used to derive estimates for the SCC. An IAM combines a global economic model with a model of the physical climate system and the carbon cycle. IAMs are based on estimates for the costs of a certain level of climate change [76]. These costs are used to calibrate the damage functions of the IAMs, which represent the costs of climate change for any level of global warming.

The range of estimates of the SCC found in the literature is large. There are various reasons why individual studies investigating the SCC tend to provide wide ranges and why these ranges vary considerably between different studies. A key factor responsible for variations in SCC estimates is the uncertainty related to future climate change, as well as its economic impacts and the potential of societies to adapt. Different methodological approaches also play a role in explaining the wide range of SCC estimates found in the literature. Methodological approaches differ, among other things, in the choice of a welfare function, the choice of a discount rate, the choice of whether or how to take into account potential aversion towards very high-consequence impacts of climate change and the choice of a time horizon [77–81].

Table 5 shows the SCC estimates provided by a US government-commissioned study. The Interagency Working Group on Social Cost of Carbon was tasked with deriving SCC estimates "to allow agencies to incorporate the social benefits of reducing carbon dioxide (CO_2) emissions into cost-benefit analyses of regulatory actions" [82]. While the authors acknowledge and discuss various general shortcomings of IAMs in their report, they nonetheless rely on three commonly used IAMs to derive a recommended range of SCC values. For the working group's SCC calculations, a range of socio-economic and emissions scenarios were used. The three values shown in columns 2, 3 and 4 of Table 5 are based on three different discount rates and are averages of the three IAMs used across the entire range of socio-economic and emissions scenarios. To represent the possibility of higher-than-expected economic impacts from climate change, the study also reports the value of the 95th percentile of the SCC estimates at a 3% discount rate. This value is shown in column 5 of Table 5.

Table 5. Social cost of carbon estimates of CO_2 emissions from the Interagency Working Group on Social Cost of Carbon.

	Average			95th Percentile
Discount rate	5%	3%	2.5%	3%
SCC value (in €$_{2015}$/ton)	11	37	58	109

Source: [82]. Notes: The CPI Inflation Calculator from the US Department of Labor (http://www.bls.gov/data/inflation_calculator.htm) was used to convert the USD_{2007} values provided in the original study to USD_{2015} values, before applying an exchange rate of 1.1 USD/EUR for conversion into EUR. The values refer to CO_2 emissions in the year 2015.

Other studies, using mostly older versions of the three commonly used IAMs, tend to show lower values for the SCC. (A meta-analysis of 75 SCC studies released between 1982 and 2012 finds a mean value for the SCC of 7 USD per ton of CO_2 for the year 2010 at a 3% discount rate [83]). In recent years, many authors have criticised the SCC values typically derived from IAMs and have provided a number of arguments supporting their belief that these values are systematically too low [80,84–87]. Many authors argue that there is a strong case for using lower discount rates than those used for central SCC estimates in most studies (typically around 3%). As Table 5 indicates, the choice of discount rate has a considerable influence on the SCC estimate.

Furthermore, many authors argue that the IAMs typically used lead to SCC estimates that are too low for at least the following two additional reasons. Firstly, several types of climate change impacts are not, or not fully, included in the IAMs typically used to derive SCC. Among these impacts are the potential secondary social effects of climate change, such as damage resulting from climate change-induced armed conflicts, the negative impact of climate change on non-market goods such as biodiversity, and the potentially significant damage from increasing ocean acidification [80,88,89]. Secondly, the natural tendency to be risk-averse in the face of improbable but extremely severe consequences of future climate change is typically not captured in SCC estimates. This is especially important regarding the potentially catastrophic effects associated with tipping points [79,90–92].

Several authors have derived considerably higher SCC values than are typically reported from standard IAM runs by using lower discount rates and/or addressing the aforementioned shortcomings of IAMs. For example, van den Bergh and Botzen [80] conclude that a lower bound to the SCC of €114 (US$125) per ton of CO_2 can be derived when using a low discount rate and when taking low-probability/high-impact climate outcomes as well as risk aversion into account. The authors point out that this estimate still does not include various difficult to quantify climate change damage, so they argue that their lower bound of €114 per ton of CO_2 should be regarded as a conservative estimate. Kopp et al. [90] have conducted a thorough sensitivity analysis of the SCC, using a modified version of the IAM DICE to derive scenarios with varying assumptions about the climate change damage specifications, calculating each scenario's SCC for different levels of risk aversion. Based on the different model specifications, the authors arrive at a broad range of SCC estimates. Assuming medium risk aversion, their median SCC values range between €29 and €136; assuming high risk aversion, this range increases to €34–€626. These results illustrate that different assumptions on how to formalise future climate change damage can lead to considerably higher SCC values compared to those obtained with standard damage functions, especially when combined with a highly risk-averse attitude. It is not possible to choose a "best" estimate from the broad range of SCC estimates found in the literature. Table 6, therefore, shows the lifecycle GHG emissions costs of various types of electricity generation using a broad range of SCC estimates from the literature.

Table 6. Lifecycle GHG emissions costs of electricity generation technologies assuming a social cost of carbon of €$_{2015}$11 (low), €$_{2015}$114 (medium) and €$_{2015}$626 (high) per ton of CO_2-equivalent (in €-cent$_{2015}$/kWh).

Technology/Energy Source	Low	Medium	High
Lignite	1.0	10.2	56.2
Coal	0.9	9.0	49.6
Natural gas	0.4	4.5	24.8
Coal CCS (post combustion)	0.3	3.0	16.4
Coal CCS (oxy-fuel)	0.2	2.0	11.0
Natural gas CCS	0.1	1.5	8.3
Biomass	<0.1	0.4	2.3
Hydro	<0.1	0.1	0.4
Solar PV	<0.1	0.3	1.7
Wind (onshore)	<0.1	0.1	0.7
Wind (offshore)	<0.1	0.1	0.6
CSP	<0.1	0.2	1.3
Geothermal	<0.1	0.5	2.5
Ocean	<0.1	0.1	0.5
Nuclear (LWR)	<0.1	0.1	0.8

Sources: Calculations based on lifecycle GHG emissions data from [93] (fossil fuels); [94] (renewable energy sources) and [95] (nuclear power).

The lower value of €11 per ton of CO_2 is the central value from the Interagency Working Group on Social Cost of Carbon [82] for emissions in the year 2015 at the relatively high discount rate of 5%. For the median value, €114 per ton of CO_2 is chosen, corresponding to the "lower bound" estimate by van den Bergh and Botzen [80]. The high value of €626 is based on the upper SCC value derived by Kopp et al. [90] when assuming high risk aversion. It should be noted that this range, although quite large, still fails to represent the full range of SCC estimates found in the literature.

3.3.2. Impacts of Non-GHG Pollution Caused by Using Various Energy Sources

The exploitation, transportation and conversion of fossil fuel energy sources and biomass invariably leads to the release of various forms of pollutants into the environment. These pollutants can affect air, water and soil quality and can have negative effects on human health, crops, building materials and the natural environment. Damage to human health resulting from air quality impairment is generally regarded as the most important consequence of such pollution [96] and is, therefore, the focus of this section. Power plants are prominent sources of pollutants such as nitrogen oxides, sulphur oxides, particulate matter, carbon monoxide, mercury, cadmium and lead [97].

Exposure to air pollution from power plants has been linked with various adverse human health effects. These include [98–104]:

- Neurological damage, especially to foetuses, newborns and children, leading e.g., to mental retardation, seizures or delayed development;
- Cardiovascular morbidity and mortality, e.g., strokes;
- Pulmonary morbidity and mortality, e.g., lung cancer;
- Respiratory diseases, especially in children, e.g., asthma.

Particulate matter (PM), especially fine particulate matter ($PM_{2.5}$) consisting of particles with a diameter of 2.5 micrometres or less, has been identified by numerous studies to be the most significant pollutant from power plants to cause negative health effects [105,106].

Unlike GHG emissions, which mix quickly within the earth's atmosphere, one unit of an air pollutant can result in different effects and, therefore, different costs depending on the location and characteristics of the source of the pollution. Representative estimates for the air pollution costs of power plants have been derived in the past for both the EU and the USA. Table 7 shows the lifecycle damage costs of air pollution per kWh for different kinds of newly-built power plants in

Europe, as provided by the European research project "New Energy Externalities Development for Sustainability" (NEEDS) [107]. The table does not include estimates of damage due to climate change or negative effects on biodiversity (including land use), as these effects are discussed in separate sections of this article.

Table 7. Lifecycle air pollution costs of state-of-the-art (in around 2009) electricity generation technologies (2025 for CCS technologies) (in €-cent$_{2015}$/kWh).

Technology/Energy Source	Health Impacts	Crop Yield Losses	Material Damage	Sum
Nuclear power	0.07	0.00	0.00	**0.08**
Offshore wind	0.07	0.00	0.00	**0.07**
Ocean energy	0.15	0.00	0.00	**0.15**
CSP	0.15	0.00	0.00	**0.15**
Natural gas (CCGT)	0.39	0.01	0.01	**0.41**
Natural gas (CCGT, with post-combustion CCS)	0.34	0.01	0.01	**0.36**
Solar PV	0.59	0.00	0.01	**0.60**
Lignite	0.90	0.02	0.01	**0.94**
Hard coal	1.31	0.02	0.02	**1.36**
Hard coal (with post-combustion CCS)	1.43	0.04	0.02	**1.50**
Hard coal (with oxy-fuel CCS)	1.04	0.02	0.02	**1.08**
Biomass	1.91	0.07	0.04	**2.02**

Source: Data from [107].

It should be stressed that the power plants for which these pollution damage costs were calculated within the NEEDS project are generic power plants that were state-of-the-art around the year 2009. Currently operating power plants (in many cases decades old) typically cause much higher pollution damage, as they tend to use less advanced pollution control technologies and tend to be less efficient. The National Research Council study [96], for example, modelled the pollution damage for 406 coal-fired power plants operating in the United States in 2005 and found an average damage of 3.2 \$-cent$_{2007}$/kWh (3.3 €-cent$_{2015}$/kWh) for the electricity from all plants and an average damage of 12 \$-cent$_{2007}$/kWh (12.5 €-cent$_{2015}$/kWh) for the 5% of electricity from the most damaging coal-fired power plants. These figures include only the plants' emissions, not the full lifecycle emissions.

Epstein et al. [108] noted that the concentration-response function for $PM_{2.5}$ derived by Pope et al. [101] and used by both the National Research Council study and the NEEDS study provided "a low estimate for increases in mortality risk with increases in $PM_{2.5}$ exposure". Epstein et al. [108] point to a study by Schwartz et al. [109] that puts forward an estimate for $PM_{2.5}$-related mortality considerably higher than that of Pope et al. [101]. According to Epstein et al. [108], using the concentration-response function of the study by Schwartz et al. [109] would lead to damage almost three times higher. Machol and Rizk [110] also find much higher external health costs than the National Research Council for coal power generation in the USA [96]. The differences in damage cost estimates between the studies highlight the considerable uncertainties in this field. The main uncertainties concern the negative health effects of pollutants, especially at relatively low levels, and the appropriate values to choose for a statistical life or a life year.

3.3.3. Landscape and Noise Impacts

Electricity generation plants may impact on people's welfare if they are affected by the visual appearance of these plants, by the landscape changes they cause or by the noise they emit. Wind power plants have been the most frequent subject of recent public discussion and scientific literature in terms of their impact on the landscape and the noise pollution they create.

One strand of literature on the landscape and noise externalities of wind power plants relies on the *revealed* preference method of examining the impact that new wind turbines (or the announcement of wind turbine development) have on the market value of nearby houses or properties. Results from these studies are mixed, with studies for North America generally finding no statistically significant relationship between wind turbine development and housing or property prices [111–114], but studies for several European countries finding evidence of a negative relationship [115–118]. These differences in the findings between European and US studies suggest that people in the USA are generally less disturbed by wind power plants located near their houses than people living in Europe. However, no literature was found that examines the reasons for these differences.

Another strand of literature relies on *stated* preference methods to infer how individuals value changes in their environment by establishing hypothetical markets through surveys. These studies [119–122] find that many people would be willing to pay to increase the distance of wind turbines to their homes or to the recreational areas they visit during holidays, up to a certain distance. Several of these studies find that younger people hold weaker preferences for reducing the disamenity impacts of wind turbines than older people. Ladenburg and Lutzeyer [120] note that an interesting question in this regard is whether this "age effect" is permanent or not. If it is permanent, i.e., if it is a generation effect, then the external landscape cost of wind power, if all things remain equal, can be expected to decline in the future.

Most of the literature sources examining visual and noise disamenities from wind power plants do not provide estimates, or enable estimates to be derived, for the related external costs per unit of generated electricity. Table 8 lists estimates for the external costs of landscape and noise impacts from five studies which provide this kind of information. As seen in Table 8, the estimates vary widely. However, all but one estimate is around 0.3 €-cent/kWh or lower, with the notable exception being a range of about 0.5–2 €-cent derived from a study for The Netherlands [115]. The differences in the cost estimates are likely to be due mainly to differences in the studies' geographical scope as well as their methodological approaches. As mentioned above, in Europe people generally appear to feel more negative about wind power plants than in the US, and since the Netherlands is one of the most densely populated countries in Europe, more people tend to be affected by wind power plants compared to countries with a smaller population density. In terms of methodology, stated preference methods may tend to underestimate the full disamenity costs, as these methods may not capture all types of impacts (e.g., only visual but not noise impacts).

Table 8. Costs of landscape and noise impacts of onshore and offshore wind power plants at various locations in Europe and the USA according to several studies.

Type of Wind Power	Study	Geographical Scope	Method	Costs of Landscape and Noise Impacts (in €-cent/kWh)	Comments
Onshore	[115]	The Netherlands	Revealed preference	0.90	Average; full range: 0.5–2.0; own assumptions made to derive per kWh costs: home buyers consider disamenity over 25 years and the average full load hours of onshore wind turbines in the Netherlands are 2300/a
	[123]	South Evia, Greece	Stated preference	0.27	-
	[124]	Denmark	Revealed preference	0.02	Investigated area sparsely populated
Offshore	[119]	Delaware, USA	Stated preference	0.28	Wind farm assumed to be 3.6 miles from the coast
				0.07	Wind farm assumed to be 6 miles from the coast
	[125]	Lake Michigan Area, USA	Stated preference	0.08	Mean value provided

Hydropower plants (especially those with dams) may also have relevant external landscape effects [126]. Several studies examine the impact of hydropower dams on nearby property prices [127–129] or use other revealed preference or stated preference methods to learn about people's preferences (e.g., concerning recreational usage) for free-flowing rivers and dammed river stretches [130–133]. However, results from these studies are not conclusive and they do not enable the related externalities from this technology to be quantified. A key challenge to establishing a general figure for the landscape externality of hydropower plants is that these plants' structures and impacts tend to differ significantly from one location to another.

The NEEDS study has chosen not to attempt to quantify damage derived from negative visual impacts for any of the technologies it analyses, noting that this damage is "affected by a considerable variability in time and space, which makes it impossible to adopt benefit transfer methods" [134]. At the same time, the authors of the NEEDS study state that there appears to be a "reasonable consensus" that this type of externality is not substantial compared to other types of externalities.

3.3.4. Impacts on Ecosystems and Biodiversity (Non-Climate Change-Related)

Electricity generation from various sources may lead to negative impacts on ecosystems and biodiversity. Impacts on ecosystems may take the form of damage to land, plant life, or animals. If, as a result of these impacts, the survival (locally or even globally) of a plant or animal species is threatened, biodiversity may be reduced.

The monetary impacts on ecosystems from human-induced climate change should ideally be included in the cost estimates for the GHG emissions discussed in Section 3.3.1. However, many of the IAMs used to estimate GHG emissions costs do not take ecosystem impacts fully into account [79,135].

Table 9 shows estimates for the biodiversity costs of impacts caused by various forms of electricity generation as provided by the NEEDS study. Costs are shown separately for the impacts of airborne emissions and land-use changes and are assessed for newly-built, state-of-the-art power plants around the year 2009 (with the exception of CCS power plants, for which cost estimates are provided for the year 2025, as these kinds of plants were not in operation in 2009). The sum of both cost elements is low for most technologies when compared to the most relevant types of quantifiable external costs, i.e., GHG emissions costs (see Table 6) and health impact costs (see Table 7).

Table 9. Estimates for the costs of biodiversity impacts of state-of-the-art electricity generation technologies around the year 2009 (2025 for CCS technologies) (in €-cent$_{2015}$/kWh).

Technology/Energy Source	Due to Airborne Emissions	Due to Land Use Changes	Sum
Nuclear power	<0.01	0.01	<0.1
Offshore wind	0.00	n.a.	n.a.
Ocean energy	0.01	0.00	<0.1
CSP	0.01	n.a.	n.a.
Natural gas (CCGT)	0.04	0.01	<0.1
Natural gas (CCGT, with post-combustion CCS)	0.02	0.02	<0.1
Solar PV	0.02	n.a.	n.a.
Lignite	0.09	0.01	0.1
Hard coal	0.11	0.06	0.2
Hard coal (with post-combustion CCS)	0.21	0.07	0.3
Hard coal (with oxy-fuel CCS)	0.09	0.07	0.2
Biomass	0.24	0.82	1.1

Source: Data from [107].

It should be emphasised that due to a lack of data and a lack of a well-established methodology, these estimates of impacts on biodiversity are crude and imperfect. The complexity of nature's interdependencies and the contested question of whether animals and plants have an intrinsic value beyond their immediate value to mankind make such estimates a difficult exercise. Consequently, the figures cited here and shown in Table 9 should be treated with caution.

Furthermore, the cost estimates provided in Table 9 are not based on a full lifecycle assessment. Studies that attempt to systematically quantify and monetise the lifecycle effects on ecosystems, especially of fossil and nuclear fuel extraction, are not available.

Finally, biodiversity may also be affected directly by the physical structures of the power plants and their supporting equipment; this aspect is not included in the estimates provided in Table 9. This is most relevant for birds and bats, which are at risk of colliding with the physical structures. Collisions by birds and bats are most frequently discussed in the public domain and the literature in relation to wind power plants [136,137]. There are also indications of bird and bat deaths at solar thermal power plants and large-scale solar PV plants [138,139], although it should be noted that the estimated avian mortality from both wind and solar power plants is reported to be significantly lower than from other human structures or activities, such as buildings and road vehicles [139].

Due to a lack of reliable and representative data, the specific threat that bird and bat fatalities at these and other types of power plants pose to biodiversity is difficult to gauge and clearly even more difficult to monetise. To the author's knowledge, to date there have been no studies that attempt to monetise the potential damage to biodiversity from bird or bat collisions.

3.3.5. External Costs Associated with Radionuclide Emissions

Radionuclide emissions can occur and be hazardous for human health during various stages of the nuclear power lifecycle. The likelihood and expected damage caused by large-scale nuclear accidents, as well as the question of how to monetise this damage, are highly contested issues in the literature and are the main reason for the wide divergence of external cost estimates of nuclear power. It should be noted that, in principle, large-scale accidents at other types of power plants may also lead to external costs. However, these non-internalised costs of non-nuclear accidents are reported to be negligible [140,141].

Severe accidents at nuclear power stations or other nuclear facilities, defined as accidents in which significant amounts of radioactive substances are released into the environment, have two important characteristics: the probability of such an accident occurring is very small and the potential damage is very high. The most common method for estimating the cost of a potential future accident is to calculate the summation of the probability of the occurrence of a scenario (P_i) leading to an accident multiplied by the monetised damage from that accident (C_i) over all plausible scenarios (i). This "expected damage" approach [142] can be represented by:

$$\text{Expected value of damage} = \sum P_i \cdot C_i$$

Studies that use this method typically conclude that the costs of a severe nuclear accident are small when expressed on a per kWh basis. However, using this method for determining the costs to society of a large-scale nuclear accident is frequently criticised in the literature. Critics point out that the public is generally very concerned about large-scale nuclear accidents and would be willing to pay much more than the expected value of damage to reduce or prevent the risks associated with a severe nuclear accident—even if the probability of such an accident is small. This discrepancy between expected damage calculations and public preferences might be due to a general aversion to risk of significant damage. Regarding severe nuclear accidents, people might not only be anxious about the negative impacts on their own health, but could also feel hostile about the drastic changes to society that could potentially ensue [143,144].

However, not only is the question of how to interpret or weight the expected value of damage from a nuclear accident heavily debated in the literature, but the calculation of the expected value itself is also difficult and contentious. Both the probability (P) and the cost (C) of a nuclear accident scenario are difficult to determine. The probability of a severe nuclear accident is typically estimated by applying a probabilistic safety assessment (PSA). A PSA evaluates the potential causes of an accident, the probabilities of occurrence and the corresponding expected environmental releases [145]. Numerous PSA studies have been carried out in the past for different types of nuclear reactors and they typically conclude that for up-to-date reactor designs severe nuclear accidents are likely to happen no more than once every 100,000 to 10 million reactor years [142].

However, doubts are expressed by some authors about whether the PSA values are reliable estimates of the actual risk of severe accidents, even at newly-built reactors. It is argued that certain events, such as human misconduct, undiscovered manufacturing defects or complex, cross-linked system reactions can only be described in an incomplete manner by a PSA [144]. Furthermore, it is obviously extremely difficult to quantify—especially decades in advance—the risks to nuclear facilities posed by terrorism or warfare. Studies attempting to quantify the externalities of nuclear power typically note that potential safety risks posed by terrorism are not taken into account [134,146].

Beyond the uncertainty about the probability of severe nuclear accidents, there are also significant uncertainties regarding the costs of such accidents if they occur [142,147,148].

It can be concluded that due to high uncertainties and methodological challenges it is extremely difficult, if not impossible, to derive from the literature a meaningful range for the overall external costs of electricity generation from nuclear power. However, there is a general consensus in the literature that the external costs of nuclear power plants' *normal* operation (including damage caused by lifecycle GHG emissions and other pollutants as discussed above) are significantly lower than those for fossil fuel based electricity generation. Based on the NEEDS study [107] and Rabl and Rabl [146], a likely cost range for the external costs of normal operation may be 0.1–0.4 €-cent/kWh. External costs from nuclear accidents, however, are much more uncertain. Rabl and Rabl [146] derive a range of about 0.1–2.3 €-cent/kWh with a central value of about 0.4 €-cent/kWh.

Due to the profound empirical and methodological challenges in quantifying the external costs of nuclear electricity generation, many authors suggest that any estimates of these kinds of costs should be treated with great caution—even more so than estimates of the external costs of other electricity generation technologies. Some authors suggest that ranking nuclear power and other power generation technologies should not be based on highly uncertain social cost estimates, but should rather rely on alternative tools, such as Multi Criteria Decision Analysis (MCDA) [134].

3.3.6. Other Potential External Costs

Other potential externalities of electricity generation are occasionally discussed in the literature. Among these additional potential externalities are:

- Supply disruptions [134,149,150];
- Unintended funding of terrorism through the purchase of fossil fuels or uranium [151];
- Resettlement of people [152–155];
- Non-renewable resource extraction [156–158];
- Water withdrawal, consumption and contamination [159];
- Increased seismicity [160];
- Toxicity of materials used to build/manufacture plants [159];
- Type of ownership/preferences for self-subsistence [161,162].

Whether all these effects are externalities or not and, if they are, whether their respective costs are relevant or not is difficult to ascertain. To the author's knowledge, no quantitative and universal estimates of these potential externalities exist.

4. Synthesis: Comparing the Social Costs of Electricity Generation Technologies

4.1. Current Costs

Based on the extensive literature review presented in Section 3, Tables 10 and 11 offer an overview of the social costs of electricity generation for various types of newly-built power plants in Europe and the USA respectively. As mentioned in Section 3.1.5, the analysis is limited to selected technologies for reasons of brevity.

The tables include available quantitative estimates for different types of external costs—albeit in many cases with considerable uncertainties. Indications are given in the tables about the role played by two additional types of external costs, which may be relevant but for which understanding is insufficient to derive meaningful quantitative estimates. The additional potential non-quantifiable external costs listed in Section 3.3.6 are not listed in Table 10 or Table 11 as, based on the literature, it is not possible to assess whether these are relevant or not. However, it should be mentioned that these potential additional external costs appear to be more relevant for nuclear power and fossil fuel technologies than for renewable energy technologies.

All the elements of system costs, as well as all external costs other than those associated with GHG emissions, vary significantly from one type of electricity system to another, and sometimes even within a particular electricity system. However, for reasons of simplification and because the information provided by the literature was deemed to be insufficient to confidently derive ranges for the external costs and the system costs, only point estimates of typical values are provided in the tables below. It should be kept in mind that, in specific circumstances, actual costs may deviate considerably from the values shown here. For plant-level costs, on the other hand, ranges as derived in Section 3.1.5 are included in the tables. There is also insufficient information in the literature to reliably quantify differences in system costs and external costs between Europe and the USA, so these are assumed to be identical in both regions, with the exception of the landscape and noise disamenity costs of onshore wind power. This is an oversimplification, as it is likely that due to (among other things) differences in geography, population density and solar and wind resources, there are non-negligible differences in the specific system costs and air pollution costs between Europe and the USA.

Using past annual transmission and distribution investments in Germany [163], it is estimated that average transmission costs of non-variable, dispatchable electricity generation are around 0.5 €-cent/kWh. Median estimates for the additional costs for grid extension and reinforcement for VRE electricity generation are between 0.1 and 1.4 €-cent/kWh, with the specific costs of solar PV tending to be a bit higher than for wind. Here we assume additional costs of 0.5 €-cent/kWh for electricity from onshore and offshore wind and of 1 €-cent/kWh for solar PV power plants. This leads to total transmission costs of 1 €-cent/kWh for electricity generation from wind power plants (both onshore and offshore) and of 1.5 €-cent/kWh for electricity generation from solar PV power plants.

Balancing costs are also generally believed to be much more significant for electricity generation from VRE sources than for electricity generation from dispatchable sources. The few literature sources available which estimate the balancing costs of dispatchable power plants indicate that these costs for these plants are negligible. It is assumed in this paper for simplicity that these costs are zero for dispatchable power plants. Balancing costs for electricity generation from wind are given by various literature sources at about 0.3 €-cent/kWh, with no clear correlation with wind penetration level. Few sources provide information on the balancing costs of electricity generation from solar PV plants, but the quantitative and qualitative information available suggests specific balancing costs are likely to be somewhat lower for solar PV than for wind. Specific balancing costs for electricity generation from solar PV power plants are, therefore, assumed to be 0.2 €-cent/kWh in this article.

Table 10. Overview of the estimated specific social costs of electricity generation in Europe from several types of current newly-built power plants.

Type of Cost	Costs in €-cent/kWh						
	Renewables			Nuclear (at a 3% Discount Rate)	Nuclear (at a 6% Discount Rate)	Fossil Fuels	
	Onshore Wind	Offshore Wind	Solar PV (Utility-Scale)			Natural Gas (CCGT)	Hard Coal
Plant-level costs							
Installation costs (central values)	4.4	7.6	5.8	3.4	6.2	0.7	1.5
O&M costs (central values)	2.0	3.6	2.0	1.6	1.6	0.6	0.8
Fuel costs (central values)	0.0	0.0	0.0	0.9	0.9	4.9	2.0
Sum of plant-level costs (w/o CO_2 costs) (central values; ranges in parenthesis)	**6.4** (2.5–9.7)	**11.2** (7.5–14.9)	**7.8** (5.3–10.1)	**5.8** (4.8–6.9)	**8.6** (6.8–10.1)	**6.2** (5.9–6.7)	**4.3** (3.3–4.8)
System costs							
Grid costs	1.0	1.0	1.0	0.5	0.5	0.5	0.5
Balancing costs	0.3	0.3	0.2	0	0	0	0
Profile costs (additional costs for VRE plants for shares of around or below 10% for wind and solar PV each)	1.0	1.0	1.0	0	0	0	0
Sum of system costs	**2.3**	**2.3**	**2.2**	**0.5**	**0.5**	**0.5**	**0.5**
Quantifiable external costs							
GHG emissions costs (at 114 €/t CO_2)	0.1	0.1	0.3	0.1	0.1	4.5	9.0
Air pollution costs (state-of-the art plants)	<0.1	<0.1	0.3	<0.1	<0.1	0.4	1.4
Landscape and noise disamenity costs	0.5	0.2	0	0	0	0	0
Sum of quantifiable external costs	**0.6**	**0.3**	**0.6**	**0.1**	**0.1**	**4.9**	**10.4**
SUM OF ALL QUANTIFIABLE COSTS (with central plant-level values; with plant-level ranges in parenthesis)	**9.3** (5.4–12.6)	**13.8** (10.1–17.5)	**10.6** (8.1–12.9)	**6.4** (5.4–7.5)	**9.2** (7.4–10.7)	**11.6** (11.3–12.1)	**15.2** (14.2–15.7)
Potentially relevant non-quantifiable external costs							
Radioactive contamination (especially resulting from nuclear accidents)	-	-	-	x	x	-	-
Ecosystem and biodiversity impacts (non-climate change related)	x	x	x	x	x	x	x

Sources: The original sources of the data presented in this table, as well as (where applicable) the assumptions made and approaches taken to derive representative values, can be found in the discussion of each cost type in Section 3 and in the text of this subsection (Section 4.1).

Table 11. Overview of the estimated specific social costs of electricity generation in the USA from several types of current newly-built power plants.

Type of Cost	Costs in €-cent/kWh						
	Renewables			Nuclear (at a 3% Discount Rate)	Nuclear (at a 6% Discount Rate)	Fossil Fuels	
	Onshore Wind	Offshore Wind	Solar PV (Utility-Scale)			Natural Gas (CCGT)	Hard Coal
Plant-level costs							
Installation costs (central values)	2.7	7.4	3.1	3.4	6.2	0.7	2.2
O&M costs (central values)	1.4	3.6	0.9	1.6	1.6	0.5	1
Fuel costs (central values)	0	0	0	0.9	0.9	2.7	1.7
Sum of plant-level costs (w/o CO_2 costs) (central values; ranges in parenthesis)	**4.1** (2.7–9.1)	**11.0** (7.5–14.9)	**4.0** (2.8–5.4)	**5.8** (4.8–6.9)	**8.6** (6.8–10.1)	**3.8** (3.4–4.5)	**4.9** (4.0–5.7)
System costs							
Grid costs	1.0	1.0	1.0	0.5	0.5	0.5	0.5
Balancing costs	0.3	0.3	0.2	0	0	0	0
Profile costs (additional costs for VRE plants for shares of around or below 10% for wind and solar PV each)	1.0	1.0	1.0	0	0	0	0
Sum of system costs	**2.3**	**2.3**	**2.2**	**0.5**	**0.5**	**0.5**	**0.5**
External costs							
GHG emissions costs (at 114 €/t CO_2)	0.1	0.1	0.2	0.1	0.1	4.5	9.0
Air pollution costs (state-of-the art plants)	<0.1	<0.1	0.2	<0.1	<0.1	0.4	1.4
Landscape and noise disamenity costs	0.2	0.2	0	0	0	0	0
Sum of quantifiable external costs	**0.3**	**0.3**	**0.4**	**0.1**	**0.1**	**4.9**	**10.4**
SUM OF ALL QUANTIFIABLE COSTS (with central plant-level values; with plant-level ranges in parenthesis)	**6.7** (5.3–11.7)	**13.6** (10.1–17.5)	**6.6** (5.4–8.0)	**6.4** (5.4–7.5)	**9.2** (7.4–10.7)	**9.2** (8.8–9.9)	**15.8** (14.9–16.6)
Potentially relevant non-quantifiable external costs							
Radioactive contamination (especially resulting from nuclear accidents)	-	-	-	x	x	-	-
Ecosystem and biodiversity impacts (non-climate change related)	x	x	x	x	x	x	x

Sources: The original sources of the data presented in this table, as well as (where applicable) the assumptions made and approaches taken to derive representative values, can be found in the discussion of each cost type in Section 3 and in the text of this subsection (Section 4.1).

Literature estimates on specific profile costs vary considerably and generally increase as the penetration level of VRE generation grows. Currently, in most electricity systems in Europe and the USA, the respective shares of wind power generation are below 10% and of solar PV generation below 5%, so specific marginal profile costs are currently relatively low and are assumed in this article to be 1 €-cent/kWh for both wind and solar PV. No reliable information was found on the difference between profile costs for electricity generation from onshore wind and offshore wind, so no differentiation between the two could be made. However, it is likely that the generally higher capacity factors and steadier generation of offshore wind turbines mean that these are associated with lower profile costs than onshore turbines.

While electricity systems with only dispatchable power plants also require some balancing and excess generating capacities, the associated costs for dispatchable power plants are relatively small and are assumed to be zero. It should be stressed that this is only true under the assumption that the electricity system contains a cost-optimal mix of thermal baseload power plants (fossil fuel and/or nuclear power). This assumption allows for no system costs to be allocated to baseload power plants but it also means that if there were plans to significantly increase the penetration of nuclear power, for example, the marginal costs of additional plants would eventually be higher than indicated in this article.

It should be stressed that in the following tables the *marginal* profile costs are given (as opposed to the *average* profile costs), as the aim is to compare the cost of additional electricity generation from any one technology. This also means that in Tables 10–12 and even more so in Tables 13–15, the average costs of wind and solar PV electricity generation are lower than the marginal costs shown.

In terms of the costs of GHG emissions, the medium value for the SCC as derived in Section 3.3.1 is used. As there is considerable disagreement about the "appropriate" SCC value and as this type of external cost significantly influences the social costs of fossil fuel technologies, Table 12 provides a sensitivity analysis of the quantifiable social costs using the lower and higher SCC values derived in Section 3.3.1. For reasons of brevity, this sensitivity analysis is only shown for Europe. For air pollution costs, the values from the NEEDS study as presented in Section 3.3.2 are used. As the specific (life-cycle) GHG and air pollution emissions of solar PV plants are based on European conditions and typical solar PV capacity factors in the US are roughly twice those in Europe, the specific GHG and air pollution costs of solar PV plants in the USA are assumed to be half of those in Europe.

As a third quantifiable external type of cost, the landscape and noise disamenity costs are also estimated based on the literature discussed in Section 3.3.3. These costs are assumed to be relevant only for onshore and offshore wind power and not for any other type of power plant. For onshore wind, disamenity costs of 0.5 €-cent/kWh are assumed for Europe. This corresponds to the lower value derived from the study for the Netherlands [115], because other studies (such as [123]) arrive at lower costs and the population density of the Netherlands is much higher than the European average. For the USA, disamenity costs for onshore wind appear to be lower and are assumed to be 0.2 €-cent/kWh in this article. For offshore wind, disamenity costs for both Europe and the USA are assumed to be 0.2 €-cent/kWh.

Due to the extremely wide range of estimates of the external costs of potential nuclear accidents, this type of externality is classified in this article as a "non-quantifiable" external cost. While cost estimates of the impact on the ecosystem and on biodiversity do exist, these estimates do not appear to be comprehensive and, due to a lack of similar analysis in the literature, it is unclear how reliable they are. Therefore, the costs of ecosystem and biodiversity impacts are also classified as "non-quantifiable".

Table 12. Sensitivity to the assumed social cost of carbon value of the estimated specific social costs of electricity generation in Europe from several types of current newly-built power plants.

Type of Cost		Costs in €-cent/kWh						
		Renewables			Nuclear (at a 3% Discount Rate)	Nuclear (at a 6% Discount Rate)	Fossil Fuels	
		Onshore Wind	Offshore Wind	Solar PV (Utility-Scale)			Natural Gas (CCGT)	Hard Coal
GHG emissions costs	Low (11 €/t CO_2)	<0.1	<0.1	<0.1	<0.1	<0.1	0.4	0.9
	Medium (114 €/t CO_2)	0.1	0.1	0.3	0.1	0.1	4.5	9.0
	High (626 €/t CO_2)	0.7	0.6	1.7	0.8	0.8	24.8	49.6
All other quantifiable costs (with central plant-level values)		**9.2**	**13.7**	**10.3**	**6.3**	**9.1**	**7.1**	**6.2**
SUM OF ALL QUANTIFIABLE COSTS (with central plant-level values)	Low CO_2 costs (11 €/t CO_2)	**9.2**	**13.7**	**10.3**	**6.3**	**9.1**	**7.5**	**7.1**
	Medium CO_2 costs (114 €/t CO_2)	**9.3**	**13.8**	**10.6**	**6.4**	**9.2**	**11.6**	**15.2**
	High CO_2 costs (626 €/t CO_2)	**9.9**	**14.3**	**12.0**	**7.1**	**9.9**	**31.9**	**55.8**

Sources: The original sources of the data presented in this table, as well as (where applicable) the assumptions made and approaches taken to derive representative values, can be found in the discussion of each cost type in Section 3 and in the text of this subsection (Section 4.1).

Table 13. Overview of the estimated specific social costs of electricity generation in Europe from several types of power plants assumed to start operating in 2040.

Type of Cost	Costs in €-cent/kWh						
	Renewables			Nuclear (at a 3% Discount Rate)	Nuclear (at a 6% Discount Rate)	Fossil Fuels	
	Onshore Wind	Offshore Wind	Solar PV (Utility-Scale)			Natural Gas (CCGT)	Hard Coal
Sum of plant-level costs (w/o CO_2 costs) (central values; ranges in parenthesis)	**5.5** (2.3–8.3)	**7.6** (4.7–11.1)	**4.6** (3.0–6.2)	**5.8** (4.8–6.9)	**8.6** (6.8–10.1)	**6.2** (5.9–6.7)	**4.3** (3.3–4.8)
Grid costs	1.0	1.0	1.0	0.5	0.5	0.5	0.5
Balancing costs	0.3	0.3	0.2	0	0	0	0
Profile costs (additional costs for VRE plants for shares of around 35% for wind and 15% for solar PV)	2.5	2.5	2.5	0	0	0	0
Sum of system costs	**3.8**	**3.8**	**3.7**	**0.5**	**0.5**	**0.5**	**0.5**
Sum of quantifiable external costs	**0.5**	**0.2**	**0.1**	**0.1**	**0.1**	**4.9**	**10.4**
SUM OF ALL QUANTIFIABLE COSTS (with central plant-level values; with plant-level ranges in parenthesis)	**9.8** (6.6–12.6)	**11.6** (8.5–15.1)	**8.4** (6.8–10.0)	**6.4** (5.4–7.5)	**9.2** (7.4–10.7)	**11.6** (11.3–12.1)	**15.2** (14.2–15.7)

Sources: The original sources of the data presented in this table, as well as (where applicable) the assumptions made and approaches taken to derive representative values, can be found in the discussion of each cost type in Section 3 and in the text of this subsection (Section 4.2).

Table 14. Overview of the estimated specific social costs of electricity generation in the USA from several types of power plants assumed to start operating in 2040.

Type of Cost	Costs in €-cent/kWh						
	Renewables			Nuclear (at a 3% Discount Rate)	Nuclear (at a 6% Discount Rate)	Fossil Fuels	
	Onshore Wind	Offshore Wind	Solar PV (Utility-Scale)			Natural Gas (CCGT)	Hard Coal
Sum of plant-level costs (w/o CO_2 costs) (central values; ranges in parenthesis)	**3.7** (2.3–7.2)	**7.6** (4.7–11.1)	**2.7** (1.6–3.4)	**5.8** (4.8–6.9)	**8.6** (6.8–10.1)	**3.8** (3.4–4.5)	**4.9** (4.0–5.7)
Grid costs	1.0	1.0	1.0	0.5	0.5	0.5	0.5
Balancing costs	0.3	0.3	0.2	0	0	0	0
Profile costs (additional costs for VRE plants for shares of around 35% for wind and 15% for solar PV)	2.5	2.5	2.5	0	0	0	0
Sum of system costs	**3.8**	**3.8**	**3.7**	**0.5**	**0.5**	**0.5**	**0.5**
Sum of quantifiable external costs	**0.3**	**0.2**	**0.1**	**0.1**	**0.1**	**4.9**	**10.4**
SUM OF ALL QUANTIFIABLE COSTS (with central plant-level values; with plant-level ranges in parenthesis)	**7.8** (6.4–11.3)	**11.6** (8.7–15.1)	**6.5** (5.4–7.2)	**6.4** (5.4–7.5)	**9.2** (7.4–10.7)	**9.2** (8.8–9.9)	**15.8** (14.9–16.6)

Sources: The original sources of the data presented in this table, as well as (where applicable) the assumptions made and approaches taken to derive representative values, can be found in the discussion of each cost type in Section 3 and in the text of this subsection (Section 4.2).

Table 15. Overview of the estimated specific social costs (central values) of electricity generation in Europe from several types of power plants built in 2040 depending on how profile costs are allocated.

Type of Cost		Costs in €-cent/kWh						
		Renewables			Nuclear (at a 3% Discount Rate)	Nuclear (at a 6% Discount Rate)	Fossil Fuels	
		Onshore Wind	Offshore Wind	Solar PV (Utility-Scale)			Natural Gas (CCGT)	Hard Coal
Sum of plant-level costs...	...when all of the profile costs are allocated to VRE generation	**5.5**	**7.6**	**4.6**	**5.8**	**8.6**	**6.2**	**4.3**
	...when parts of the profile costs are allocated to baseload generation	**5.5**	**7.6**	**4.6**	**8.9**	**13.6**	**6.9**	**5.7**
Sum of system costs...	...when all of the profile costs are allocated to VRE generation	**3.8**	**3.8**	**3.7**	**0.5**	**0.5**	**0.5**	**0.5**
	...when parts of the profile costs are allocated to baseload generation	**2.8**	**2.8**	**1.2**	**0.5**	**0.5**	**0.5**	**0.5**
Sum of quantifiable external costs		**0.5**	**0.2**	**0.1**	**0.1**	**0.1**	**4.9**	**10.4**
SUM OF ALL QUANTIFIABLE COSTS...	...when all of the profile costs are allocated to VRE generation	**9.8**	**11.6**	**8.4**	**6.4**	**9.2**	**11.6**	**15.2**
	...when parts of the profile costs are allocated to baseload generation	**8.8**	**10.6**	**5.9**	**9.5**	**14.2**	**12.3**	**16.6**

Sources: The original sources of the data presented in this table, as well as (where applicable) the assumptions made and approaches taken to derive representative values, can be found in the discussion of each cost type in Section 3 and in the text of this subsection (Section 4.2).

As Table 10 shows, when only considering the quantifiable social costs and neglecting differences in investment risks, nuclear power is currently the cheapest option for electricity generation in Europe, although onshore wind power at good sites can have comparable costs. Assuming, on the other hand, that the greater investment risks for nuclear power plants are adequately captured by a higher discount rate of 6%, both nuclear power and typical onshore wind power plants exhibit virtually the same quantifiable social central value cost of just over 9 €-cent/kWh. In the USA, nuclear power (when neglecting higher investment risks), utility-scale solar PV and onshore wind power plants currently exhibit the lowest quantifiable social costs, with their central values all between 6 and 7 €-cent/kWh. Regarding the values for nuclear power, it should be stressed that these costs do not include the risks associated with accidents at—or attacks on—nuclear power facilities.

4.2. Expected Costs in 2040

Tables 13 and 14 show the estimated social costs of electricity generation in Europe and the USA for plants to be built in 2040. For these tables, it is assumed that the plant-level costs of renewable energy technologies will continue to decline in the coming decades due to further reductions in investment and O&M costs. Specifically, capital costs and O&M costs in 2040 for onshore wind, offshore wind and solar PV are taken from Teske et al. [6], which use an experience curve approach to estimate future costs. The capacity factors are assumed to remain constant, with the exception of solar PV in the USA. For this technology the central estimate for capacity factor was assumed to decline from the current value of 25.8% to 23%, given that it is likely that future deployment at higher penetration rates will no longer be able to focus so strongly on the best solar irradiation sites [43]. The costs of electricity generation from fossil fuel technologies remain constant, under the assumption that any technological learning that may still take place between today and 2040 will be compensated for by rising fuel prices. The costs of power generation from nuclear power also remain constant, under the assumption that the nuclear industry will be successful in avoiding the type of cost increases that have been observed in past decades, especially in the USA and Europe [164–166].

In 2040, the penetration rate of VRE technologies in Europe and the USA is likely to be much higher than today, perhaps around 50% [30,167]. Therefore, for the marginal specific profile costs of VRE electricity generation in 2040, the cost estimates in the literature for higher VRE shares are relevant. It is assumed that solar PV will have a share of about 15% and will cause specific marginal profile costs of 2.5 €-cent, while the same marginal costs are assumed to accrue for wind power for an anticipated share of about 35%. These marginal profile cost estimates for wind and solar PV are somewhat lower than those found by Ueckerdt et al. [51] for similar VRE shares. Lower values were chosen because the other two studies cited in Section 3.2.3 arrive at lower marginal and/or average profile costs than Ueckerdt et al. [51], even at penetration rates at which VRE overproduction costs (which are not included in the other two studies) do not yet play a role according to Ueckerdt et al. [51].

For the sake of simplicity, all other system costs are held constant at their current values, although specific balancing costs, for example, may decline over time as a result of technological progress. For the most part, the external costs are also assumed to remain constant, although the expected further improvements in the lifecycle GHG and air pollution emissions for wind and solar PV plants are taken into account. Detailed information about the specific assumptions can be found in the Supplementary Materials. For reasons of brevity, the non-quantifiable external costs are not listed again in Tables 13 and 14.

As it is a matter of debate whether or not it is appropriate to allocate the full profile costs of additional VRE power generation to the new VRE power plants, Table 15 takes another approach to allocating these costs in a technology specific comparison for 2040. This alternative approach assumes that the additional costs caused by new VRE power generation in the residual system are allocated to the dispatchable power plants, as this is where these costs actually manifest themselves. Specifically, it is assumed that the capacity factors of the dispatchable power plants decrease from 85% (current estimate) to 50% in 2040. This leads to considerably higher plant-level costs of the dispatchable power plants. Taking such an approach, the profile costs of VRE electricity generation consist only of the overproduction costs, as the additional costs accruing in the residual system are now reflected in the higher costs of dispatchable electricity generation. Following Ueckerdt et al. [51], the overproduction costs are assumed to be 1.5 €-cent/kWh for wind for a share of 35% and negligible for solar PV for a share of 15%.

As Table 13 suggests, in Europe and the USA further plant-level cost reductions for solar PV and wind power by 2040 are expected to be partly compensated (solar PV, offshore wind) or even overcompensated (onshore wind) by higher system costs, if profile costs are fully allocated to VRE power generation. Therefore, in Europe, nuclear power may still be the least expensive option in terms of quantifiable social costs, when not accounting for its higher investment risks. If these are taken into consideration by using a higher discount rate of 6%, the central cost estimate is lowest for solar PV (8.4 €-cent/kWh), followed by nuclear power (9.2 €-cent/kWh) and onshore wind (9.8 €-cent/kWh). When the increase in the specific costs of the residual system due to additional VRE power penetration is not allocated to wind and solar PV, but to the dispatchable power plants that will suffer from lower capacity factors, solar PV and onshore wind can be expected to be the cheapest options in 2040, followed by nuclear power and offshore wind.

In the USA, by 2040, when fully allocating the profile costs to VRE power generation and ignoring differences in investment risks, both nuclear power and solar PV can be expected to have virtually the same quantifiable social costs, followed by onshore wind. Solar PV and onshore wind are clearly expected to be the options with the lowest quantifiable social costs if the additional risks of nuclear power investments are taken into account (by using a 6% discount rate) and/or if parts of the profile costs are allocated to the dispatchable plants.

In both Europe and the USA, electricity from offshore wind, solar thermal power plants and coal CCS plants (the latter two are not shown in the tables) is expected to remain more expensive than electricity from other low-carbon sources, namely onshore wind, solar PV and nuclear power [21,168].

5. Conclusions and Further Research Needs

The literature review in Section 3 and the synthesis in Section 4 emphasise that not only plant-level costs, but also system costs and external costs are relevant when comparing the social costs of electricity generation. According to the cost estimates used here, system costs may (in the future) constitute more than 50% of the total social costs of VRE power generation at relatively high VRE market penetration (and assuming that the profile costs of additional VRE power generation are allocated entirely to VRE power generation itself). The quantifiable external costs, on the other hand, are most relevant for fossil fuel power generation and may account for about 25% of the total quantifiable social costs of coal power at low SCC assumptions and for about 90% at high SCC assumptions. These findings emphasise that all three cost categories (plant-level costs, system costs and external costs) should be taken into account when attempting to advise society and policymakers on a least-cost approach to future electricity supply.

Table 16 underscores this conclusion by providing for each identified sub-category of costs its relevance in social cost comparisons of different electricity generation technologies. "Low" relevance means that the maximum differences in a certain category of costs between individual technologies are less than 0.5 €-cent/kWh; "medium" relevance means that these differences are between 0.5 and less than 2 €-cent/kWh; and "high" relevance means that they are 2 €-cent/kWh or higher. Based on the extensive literature review, Table 16 also provides an assessment by the author of the current scientific understanding regarding each cost category.

Table 16. Assessment of the relevance of individual cost categories for social cost comparisons for electricity generation technologies and of the scientific understanding of each category.

Cost Category	Relevance for Comparing Costs	Scientific Understanding
Plant-level costs		
Capital costs	High	High
Fuel costs	High	Moderate to high
Market costs of GHG emissions	High	High
Non-fuel O&M costs	High	Moderate to high
System costs		
Grid costs	Low to medium	Moderate
Balancing costs	Low	Moderate to high
Profile costs	Medium to high	Moderate
External costs		
Social costs of GHG emissions	Medium to high	Low
Impacts of non-GHG pollution	Medium	Low to medium
Visual impacts and impacts of noise	Low to medium	Low to medium
Impacts on ecosystems & biodiversity (non-climate)	Unclear	Low
Costs associated with radionuclide emissions	Unclear	Low
Other potential external costs	Unclear	Very low

This literature review of the social costs of electricity generation thus illustrates what types of costs should ideally be included in any analysis that aims to inform policymakers on least-cost developments of the electricity system. Any such advice should also clearly communicate the considerable uncertainties surrounding the social costs of electricity generation regarding, among other things:

- The costs to assign to specific CO_2 emissions;
- The costs to assign to specific air pollution emissions;
- The types of costs that are highly location-specific, such as disamenity costs;
- The profile costs of VRE power generation in future electricity systems with very high VRE shares;
- The relevance of several potential externalities (including the costs of potential nuclear accidents) for which no widely accepted methods of quantification exist.

Notwithstanding these uncertainties, the analysis in this paper suggests that even at low SCC estimates, the “new” renewable technologies of onshore wind and (in some regions of the world) solar PV can already compete with fossil fuel technologies in terms of the total social costs. Furthermore, in the USA, onshore wind and solar PV exhibit not only lower quantifiable social costs than fossil fuel technologies, but also similar costs to nuclear power as a competing low-carbon technology, even if the higher investment risks of nuclear power and the risks associated with radionuclide release are ignored. In Europe, this is true for onshore wind plants at favourable sites. In the longer term, the relative costs of low-carbon electricity generating technologies will largely depend on the system costs caused by additional VRE power generation and the allocation of these costs.

Future research can help to improve our understanding of the total social costs of electricity generation. This is true in terms of the landscape and noise disamenity costs of wind power and possibly other types of power plants. Future research could, for example, attempt to shed light on the apparent differences in these costs from one country to another, how these costs can be expected to evolve in the future and what measures can be taken to minimise these costs. Furthermore, as the penetration of VRE power generation is expected to increase considerably in the coming decades, the question of how steeply system costs will rise and how to minimise these costs is of growing importance. For example, studies could investigate the optimal mix of residual power plants, the optimal design and deployment of VRE power plants or the potential for better demand response, possibly supported by the stronger integration of the power, heat and fuel markets.

Finally, the limitations of a technology-specific comparison of electricity generation costs, as attempted in this study, should be emphasised.

Firstly, as discussed above, the literature review has demonstrated that considerable uncertainties remain in the quantification of the social costs of electricity generation. This uncertainty is especially high in relation to externalities for which quantification (in the form of a useful range of values) remains elusive. Among these externalities are potential accidents or attacks on nuclear power facilities. The author of this article agrees with the perspective that, due to the potential of extremely high social impacts of such incidences, deriving a specific cost for nuclear accidents is futile and, instead, societies should agree on whether or to what extent they wish to use this technology.

Secondly, and more generally, the electricity system is a highly-interconnected system, in which different power plants and electricity consumers interact with one another. The costs of generating and supplying electricity from any one specific power plant depend on the characteristics of the existing electricity system, such as the mix of power plants, the quality of the electricity grid and the nature and flexibility of electricity demand. In the overview of costs provided in Section 4 and the underlying literature sources, implicit assumptions are made about the characteristics of the electricity system. Consistent analysis of the future cost of supplying electricity in any specific electricity system can, therefore, only be obtained by sophisticated system modelling. While such modelling can calculate and compare the total system costs of different scenarios, the system interdependencies make it impossible to unambiguously allocate these costs to different types of electricity generation technologies on a per kWh basis.

Supplementary Materials: The following is available online at www.mdpi.com/1996-1073/10/3/356/s1, File S1: Input parameters for plant-level LCOE calculations.

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4. A Review of Factors Influencing the Cost Development of Electricity Generation Technologies

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Review

A Review of Factors Influencing the Cost Development of Electricity Generation Technologies

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Abstract: This article reviews the literature on the past cost dynamics of various renewable, fossil fuel and nuclear electricity generation technologies. It identifies 10 different factors which have played key roles in influencing past cost developments according to the literature. These 10 factors are: deployment-induced learning, research, development and demonstration (RD&D)-induced learning, knowledge spillovers from other technologies, upsizing, economies of manufacturing scale, economies of project scale, changes in material and labour costs, changes in fuel costs, regulatory changes, and limits to the availability of suitable sites. The article summarises the relevant literature findings for each of these 10 factors and provides an overview indicating which factors have impacted on which generation technologies. The article also discusses the insights gained from the review for a better understanding of possible future cost developments of electricity generation technologies. Finally, future research needs, which may support a better understanding of past and future cost developments, are identified.

Keywords: electricity generation technologies; cost development; technological learning; economies of scale; literature review

1. Introduction

Access to electricity is widely regarded as a prerequisite for an appropriate standard of living and social integration [1], yet in 2012 more than one billion people still lacked this access [2]. At the same time, electrical appliances continue to grow in importance in the daily lives of billions of people. Consequently, the share of electricity in final energy demand has steadily grown over the past decades [3]. This trend is expected to continue in future decades as climate change mitigation strategies involve replacing fossil fuels with electricity in end-use applications [4–6]. Ensuring the sufficient provision of electricity generated by environmentally and socially acceptable means will therefore continue to be an important objective for policymakers around the world. As multiple different generation technologies are available, each with their unique advantages and disadvantages, a key question facing society and policymakers is what combination of technologies should make up the future electricity generation mix.

Various factors play a role in deciding the preferred electricity generation technologies for any given society. While differences in environmental and social impacts undoubtedly play an important role, so do differences in market costs. Market costs are comprised of investment costs (including financing costs), fuel costs, fixed and variable operation and maintenance costs and decommissioning costs. An important objective for policymakers is to minimise or limit the market costs associated with meeting future electricity demand. Today, a large number of electricity and energy system models exist that aim to inform policymakers on the lowest cost solutions for meeting future electricity demand (see for example [7,8]). These models, which are often used to look decades into the future, include assumptions about plausible future technology cost developments. In order to have a good understanding of these, it is important to recognise which factors have influenced technology costs in the past. This literature review aims to provide an exhaustive overview of the available knowledge regarding the key factors that have influenced past cost developments of electricity generation technologies.

It should be noted that aside from the market costs discussed in this article, external costs and system costs are both relevant. The latter includes, for example, transmission costs and balancing costs. System costs (as opposed to market costs) will become increasingly important in future electricity systems in which the share of fluctuating electricity generated from wind turbines and solar photovoltaics (PV) increases considerably [9]; see also Section 3.

The following section, Section 2, introduces all the factors found to influence the market costs of electricity generation technologies. It discusses the role each factor has played in past cost developments for different electricity generation technologies. Section 3 briefly discusses which factors might become more or less relevant in shaping future costs for each type of technology. Finally, Section 4 draws conclusions and addresses future research needs.

2. Factors Influencing the Market Costs of Electricity Generation Technologies

Based on an extensive literature review, this section discusses the main factors influencing the development of the market costs of electricity generation technologies over time. Over the past few decades, much empirical research has sought to explain past cost changes and to attribute these changes to a number of different factors. Initially, and particularly from the late 1970s onwards, studies focused on explaining observed changes in the costs of large-scale fossil fuel and nuclear power plants, with the available cost data usually going back to the 1960s or 1970s. Since around the year 2000, many studies have focused on renewable energy technologies, especially wind and solar PV, with the available cost data typically ranging back to the 1980s or 1990s. This article focuses on 10 factors identified by the literature review as relevant in influencing electricity generation costs in the past. These 10 factors can be grouped into four categories, as shown in Figure 1.

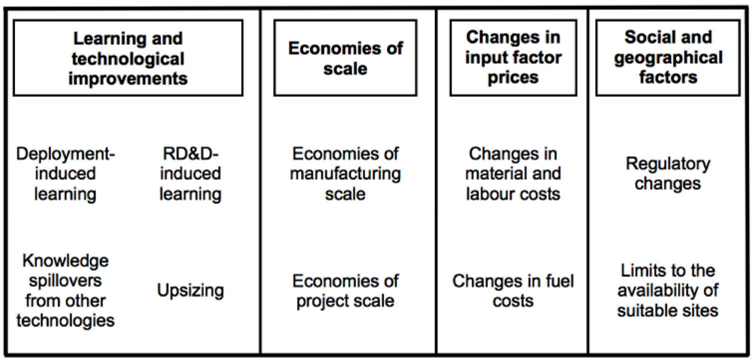

Figure 1. Factors influencing the market costs of electricity generation technologies as identified by the literature review.

These 10 factors will be discussed individually in the following subsections, with the final subsection offering a summary. It should be noted that factors influencing costs can either affect a technology's investment (or capacity) costs or they can affect "only" its generation costs. The latter is typically the case for two of the factors, "changes in fuel costs" and "limits to the availability of suitable sites". As deployment-induced learning, research, development and demonstration (RD&D)-induced learning, knowledge spillovers and upsizing can also lead to fuel efficiency improvements, generation costs may also be affected by these factors, which are subsumed in the category "learning and technological improvements". It should also be noted that due to the lack of available literature sources on past cost developments of combined heat and power (CHP) plants, this technology is not included in this study's discussions.

Market structure is not included as a factor in this study, as no quantitative estimates about the effects of market structure on the costs of specific electricity generation technologies could be found in the literature. This does not necessarily mean that such effects do not exist or are negligible; it probably points to the difficulties of operationalizing this factor in empirical studies. Many authors argue that differences in market structure can affect the actual costs of a technology by, for example, influencing a company's internal efficiency [10] or the level of innovation within an industry [11]. Specifically, it is sometimes argued that technological learning requires competitive markets [12,13], although this view is not shared universally by the theoretical and empirical literature on the relationship between an industry's degree of competition and its level of innovation [14,15]. It should be noted that there is no dispute that the market structure and the respective level of competition has an effect on market prices. For some electricity generation technologies, there are strong indications that historic price developments were heavily influenced for several years by companies able to exert market power [16,17].

Similarly, the identified literature does not provide sufficient quantitative information about differences in the effects of policy measures such as carbon pricing or renewable energy support mechanisms on the cost development of specific electricity generation technologies. As these types of policy measures tend to change the rate of deployment of different technologies, they can indirectly lead to technology cost changes by affecting deployment-induced learning. However, quantitative estimates of any additional effects of such policy measures on technology costs could not be identified in the literature and, therefore, are not included in this review, although there is a large strand of literature that discusses the idea that certain forms of environmental regulation may induce technological innovation [18,19]. At the same time, it is sometimes argued in the literature that policies such as feed-in tariffs "may discourage competition among various renewable energy sources and therefore deter innovation" [20].

2.1. Learning and Technological Improvements

Learning and technological improvements have been identified as an important driver for lowering the market costs of electricity generation. Various sources of learning and technological change are discussed in the literature. The respective contributions of these sources to the observed cost reductions of a technology are frequently debated, as it has proved very difficult to empirically separate the contributions made by individual sources. Most notably, there is an ongoing discussion among researchers about the relative importance of deployment-induced learning compared to RD&D-induced learning.

2.1.1. Deployment-Induced Learning

A large volume of empirical research indicates that specific costs fall as experience in terms of production and use of a particular technology increases. Initially, such learning was investigated at individual company level [21] but, progressively, similar observations were made at the industry level. These industry level observations suggest that a significant share of the knowledge gained by individual companies and their customers through experience can eventually be appropriated by other companies and customers (i.e., the spillover effect). Alternatively, or additionally, some learning may take place at the industry level; for example, through exchanges between company representatives within associations or at conferences.

There is the suggestion in the literature that experience gained by deployment can lead to learning via at least three different channels:

- Learning-by-doing: as more and more units of a technology are produced, managers gain experience with the production process and may learn how to improve it, e.g., by increasing work specialisation or by reducing waste. Workers may become more efficient in their respective tasks as they continuously repeat their individual production steps.
- Learning-by-using: this can be regarded as the "demand-side counterpart" [22] of learning-by-doing. Users may gain experience by using a technology and learn how to install and operate it more

efficiently. The existence of formal user groups who interact with each other can strengthen this kind of learning through networking effects [23].

- Learning-by-interacting: by informing them about problems related to the use of a technology, users or project developers enable manufacturers to learn from actual on-site experiences of the product. Manufacturers can use this information to improve their respective products [24–26]. Furthermore, companies, users, project developers and other stakeholders—such as research institutes and policymakers—can learn from one another through the formal and informal exchange of information [27–29].

Some authors (for example de La Tour et al. [30], Gross et al. [27] and Junginger et al. [28]) consider the interaction between users and manufacturers to be part of learning-by-using. This view is not shared here, in order to emphasise the difference between learning that takes place solely on the user side (learning-by-using) and learning that takes place through the interaction between users and manufacturers (learning-by-interacting).

Numerous empirical studies show a strong negative correlation between a technology's deployment and its cost (or price). Many of these studies derive so called one-factor experience curves. These curves depict the relationship between a technology's specific costs as the dependent variable and the technology's experience (using deployment or production as a proxy) as the independent variable. The learning rate shows the rate at which a technology's cost is found to decrease for each doubling of experience. Other meta-studies [27,31,32] have already looked in detail at observed learning rates for electricity generation technologies, so this article will not focus on this aspect.

2.1.2. Upsizing (Economies of Unit Scale)

The typical unit sizes of many electricity generation technologies have increased over time. This phenomenon can be referred to as upsizing. An increase in size is usually associated with lower manufacturing, installation and/or operating costs per unit of capacity. These economies of unit scale should be distinguished from economies of scale relating to manufacturing or project scale. The latter do not involve changes in the technology itself, which is why they are not included in the category "learning and technological improvements", but are examined in a separate "economies of scale" category.

For wind turbines, literature findings indicate that initially, until about the early or mid-1990s, the scaling up of wind turbine units led to economies of unit scale, as larger turbines offered scale effects in terms of turbine and tower manufacture, as well as in installation costs, driving down specific investment costs. Economies of unit scale also led to savings in operation and maintenance costs and enabled more wind to be captured, further driving down generation costs [27,33]. According to a model based on real turbine cost data developed by Coulomb and Neuhoff [34], economies of scale in wind turbines when measured in specific capacity costs were positive until rotor diameters reached 34 m, typically corresponding to unit capacities of about 400 kW–500 kW. Observing list prices of wind turbines in Germany between 1991 and 2001, Junginger et al. [33] report that for all turbines of up to about 600 kW, the per kW list prices for larger turbines were consistently smaller than for smaller turbines. However, this relationship did not hold for the bigger turbines: "Since the introduction of the 600 kW turbine in 1995, the trend of decreasing turbine list prices with increasing turbine size seems to be diminishing."

Madsen et al. [35] find considerable economies of unit scale in their econometric analysis of wind turbines produced in Denmark between 1983 and 1998, a time period in which the vast majority of newly installed wind turbines had a capacity of 600 kW or less. Depending on the regression model specifications, a doubling in unit scale was found to lead to a decrease in specific wind turbine prices of between 7% and 15%.

Beyond a turbine unit threshold of about 500 kW, Coulomb and Neuhoff [34] find diseconomies of unit scale. This is explained by the fact that the larger the wind turbine, the greater the cost effect of the relative increased weight. According to a rule of thumb cited by Coulomb and Neuhoff [34] and Milborrow [36], rotor weights increase by the cube of the rotor diameter, whereas energy yields increase only by the square of the rotor diameter.

In fact, Bolinger and Wiser [37] find turbine upscaling to be the most important individual driver for explaining the observed price increases in turbines sold in the USA between 2001 and 2010, contributing to a cost increase of 230 USD/kW. Ek and Söderholm [38], in their econometric analysis, also find negative scale effects measured as costs per kW: for each doubling in capacity, specific costs increase by 11%. However, the negative scale effects were not found to be statistically significant. The authors use average turbine costs from five European countries over the time period from 1986 to 2002, controlling for cumulative global capacity (intending to capture learning-by-doing effects) and research and development (R&D) stock (intending to capture learning-by-searching effects; see the following subsection).

It should be pointed out that the presence of diseconomies of unit scale, when measured on a per kW basis, does not mean that turbines have become too large. Such a statement requires an assessment that includes all the costs and benefits of installing larger turbines. Specifically, any diseconomies of unit scale in terms of the production and transport costs of larger wind power plants were, and are, likely to be compensated by cost savings in installation and maintenance and the potential for gaining access to better wind conditions, allowing for higher levels of energy production [34,37].

This assumption is supported by empirical analyses of wind power *project* costs in the USA: per kW costs of wind projects in the USA from 2012 to 2014 were found to be practically identical, irrespective of whether the turbines employed had a capacity of 1–2 MW, 2–3 MW or more than 3 MW [39,40]. In his regression analyses of the price of electricity from wind power projects built in the USA between 1999 and 2006, Berry [41] also found that turbine size was not a relevant variable for explaining price differences, noting that the cost-increasing and cost-decreasing effects of larger turbines may cancel each other out.

Unlike economies of manufacturing and economies of project scale, economies of unit scale are not believed to have played an important role in past cost decreases of electricity generation from PV plants, as solar panels have not seen a considerable change in typical per-unit scale [42]. For concentrating solar power (CSP) plants, there is little information in the literature about possible economy of unit scale effects. Pilkington Solar International [43] states that for CSP power plants in the range of 40–160 MW, specific system costs decline by 12% and levelized electricity costs by about 15% for each doubling in plant size. However, it should be noted that the assumptions behind these calculations are based only on a very limited number of early CSP plants.

A number of econometric studies have tried to shed light on the various factors affecting the cost development of nuclear reactors. The majority of these studies have analysed the nuclear power industry in the USA, not least because cost data for individual nuclear power plants built in the USA have long been publicly available.

From past experience in several countries, it is known that larger nuclear power plants tend to exhibit longer construction times than smaller ones (see for example [44]). As longer construction times lead to higher time-related costs, notably increased interest payments and additional inflation costs, any study investigating the unit scale effect of nuclear power plants should include the time-related costs and should not solely consider overnight costs, as these, by definition, do not include interest payments and other time-related costs.

However, for the US nuclear industry only two studies were found that take the cost effects of longer construction times into account in their econometric analysis. These two studies draw different conclusions regarding the relationship between unit scale and specific costs for nuclear power plants (see also [45]). While Komanoff [46] finds a 10% reduction in costs per kW for each doubling in unit size when taking into account the effects on costs of longer construction times, Cantor and Hewlett [47] arrive at a 9% increase in costs for each doubling of capacity. The latter study thus implies diseconomies of scale, stating that it is possible "that the industry has attempted to build units that are too large to be efficiently managed by the constructors" [47]. Findings on economies of unit scale are also inconclusive when examining analyses that do not take the cost effects of longer construction times into consideration [45–51].

For the Japanese nuclear power industry, Marshall and Navarro [52] study the relationship between reactor costs and unit size for 34 reactors built in Japan between 1966 and 1987. They find economies of unit scale when using overnight cost data but find no statistically significant relationship between cost and unit size when using cost data that takes into account the effects of construction time on reactor costs.

Escobar Rangel and Lévêque [53] analyse the development of total costs (including time-related costs) for the French nuclear programme, following the publication in 2012 of cost data for each of the nuclear power plants built in France [54]. The regression results from Escobar Rangel and Lévêque [53] indicate diseconomies of scale for the French nuclear power plant programme. However, the authors note that in their regression analysis they are unable to separate the effects of size changes from those of reactor design changes, as larger nuclear power plants in France tend to exhibit significant design changes compared to earlier and smaller reactors and some of these design changes may have been made for other reasons than to enable reactor size increases. Therefore, it cannot be ruled out that the diseconomies of scale discovered are mainly the result of methodological limitations.

For coal power plants, reductions in the costs observed for new plants prior to the 1970s have been "mainly attributed to economies of scale in all power plant components, including the generator, turbine, and boiler" [55]. Joskow and Rose [56] find economies of scale in their evaluation of 411 coal power plants larger than 100 MW in the USA that began operating between 1960 and 1980. The authors control for various characteristics, including learning effects, compliance with environmental regulations and changes in input prices. They find a decrease in specific costs of 12% for each doubling in unit size. Looking only at the 110 supercritical coal power plants in the sample, specific costs were found to decrease more significantly (by between 20% and 27%, depending on the regression model specifications) for each doubling in unit size. The authors note that fully exploiting these scale effects requires moving from subcritical plants to supercritical plants, as the latter become less expensive on a per kW basis at plant sizes of around 500 MW [56]. McCabe [49] likewise found considerable economies of scale in a similar range for 106 supercritical power plants installed in the USA between 1960 and 1980.

However, some authors have pointed towards the apparent limits of exploiting economies of unit scale in coal power plants [56,57]. Supercritical coal power plants, which—according to the literature cited above—exhibit larger potential for economies of unit scale compared to subcritical coal power plants have experienced problems in regard to operating reliability due to their high technological complexity. According to Grubler [58], economies of unit scale consequently failed to lead to substantial reductions in electricity generation costs after the 1960s. There are also demand-side restrictions to building ever larger power plants: investors are reluctant to commit to large-scale power plants at times when future electricity demand is uncertain.

2.1.3. Research, Development and Demonstration (RD&D)-Induced Learning

RD&D activities are widely considered to be another important driver for improving energy technologies and forcing down electricity generation costs. RD&D activities encourage experimentation with a technology's design, creating opportunities for learning and innovation. Technologies can either profit from RD&D activities specifically aimed at those technologies, or from the spillover effects from basic research or from successful RD&D activities targeting other technologies. This subsection discusses direct learning through RD&D activities, while spillover effects are discussed in the following subsection.

Many scholars suggest that the traditional one-factor experience curve neglects the critical role that RD&D plays in improving technologies over time. According to this view, many of the historic cost reductions observed in energy technologies and attributed to "learning-by-doing" by traditional one-factor experience curves are, in fact, the result of RD&D activities. In the past decade and a half in particular, attempts have been made to quantify the effects of RD&D on past energy technology cost developments based on an extension of the traditional one-factor experience curve to a two-factor or multi-factor experience curve. These two or multi-factor experience curves are derived by statistically capturing not only the effects of technology deployment but also the effects of RD&D expenses (and, in the case of multi-factor experience curves, the effects of additional independent variables) on technology costs. Some authors express the hope that defining both learning-by-doing and learning-by-searching rates for individual technologies will assist policymakers in the optimal allocation of scarce public resources between support for RD&D and market diffusion [59,60].

However, in practice, there are various difficulties in determining the RD&D effects. Firstly, past RD&D expenses for a certain technology can be difficult to identify, especially as RD&D investment levels by private companies are often not made publicly available. (As a consequence, empirical studies typically restrict their analysis to publicly financed RD&D.) Secondly, it can be argued that it is not the RD&D expenses themselves that influence technology costs, but rather the knowledge gained through the RD&D activities. However, it is not possible to precisely establish the time lag between RD&D expenses and the corresponding growth in the knowledge stock. Similarly, it is unclear to what extent the knowledge gained through RD&D should be assumed to depreciate over time. Consequently, it has proved difficult to reliably quantify the effects of RD&D activities on the development of energy technology costs.

Attempts to quantify the effects of RD&D expenses on technology costs have been made primarily in regard to onshore wind power. Table 1 shows literature estimates for the learning-by-searching rate of this technology. Analogous to the learning-by-doing rate, the learning-by-searching rate indicates by how much a technology's specific costs are expected to reduce as RD&D-based knowledge about the technology is doubled. Learning-by-searching estimates in the literature vary considerably for individual technologies, with the estimates for wind power varying, for example, from between 3% and 32% (see Table 1). Differences in estimates in the literature can be explained inter alia by differences in the geographical domain analysed, the period studied, the operationalisation of knowledge and the nature of the additional independent variables taken into account.

The wide range of learning-by-searching rates found in the literature, combined with the aforementioned difficulty of adequately capturing a technology's knowledge stock, indicate that these rates should be interpreted with care. Cautious interpretation is also supported by a sensitivity analysis by Söderholm and Sundqvist [20], who analyse onshore wind power cost developments. The authors find that adding a time trend in their regression analysis leads to negative learning-by-searching rates that are no longer statistically significant, as the time trend "tends thus to pick up most of the variation previously ascribed to the R&D-based knowledge stock." Lindman and Söderholm [61] note the difficulty in quantifying the role of RD&D in wind power cost developments as cumulative RD&D expenses, in addition to other potential independent variables (e.g., the size of wind turbines), increase over time, making it difficult to statistically separate the impacts made by each variable.

De La Tour et al. [30] find that during the period from 1999 to 2011 a model using only global cumulative PV capacity and the price of silicon is better able to explain price developments of PV modules than a model using other explanatory variables, including the knowledge stock. They measure the knowledge stock using the cumulative number of patent families (a set of patents granted in different countries for the same innovation) as a proxy for innovation and use an annual depreciation rate of 10% to account for technology obsolescence. The authors point out that the high correlation between knowledge stock and cumulative capacity leads to a reduction in the accuracy of their model when knowledge is included as an explanatory variable. Similarly, Wiebe and Lutz [62] do not find a statistically significant learning-by-searching rate in their analysis of global price developments of PV modules between 1992 and 2012.

Table 1. Literature estimates for the learning-by-searching rate of onshore wind power plants.

Literature Source	Geographical Domain	Independent Variable (Knowledge)	Dependent Variable (Costs or Prices)	Period	LbS Rate (%)	R^2	Additional Independent Variable(s) Controlled for
[63]	OECD countries/USA [1]	Cumulative public RD&D expenditure (time lag: 3 years)	Cost of generating electricity	1985–1995	32%	0.99 [2]	Cumulative production
[59]	Denmark, Germany, UK	Knowledge stock derived from public RD&D expenditure (time lag: 2 years, depreciation factor: 3% p.a.)	Specific investment costs	1986–2000	13%	0.72 [2]	Cumulative capacity
[64]	Global	Knowledge stock derived from public RD&D expenditure (time lag: 5 years, depreciation factor: 2.5% p.a.)	Specific investment costs	1981–1997	18%	0.95 [2]	Cumulative capacity
[65]	Denmark, Germany, Spain, UK	Knowledge stock derived from public RD&D expenditure (time lag: 2 years, depreciation factor: 3% p.a.)	Specific investment costs	1986–2000	13%	0.81	Cumulative capacity, wind generation level, feed-in-price
[20]	Denmark, Germany, Spain, UK	Cumulative public RD&D expenditure	Specific investment costs	1986–2000	7%	0.69 [2]	Cumulative capacity
		Knowledge stock derived from public RD&D expenditure (time lag: 2 years, depreciation factor: 3% p.a.)			16%	0.73 [2]	Cumulative capacity
					13%	0.77 [2]	Cumulative capacity, wind generation level, feed-in-price
[38]	Denmark, Germany, Spain, Sweden, UK	Knowledge stock derived from public RD&D expenditures (time lag: 2 years, depreciation factor: 3% p.a.)	Specific investment costs	1986–2002	21%	0.88	Cumulative capacity, economies of unit scale
[62]	Global	Knowledge stock derived from public RD&D expenditure (time lag: 15 years)	Wind turbine prices	1990–2012	3%	0.84 [2]	Cumulative capacity

Notes: [1] The geographical domains of the dependent and the independent variables differ in this experience curve. The region named first refers to the independent variable, while the country named after the slash refers to the geographical domain of the dependent variable; [2] Numbers refer to the adjusted R^2. Unlike R^2, the adjusted R^2 does not automatically increase as more explanatory variables are added. Instead, the adjusted R^2 only increases when additional explanatory variables improve the R^2 more than would be expected by chance. LbS: Learning-by-searching; OECD: Organisation for Economic Co-operation and Development; RD&D: Research, development and demonstration; p.a.: Per annum.

Berthélemy and Escobar Rangel [44] use nuclear-specific patents filed in France and the USA to construct a knowledge stock for each country, applying an annual discount factor of 10%. Based on their regression analysis they conclude that, in the case of nuclear power, more knowledge leads to higher power plants costs. The authors suggest that innovations in nuclear power may make reactors more complex and, consequently, they take longer to build and are more expensive.

2.1.4. Knowledge Spillovers from Other Technologies

Inter-industry knowledge spillovers, i.e., knowledge spillovers from other technologies, clusters of technologies or basic scientific research, are also identified in the literature as potential contributors to improvements and cost reductions for specific power generation technologies [66,67]. Such spillovers are sometimes also referred to as exogenous technological progress. Loiter and Norberg-Bohm [68] provide specific examples of wind technology innovations that originated in other industries; for example, in boat-building or aeronautics. Nemet [42] notes that key innovations in the PV industry originated in the microprocessor industry. Meanwhile, the development of combined cycle gas turbines (CCGT) benefited greatly from technological advances made inter alia in the field of jet aero engines [69,70].

Quantifying inter-industry spillover effects is very difficult, as knowledge is highly heterogeneous and unobservable [57]. Therefore, an attempt is usually made in empirical analysis to capture inter-industry spillover effects by including a simple time trend in regression models. However, in a statistical analysis of a range of technologies (not only electricity generation technologies), Alberth [71] concludes that "experience turns out to be a vastly superior explanatory variable than time in terms of forecasting error".

2.2. Economies of Scale Effects

Economies of scale describe a situation in which the specific costs of a product decline as the production capacity or project size increases. This is the case, for example, when additional production allows producers to benefit from volume discounts on materials, permits managers and workers to specialize more in their respective tasks and enables R&D and other non-production costs to be spread over a greater number of units [29,63]. Economies of scale can materialise at the level of individual companies or factories (see Section 2.2.1) and also at the level of individual projects, like wind farms, whose economics may benefit from an increase in the number of turbines installed at a certain site (see Section 2.2.2).

2.2.1. Economies of Manufacturing Scale (Mass Production)

Small-scale generation technologies (e.g., solar PV modules and onshore wind turbines) requiring little customised installation tend to exhibit higher one-factor learning rates than large-scale technologies requiring heavily customised, site-specific installation (e.g., coal or nuclear power plants) [27]. It is widely believed that these differences in learning rates are, to a significant extent, due to differences in the degree to which technologies can be standardised and mass produced in factories. Provided there is sufficient demand, the standardisation of a product allows for the upscaling of production plants to produce the same product in larger numbers, which results in economies of manufacturing scale [28]. In contrast, the on-site construction that is prevalent for large scale power plants is usually site-specific and provides little room for economies of manufacturing scale [72].

Some authors point towards the typically high correlation between an industry's production volume or its plant sizes (i.e., its average output per factory) and its experience measured as cumulative output. They maintain that much of what one-factor experience curves suggest to be learning-by-doing is, in fact, likely to be the result of economies of manufacturing scale [73,74]. Other authors stress the overlap between experience and economies of manufacturing scale, arguing that these two effects—while separate in theory—are very difficult to separate in practice. For example, scaling up production may be associated with substantial technological challenges that can only be overcome by gaining production experience [75–78].

Attempts to isolate and quantify the effects of economies of manufacturing scale on the specific costs or prices of individual technologies have been made in the past, for example for PV technology. The typical annual output of new PV cell manufacturing plants increased from less than 2 MW in the early 1990s to several 100 MW today, with some new manufacturing plants announced in 2015 exceeding an annual production capacity of 1 GW [29,79,80]. Yu et al. [29] construct a global multi-factor experience curve for PV module prices, taking into account not only experience but also manufacturing scale effects and input price effects. The authors conclude that changes in typical manufacturing plant size accounted for 20% of all price-reducing factors during the period between 1998 and 2006, while learning accounted for 48%. The scale effect was found to be less significant prior to 1998, when it accounted for less than 6% of the total price-reducing effects.

Nemet [42] disaggregates historic PV price reductions into observable technical factors: manufacturing plant size, module efficiency, silicon cost, silicon consumption, wafer size, yield and the share of poly-crystalline vs. mono-crystalline wafers. The author finds that increases in the typical size of PV module production plants accounts for 43% of the price reductions observed between 1980 and 2001. Plant size is identified as the main factor contributing to the observed price decrease, followed by improvements in module efficiency (30%). Watanabe et al. [81] also find economies of manufacturing scale effects to be more important than learning effects in explaining the cost reductions achieved by Japanese solar cell manufacturers between 1976 and 1990.

Conversely, the study by de La Tour et al. [30] finds that, as in the case of using knowledge stock, using the size of manufacturing plants as an explanatory variable does not improve a model explaining PV module price developments between 1999 and 2011. The authors explain this by pointing towards the high correlation between the size of manufacturing plants and the cumulative installed capacity of PV plants.

A limited number of literature sources evaluate whether economies of manufacturing scale have also played a role in reducing the costs of onshore wind power plants. These sources suggest that economies of manufacturing scale have indeed contributed to wind onshore cost reductions. Junginger et al. [33] point out that wind turbine manufacturers offer considerable reductions to specific turbine prices for high volume orders. Specifically, they report a price reduction of about 6% for each doubling of the order volume of a Vestas V47 660 kW wind turbine ordered by various buyers between 1998 and 2002. According to the authors, these large discounts suggest that wind turbine producers benefit considerably from economies of manufacturing scale. However, perhaps due to data limitations (see [63,82]), no studies are available that specifically investigate the relationship between the cost or price reductions of wind turbines and the average output of manufacturing plants.

Economies of scale at manufacturing level do not appear to have played a significant role in influencing the costs of fossil fuel plants in the past, even though some literature sources suggest that standardisation and the ensuing potential for mass production and economies of scale may have played a role in reducing the costs over time of fluidized bed combustion boilers [25,28]. The limited role played by economies of manufacturing scale in large-scale fossil fuel power plants can be explained by the much lower number of identical (or similar) plants required by these technologies, compared to small-scale renewable energy technologies, to achieve a certain level of electricity generation. Building fewer plants offers less possibility to benefit from economies of scale in both manufacturing and installation.

The same is true for nuclear power plants, which are typically even larger than fossil fuel plants. While the potential to take advantage of economies of manufacturing scale is, therefore, expected to be lower than for small-scale renewable technologies, the lack of sufficient standardisation is frequently cited to have prevented nuclear power from realising even this limited potential in some countries [58]. (The lack of standardisation also limits the potential of deployment-induced learning and spillover effects [27].) Over the decades, the design of nuclear reactors has seen continuous change, as manufacturers have attempted to increase economic performance or—often in response to new government regulations—safety levels [27]. According to country level overnight construction cost data from Lovering et al. [83], countries that emphasised reactor design standardisation, such as France and South Korea, experienced less pronounced cost increases or even cost decreases over time. See also Section 2.4.1 on the effects of regulations.

In contrast to the "rather laissez-faire attitude" [84] in the USA, the Japanese and (at least initially, until the 1980s) the French governments made efforts to support reactor design standardisation. This is seen as a key reason for the less pronounced cost escalation during the 1970s and 1980s in the French and Japanese nuclear power programmes compared to that of the USA [53,84,85].

2.2.2. Economies of Project Scale

Economies of scale can be relevant not only at unit level (see Section 2.1.2) and manufacturing level (see previous subsection), but also at individual power plant project level.

Some authors find evidence that the costs per wind turbine can be reduced by installing a higher number of turbines at the same site, as not all types of wind power investment costs vary proportionately according to project size. For example, all turbines at one wind farm can use a common substation and the development and construction costs are shared by a higher number of turbines [86]. Wiser and Bolinger [39,40] find that, for projects constructed in 2012/2013 and in 2014, specific investment costs of onshore wind farms in the USA tend to decline as the project size increases, although this effect is much more prevalent at the lower end of the project size range, i.e., when moving from project sizes of less than 5 MW to project sizes of between 5 and 50 MW. Qiu and Anadon [82] attempt to econometrically explain the differences in wind power electricity generation bidding prices in China's national wind project concession programmes from 2003 to 2007 and include wind farm size as one of their explanatory variables. They find that prices reduce by 6%–9% for each doubling in wind farm size. Anderson [87] uses an econometric model to determine various drivers of the costs of onshore wind power projects installed in the USA from 2001 to 2009 and finds modest economies of project scale. According to his results, doubling a wind power project's nameplate generating capacity reduces the project's per-megawatt cost by 1.2%–1.5%.

However, none of these studies [39,40,82,87] take into account the fact that small scale projects may, on average, install smaller individual turbines than medium or large scale projects. These studies, therefore, cannot rule out the possibility that the lower costs of larger wind projects may largely, or partly, be a reflection of cost reductions achieved through economies of unit scale. However, in his regression analyses, Berry [41] takes into account individual turbine size and still finds lower wind energy contract prices for larger wind farms in his sample of wind farms of 20 MW or more built in the USA between 1999 and 2006. For each additional 10 MW of wind farm generating capacity, the price in 2007 was found to be lower by about $0.62 per MWh (or 1.6% of the mean price of $38.5 per MWh).

For PV systems, a reduction in installation prices as system sizes increase is well documented. Economies of project scale allow for the allocation of fixed project and overhead costs across a larger number of installed watts [88]. For example, median prices for non-residential PV systems installed in in the USA in 2014 ranged from 4.2 USD_{2014}/W for systems up to 10 kW to 2.7 USD_{2014}/W for systems larger than 1 MW [88], meaning that very large scale systems are about 36% cheaper than very small ones.

Economies of project scale have also been observed for nuclear power plants. Komanoff [46] finds that nuclear reactors built in the USA as part of multiple reactors at a single site exhibit on average 10% lower investment costs than other reactors. According to the author, the lower costs are due to shared design efforts and common facilities, but also to the better utilisation of learning effects in construction. Similarly, Tolley et al. [45] report lower specific costs of between 5% and 7% when two nuclear reactors are built at the same time and at the same site, compared to building them at different sites and/or at different times. The reasons provided by Tolley et al. for the lower specific costs of twin reactors are the ability to reduce the down-time for both workers and the construction equipment, the cost reduction potentials related to procurement (partly also driven by the potential for economies of scale at the vendors' factory) and the higher chance of benefiting from on-site learning effects [45].

Likewise, Navarro [84] argues that one reason why the Japanese nuclear power industry was more successful than its US counterpart in containing cost increases during the 1970s and 1980s was due to its reactor siting strategy. The Japanese frequently sited four or more reactors at one site, while in the US typically only one or two (and no more than three) reactors were built at the same site. The country level overnight cost data compiled by Lovering et al. [83] indicates that specific reactor costs in countries that have frequently built reactors in pairs, or larger sets at the same site, such as France and South Korea, tend to be lower than in countries that have mostly built single reactors at one site, such as the USA and Germany.

For coal power plants completed in the USA between 1972 and 1977, Komanoff [46] finds that plants built as part of multiple units at a single site exhibit on average 10% lower investment costs than single units. According to the author, the lower costs result from common plant facilities, shared construction equipment, skill transfer in the design and construction of the plants and a joint environmental review.

2.3. Changes in Input Factor Prices

2.3.1. Changes in Material and Labour Costs

Changes in market prices for labour or for required input materials can also play an important role in a technology's cost development. Changes in input prices for energy technologies have, in the past, been attributed mainly to developments outside a certain industry (i.e., to exogenous developments), for example to changes in the overall labour market or to additional demand for certain materials from other industries. Geological scarcity or trade restrictions on certain materials may, in the future, also lead to increases in the price of some input materials.

The relevance of input price developments for the costs of energy technologies has received renewed attention since commodity prices underwent a considerable increase during the mid-2000s, remaining relatively high in historical terms for much of the period that followed (until they declined in 2014 and 2015, see [89]). Contrary to what the traditional one-factor and two-factor experience curves suggested, prices for most energy technologies increased for some years following the mid-2000s [27,90]. The price increases for commodities such as steel, cement, copper and fossil fuels (and in some cases also an increase in labour costs) were identified as the main reasons for these unexpected cost increases [91–93], underscoring the relevance of input price developments in explaining the past cost developments of energy technologies.

Quantitative estimates of the role of input price variations have been made mainly for wind and PV technologies.

Qiu and Anadon [82] found that the share of domestically-produced components of wind power plants in China is a statistically significant factor in explaining the price of electricity generation from onshore wind turbines built in China between 2003 and 2007. Specifically, doubling the share of domestically-produced components was found to be associated with price reductions of around 20%. (This rate was reduced to around 11% when year dummies were included in the econometric model to capture any additional exogenous technological change or any other changes in the market.) The authors suggest that this relationship is due to the lower labour and material costs in China compared to those in industrialised countries such as the United States and Germany. As the average share of domestically-produced components of the wind turbines installed in China increased over the time period observed, it can be assumed that lower labour and material costs have contributed to the observed decline in wind power prices.

According to an analysis by van der Zwaan et al. [94], the decline in specific costs for offshore wind parks in Europe was consistent with a one-factor learning rate of 3% between 1991 and 2008 when the price fluctuations of steel and copper are corrected for. Without such corrections, no trend in specific costs can be observed, meaning the learning rate is 0%. Correcting for fluctuations in copper and steel prices increases the explanatory power of the experience curve from an R^2 of 0.31 to an R^2 of 0.49, indicating that experience curve analysis can potentially be improved by properly taking into account input price changes. In their analysis, the authors do not take into account the effects of oil price changes on the specific costs of offshore wind projects in Europe, although BWEA and Garrad Hassan [95] suggest that oil price fluctuations may have a particularly high influence on the development of specific costs of offshore wind projects. This influence arises mainly through a secondary impact: the global oil price affects the level of offshore marine exploration and construction activity which, in turn, has the potential to divert scarce vessel resources from offshore wind when oil prices are high. Voormolen et al. [17] also find that increased commodity prices between 2000 and 2015 led to significant increases in the specific investment costs of European offshore wind farms.

Bolinger and Wiser [37] estimate that higher labour costs led to an increase in average onshore wind turbine costs of 91 USD_{2010}/kW in the USA between 2002 and 2008. This is equal to 15% of the overall observed price increase of 595 USD_{2010}/kW. The rapid global growth of the wind industry during this period is reported to have put strain on the supply of available labour, leading to increases in the wages of sufficiently skilled workers [37,90]. Raw material price changes account for 12%, with steel having the biggest effect. Increases in fossil fuel energy prices account for another 2%, according to the authors (The upscaling of turbines (31%) and currency movements (23%) were found to be the two most important explanatory variables.).

De La Tour et al. [30] find that from 1999 to 2011 a model using global cumulative PV capacity and the price of silicon is better able to explain the price developments of PV modules than a model using only global cumulative PV capacity or any other combination of different explanatory variables. They note that when correcting for the fluctuations in the price of silicon, the PV learning rate is relatively stable at around 21%, even when different time periods are chosen for the learning rate analysis. The authors contrast this finding with a study by Nemet [96], who found substantial variation in the PV learning rate depending on the time period analysed. Specifically, PV learning rates were found to be lower when data from more recent years (especially data from 2004 to 2006) were included in the analysis. However, unlike de La Tour et al. [30], Nemet [96] does not correct for fluctuations in the price of silicon in his analysis.

In their regression analysis of factors influencing PV module prices between 1976 and 2006, Yu et al. [29] also find that changes in the price of silicon play an important role in explaining past PV module price developments. In a similar analysis, Nemet [42] ascribes 12% of the overall module price reductions observed between 1980 and 2001 to a decline in silicon prices. Gan and Li [97] also highlight the impact of silicon prices on PV module costs in their analysis of global price developments of PV modules between 1988 and 2006. In their work, the authors are unable to detect a statistically significant impact on module prices due to the increasing share of modules produced in China.

According to Cohen [98], the significant increase in specific construction costs of nuclear power plants in the US throughout the 1970s and 1980s was, to some extent, the result of an increase in general labour costs. The author finds that in the period from 1976 to 1988 labour costs in nominal terms escalated at an average rate of 18.7% compounded annually and material costs by 7.7%, contributing to an annual increase in nuclear power plant construction costs of 13.6%. (The average annual national inflation rate during this period was 5.7% according to Cohen [98].) Conversely, lower labour costs, due to a combination of the slowdown in the global economy and the focus of new nuclear construction on countries with lower labour costs, are thought to have played a key role in the decrease in nuclear power construction costs during the 1990s and early 2000s [27].

2.3.2. Changes in Fuel Costs

For technologies using fossil fuels, nuclear fuels or biomass, electricity generation costs are obviously sensitive to changes in fuel prices. Since the end of World War II, real world market prices for oil and natural gas have shown an upward trend, while the reverse is true with regards to the price of coal [99,100]. The fuel price sensitivity is especially high for natural gas power plants, as fuel costs make up a relatively large share of these plants' overall generation costs [101]. Colpier and Cornland [102] find that the cost of generating electricity in newly built natural gas-fired CCGT plants in Europe and North America decreased between 1981 and 1997, mainly as a result of the decline in the price of natural gas during this period (in contrast to the longer term trend). The authors derived a learning rate for CCGT electricity generation of 15% and show that this rate would be only 6% if it were not for the observed decline in natural gas prices.

2.4. Social and Geographical Factors

2.4.1. Regulatory Changes

Regulatory changes, especially those concerning environmental, health or safety standards, can also lead to changes in the cost of electricity generation technologies. Relevant cost impacts of changes in regulations have been reported predominantly for nuclear power plants, coal power plants and wind turbines. While, in principal, both cost increases and cost decreases can stem from regulatory changes, cost increases are typically reported in the literature. This is the case because environmental, health and safety standards tend to become stricter over time, which may force technology suppliers, for example, to invest in additional components, employ more workers or search for alternative plant locations.

One example of stricter environmental regulations is the introduction of measures to price GHG emissions, such as carbon taxes or emissions trading systems. Such measures have been introduced in recent years in some countries and regions of the world, leading to market cost increases for electricity generation from technologies using fossil fuels. However, the effects of such measures on market costs are straightforward and, therefore, will not be discussed in detail here.

It should be noted that there is a close relationship between, on the one hand, changes in public acceptance for certain electricity generation technologies and, on the other hand, regulatory changes affecting these technologies [103,104]. Regulatory changes typically aim to reduce a technology's external costs, such as the health impacts of fossil fuel power generation or the societal risks of large-scale nuclear accidents, and thus also aim to increase public acceptance for these technologies. This relationship between regulatory changes and external costs also means that while stricter regulatory standards tend to increase the market costs of electricity generation, its social costs do not necessarily increase.

According to an analysis by Komanoff [46], environmental protection costs as a share of total capital costs of new coal power plants in the USA grew from roughly 8% in 1971 to 41% in 1978 and were projected to grow further to 54% by 1988. Consequently, while capital costs not associated with environmental protection measures grew by only 8% between 1971 and 1978 (from about 319 USD_{1979}/kW to 343 USD_{1979}/kW), total capital costs grew by 68% (from 346 USD_{1979}/kW to 583 USD_{1979}/kW). Most of these additional costs for environmental measures were for equipment to control the three major air pollutants produced in coal combustion: particulates, sulphur dioxide and nitrogen oxides. Further costs were reported for additional measures resulting from stricter environmental regulations, including better emissions monitoring, safer disposal of waste ash and lower pollution during the construction phase [46].

Econometric analysis by Joskow and Rose [56] suggests that the specific costs of coal power plants built in the USA between 1960 and 1980 roughly doubled after controlling inter alia for input prices, unit and project scale and learning-by-doing at company and industry level. They find that the installation of scrubbers and cooling towers required to fulfil new environmental regulations explains about 20% of this increase. The authors were unable to measure any additional responses to the new environmental restrictions but suspect that such additional measures are likely to explain some (but not all) of the remaining unexplained cost increase. (The authors suspect that "more general problems of productivity in construction" led to some of the cost increases observed over the analysed period.)

Stricter environmental regulations may impact not only on capital costs but also on operating costs. According to McNerney et al. [105], many utilities operating coal power plants in the USA reacted to the new air emissions standards of the 1960s and 1970s by switching to higher priced low-sulphur coals. In many cases the low-sulphur coal was also more expensive to ship as transport distances increased. On the other hand, rail rates fell throughout the 1980s, possibly in part due to the rail industry's deregulation throughout the 1970s and early 1980s.

There is strong consensus in the literature that stricter regulatory requirements over time were a key factor in explaining past cost increases observed for nuclear power plants in the USA and other countries [45,106]. Safety regulations and enforcement were continuously tightened from the start of commercial reactor construction in the mid-1960s until at least the late 1980s [27]. Nuclear safety regulations in countries around the world became stricter as public concerns over nuclear safety, waste disposal and proliferation grew, greater knowledge was gained about the risks of radiation and nuclear accidents—such as those at Three Mile Island (USA) in 1979 and Chernobyl (in present-day Ukraine) in 1986—occurred [103]. Stricter safety standards have led to greater technological complexity as well as to higher levels of material and labour inputs and have, consequently, contributed to longer construction times and cost increases [47,103]. In some cases, changes in regulations also required alterations to be made to nuclear power plants already under construction, meaning that some completed tasks needed to be reworked, which created additional costs and managerial complexity [46,47,104].

A review of studies analysing past developments of nuclear power plant construction costs concluded that these costs grew by about 15% annually in the USA during the 1970s and 1980s once important factors other than regulation had been controlled for [45]. However, the authors stress that this increase in costs may, to some extent, also capture the effects of additional factors not captured by the regression models of the various studies. They hypothesise that the nuclear industry may have tried to build large plants before the technology was mature enough to do so cost-effectively. McCabe [49] suggests that a deterioration in construction productivity may be another potential factor. However, he does not explain why construction productivity may have declined.

Due to the close collaboration between the French government, its agencies and the French nuclear industry, there has been relatively little regulatory uncertainty in the nuclear industry in France [58]. However, in the case of France it is also more difficult to find a measure of regulatory activity, as no public nuclear safety authority existed until 2006 [53,58]. Escobar Rangel and Lévêque [53] use two indicators of French nuclear power plants' performance as a proxy for safety improvements, arguing that such improvements can be expected to lead to more reliable plant operations. They measure the plants' performance by using the number of automatic shutdowns and the amount of energy that was not supplied by reactors due to unplanned deviations from normal operations. Their regression analysis indicates that higher safety standards are indeed related to higher specific plant costs.

According to Navarro [84], the Japanese "open and shut" process for new power plant construction was an important reason why the cost increases in the construction of nuclear power plants were less pronounced in Japan compared to the USA. This process aimed at resolving all political and procedural conflicts prior to the start of construction through negotiations involving the utility company, government representatives and political organisations representing other interests, such as environmental protection. While this process could be lengthy, once it was closed and construction approval was given, construction typically proceeded without delay.

Navarro [84] also suggests that fundamental differences between the USA and Japan in terms of antitrust laws and their enforcement may, in part, explain why the Japanese nuclear industry was better able than its US counterpart to contain cost increases over time. According to the author, antitrust regulations in Japan allow for contracting, engineering and reactor vendor responsibilities to be "confined to a small number of very large consortia that operate in a spirit of cooperation rather than competition".

According to Hewlett [107], regulatory changes not only affected construction costs but also the operation and maintenance costs of nuclear power plants. The author finds evidence that the 11%

average annual increase observed in real operation and maintenance costs of nuclear power plants in the USA from 1975 to 1987 was primarily the result of increased regulatory requirements.

Several authors describe qualitatively that certain regulatory conditions or changes affect the costs of onshore and offshore wind power plants. Vogel [108] notes that regulations addressing inter alia the noise and hub height of onshore wind turbines limit the potential for the economic optimisation of a plant's design and siting. Gross et al. [27] report that gaining planning permission for onshore wind turbines in the UK had become increasingly difficult and costly by the early 2000s, as regulatory specifications were tightened to address public concerns about the impacts of wind turbines. In some countries, financial support measures for wind power plants were, or are, tied to the condition that these plants comprise a certain proportion of domestically-produced parts. These so called "local content" rules tend to increase wind power investment costs in the respective countries by reducing the number of qualified turbine suppliers [109].

For CSP power plants, Taylor et al. [110] note that throughout the 1980s regulations in the USA set a limit on the maximum size of CSP power plants, with the limit being much lower than the cost-optimal scale of such plants. The limit was set at 30 MW for facilities that were exempted from being regulated as utilities; otherwise the limit was set at 80 MW. The cost optimal scale of a CSP plant was estimated to be around 200 MW [110]. The same regulations also limited the size of installed circulating fluidized bed (CFB) technology to below 100 MW_{el} until the year 2000. As the technology was already available for above 400 MW_{el}, the regulatory size limit is likely to have prevented power producers from taking advantage of economies of unit scale [25].

2.4.2. Limits to the Availability of Suitable Sites

The characteristics of a site where a power plant is built typically influence the cost of installing that power plant and of generating electricity. If sites with particularly suitable characteristics are rare in a country or region, the increase in the deployment of an electricity generation technology may force investors to choose less suitable sites once the best locations have been used. The need to divert to less suitable locations can be caused not only by the lack of good sites due to natural characteristics, but also by public opposition to the construction of plants at highly suitable sites. Less suitable locations are associated with higher costs for constructing and/or operating the power plant for any given level of technology development. This potential effect on the generating costs over time is believed to be most relevant for renewable energy technologies as their effective operation depends to a great extent on certain climatic or geographical conditions. The associated increases in electricity generation costs may counteract learning-induced cost decreases over time [111–114].

Many authors argue that the scarcity of suitable sites can particularly affect the cost of onshore wind power generation, as shifting from sites with very good wind conditions to less suitable sites leads to lower load factors and/or the need to install turbines with higher towers and larger rotor diameters [10,72,113,115]. Similarly, for offshore wind power it is argued that sites which are relatively cheap to exploit are typically rare. Therefore, additional deployment will eventually require the use of sites that are increasingly distant from the coastline and in increasingly deep water, leading to higher installation costs [112] as well as higher operation and maintenance costs [116]. An increasing trend in ocean depth and distance to shore of new offshore wind projects has indeed been observed in the past, for example in the UK between 2005 and 2014 [95]. Voormolen et al. [17] find that increasing ocean depth and distance to shore contributed by about one third to the observed increase in investment costs of offshore wind farms in Europe between 2000 and January 2015.

In recent years, onshore wind turbines specifically adapted to less windy sites have been developed and these turbines tend to be more expensive per installed capacity due to their higher towers and bigger rotor diameters. The adapted turbines have helped to prevent average capacity factors of onshore wind turbines from decreasing over time, even in regions where average site conditions can be expected to have deteriorated [117,118]. No literature has been found which attempts to empirically quantify the isolated cost effects of deteriorating site conditions on the installation and/or generating costs of either onshore or offshore wind power plants.

Investment and operating costs of nuclear power plants also depend, to some extent, on site characteristics. Navarro [84] reports that Japanese nuclear power plants rely exclusively on sea water cooling systems, giving them an investment cost advantage over the majority of US nuclear power plants which require cooling towers as they lack access to the sea or other big bodies of water. In France, the most suitable coastal sites for nuclear power plants were the first to be used during the country's nuclear power plant construction programme. This eventually led to the need for new nuclear power plants to be built either at inland sites, requiring the construction of cooling towers, or at poorer coastal sites, necessitating large earthworks [103]. According to MacKerron [103], this "undoubtedly" had an influence on the capital costs of the country's new nuclear power plants, but is likely to have contributed no more "than a small proportion to the total escalation in French costs". Cooling towers are reported to have added an average of between 7% and 8% to the costs of nuclear power plants built in the USA between 1971 and 1978 [46].

2.5. Summary of Cost Factors

Table 2 summarises the findings of the literature review in Sections 2.1–2.4 by indicating which factors have influenced which generation technologies. For certain important electricity generation technologies, such as biomass power plants, hydropower plants and geothermal plants, the information in the literature is very limited and, therefore, these technologies are not included. In the table, an arrow pointing downward indicates that there is clear evidence in the literature that a factor has led to cost reductions in the past, while an arrow pointing upward indicates that there is clear evidence that a factor has led to cost increases. Circles imply that the literature has generally found no effects, or only minor effects. Brackets are added in cases where the literature is not entirely conclusive and where the author's assessment of the direction of cost changes is, therefore, based on limited empirical evidence from the literature. A hyphen indicates that no information, or only insufficient information, is available to assess the effects of that particular factor on the cost of a particular technology.

Table 2. Summary of the findings of the literature review on factors influencing past cost developments of electricity generation technologies.

Categories of Cost-Influencing Factors	Cost-Influencing Factors	Wind (On- & Off-Shore)	Solar PV	CSP	Nuclear Energy	Coal	Natural Gas
Learning and Technological Improvements	Deployment-Induced Learning	↓	↓	↓	↓	↓	↓
	RD&D-Induced Learning	↓	↓	↓	(↑)	(↓)	(↓)
	Knowledge Spillovers from Other Technologies	↓	↓	(↓)	(↓)	-	↓
	Upsizing	↓/o	o	(↓)	o	↓/(o)	-
Economies of Scale	Economies of Manufacturing Scale	↓	↓	-	o	↓	(↓)
	Economies of Project Scale	↓	↓	-	↓	↓	-
Changes in Input Factor Prices	Changes in Material and Labour Costs	↑	↓/↑	-	↑	↑	-
	Changes in Fuel Costs	o	o	o	(o)	o	↑
Social and Geographical Factors	Regulatory Changes	↑	(o)	(o)	↑	↑	(↑)
	Limits to the Availability of Suitable Sites	(↑)	(o)	(o)	↑	↑	-

Notes: An arrow pointing downward indicates that there is clear evidence in the literature that a factor has led to cost reductions in the past, while an arrow pointing upward indicates that there is clear evidence that a factor has led to cost increases. Circles imply that the literature has found no effects or only minor effects. Two different signs indicate that a factor has had different effects on a technology's cost depending on the time period, with the dominant effect over the past one to two decades shown on the right hand side. Brackets are added in cases where the literature is not entirely conclusive and where the author's assessment of the direction of cost changes is, therefore, based on limited empirical evidence in the literature. A hyphen indicates that no information, or only insufficient information, is available to assess the effects of that particular factor on the cost of a particular technology. PV: Photovoltaics; CSP: Concentrating solar power.

The table shows that learning and technological improvements, as well as economies of scale, typically contribute to cost reductions, while changes in input factor prices, as well as regulatory changes and limits to the availability of suitable sites, have tended to lead to cost increases. The table provides some indications why solar PV has, in the past, exhibited higher learning rates than other technologies, as many factors have been identified which have led to PV cost decreases—while only one factor has been identified which has led to (temporary) PV cost increases. In contrast, several factors have led to cost increases in the case of nuclear power and the effect of cost decreases through deployment-induced learning has been too limited to compensate for these factors—explaining why the one-factor experience curve has been of little use in explaining past cost developments of nuclear power.

3. Insights Gained in Regard to Future Cost Developments

One intention of this review is to inform energy modellers about those factors which have been shown to be of importance in explaining past cost developments of electricity generation technologies. It stands to reason that these factors will also be the key factors influencing the future (relative) costs of electricity generation technologies. Based on assessments found in the literature, as well as on the author's own judgement, Table 3 offers a list of how some factors may be expected to become more or less important (compared to the past) in influencing a technology's future costs.

Table 3. Possible future changes in the factors influencing the cost of electricity generation technologies.

Type of Electricity Generation	Possible Future Changes in the Factors Influencing the Cost of Electricity Generation
Wind	• Limited availability of good sites is likely to become more relevant (+) • Possible stronger economies of manufacturing scale once turbine designs change less over time (−)
Solar PV	• Relevance of economies of manufacturing scale may diminish once the market no longer grows (+) • In some regions: limited availability of good sites may sooner or later play a role (+) • Chance of RD&D-induced technological breakthroughs generally believed to be bigger than for other technologies (−)
CSP	• Potential for cost-reducing growth in average unit scale is likely to be limited (+) • Availability of good sites may sooner or later play a role (+)
Nuclear Energy	• Future nuclear accidents may further tighten security regulations, leading to additional costs (+) • A stable or more predictive regulatory environment would probably reduce costs (−) • Introduction of smaller scale designs may offer more potential for learning and for economies of manufacturing scale (−)
Coal	• Economies of unit size are either already exploited or offer only limited further potential (+) • Uncertain: future evolution of fuel and CO_2 emission costs as well as relevant environmental regulation (+/−)
Natural gas	• Uncertain: future evolution of fuel and CO_2 emission costs (+/−)

The table gives, for example, indications that solar PV may sooner or later "lose" economies of manufacturing scale as a key factor leading to continuous cost reductions. This means that the one-factor PV learning rate, which has been remarkably stable for decades, could decline in the future. However, a reliable estimate of how much the rate would decline remains elusive, as there does not appear to be enough certainty in the estimates of how much manufacturing scale has, in the past, contributed to PV cost declines. Nonetheless, energy modellers can use this information, for example to reduce the learning rate of PV over time, or use a lower range of possible future PV learning rates in stochastic modelling once PV market growth slows down or comes to a halt.

In the case of nuclear power, there appears to be the potential for ending cost increases and possibly even initiating cost decreases if a stable or more predictable regulatory environment were to prevail in the future. However, it is difficult to predict whether such a regulatory environment will indeed be realised. Even if it is, it is likely that a relatively large number of new nuclear reactors (ideally very similar in design) would need to be built for deployment-induced learning and economies of manufacturing scale to be achieved to a significant extent. Whether there will be sufficient global demand for this technology in the coming decades is unclear.

For electricity generation technologies that are not yet in commercial use, no empirical analyses of cost developments exist. These technologies are, therefore, not included in the present analysis. However, knowledge about past cost drivers of electricity generation technologies may be used to try to infer information about the likely future cost developments of new electricity generation technologies. For example, MacGillivray et al. [119] assume that marine renewable energy technologies may benefit from economies of project size by mounting multiple units on the same foundation. The authors also recommend that the marine renewable energy industry focuses on economies of manufacturing scale through unit modularity, rather than on economies of unit scale, and that it attempts to take advantage of potential spillover effects from offshore wind energy.

Regarding CCS power plants, some authors suggest that future economies of project scale may be achievable by building larger plants or by clustering several plants, allowing the required CO_2 transportation network to be used more effectively [27,120]. On the other hand, Rai et al. [104] compare the regulatory complexity and the related uncertainty of CCS technology to the nuclear industry and warn that the effects of potentially unstable regulatory frameworks may counteract any future cost reductions in CCS technology. Future regulatory frameworks for CCS technology are expected to be complex because they will need to address not only the capturing of CO_2 but also its transport and storage. One example of the uncertainty associated with the regulatory framework is the as yet unresolved issue of long-term liabilities associated with how the injected CO_2 behaves [104]. Furthermore, CCS coal power plants in particular will be subject to emissions regulations (regarding mercury emissions for example [121]), which may continue to become stricter over time.

Knowledge about past cost drivers of electricity generation technologies may also inform estimates of future cost developments in the related field of energy storage technologies. Small-scale and modular technologies, such as batteries for example, can be expected to benefit to a much greater degree from deployment-induced learning and economies of manufacturing scale than large-scale storage technologies, such as pumped hydro storage or compressed air storage technology. For lead-acid batteries produced in the USA between 1989 and 2012, Matteson and Williams [122] find a strong correlation between experience and price, once material costs are excluded. They deduce a residual (i.e., non-material cost) learning rate of 24% for small lead-acid batteries and a residual learning rate of 19% for large lead-acid batteries. Large-scale storage technologies on the other hand may also be more susceptible to cost increases owing to regulatory changes.

It should be noted again that the market costs focused on in this article are only one element of the overall societal cost of electricity provision. In the coming years and decades, the evolution of system integration costs will become more important in comparing the costs of various electricity generation technologies from a societal perspective [9]. System integration costs include transmission costs and balancing costs and are not part of the definition of market costs used here. System integration costs will become more important as the share of fluctuating renewable energy sources (especially wind and solar PV) in total electricity generation continues to increase around the world. Finding ways to reduce the rise in integration costs as the share of fluctuating renewable energy sources increases will be important in order for countries around the world to fully benefit from the improvements in market costs and the comparatively low external costs of solar and wind technologies.

4. Conclusions

The preceding review of the historical cost developments of various electricity generation technologies has identified 10 factors, all of which have had a considerable influence on past cost developments. The review has highlighted the fact that the cost of the technologies is not only influenced by deployment-induced learning and research and development—the two factors typically at the centre of this discussion. In fact, knowledge spillovers and upsizing, as well as economies of manufacturing and project scale, have also contributed to reductions in the costs of electricity generation technologies over time. At the same time, changes in the price or quality of input factors, as well as regulatory changes, have tended to increase the costs of many generation technologies. The review has shown that each technology is affected by a different combination of factors influencing their market costs.

The insights gained by the review can be used by researchers to make better informed assumptions about the future cost developments of the analysed technologies, as well as of other technologies exhibiting similar characteristics. The insights can also guide policymakers in attempts to create regulatory and market conditions that are as favourable as possible for further cost reductions in electricity generation technologies.

At the same time, the literature review has illustrated the difficulties in determining quantitatively and with certainty the various factors that have influenced past cost developments. Quantification appears to be especially elusive with regards to the roles that RD&D-induced learning, knowledge spillovers and regulatory changes play. Similarly, it has proven difficult to separate the effects that some of the factors have had on the past cost developments of individual technologies, especially regarding the respective roles of deployment-induced learning, RD&D-induced learning, knowledge spillovers, upsizing and economies of manufacturing scale.

It is possible that a clear separation of the effects of these factors is neither possible nor reasonable as they may closely interact with one another. For example, considerable deployment of a technology may not just lead to learning through learning-by-doing, learning-by-using and learning-by-interacting, but is also likely to lead to further consequences: companies and governments are likely to increase their respective RD&D budgets for the technology; engineering experience is gained which may help to solve challenges associated with upsizing the technology; and a growing industry also tends to lead to bigger manufacturing plants, enabling the exploitation of economies of manufacturing scale. These interdependencies may also explain the close correlation between deployment and costs for many technologies, as indicated by experience curve analysis [31,32]—especially once changes in material and labour costs are accounted for. It would be useful if future research were to try to better understand the interrelationships between the various factors that influence technology costs.

Despite the inherent difficulties in determining and quantifying the role played by individual factors on the past cost developments of electricity generation technologies, our knowledge about these factors would certainly benefit from more empirical studies analysing as many of these factors as possible—as opposed to, for example, merely deriving one-factor experience curves. Some factors, such as economies of manufacturing scale and changes in material and labour costs, appear to be important for many technologies and can principally be quantified with some certainty. These factors should definitely be taken into account in future studies, as several studies have recently shown that this is possible and worthwhile [29,42,94].

In-depth case studies on factors influencing costs are currently rare and would ideally complement studies conducting regression analysis. Case studies have the particular potential to improve our understanding of the aforementioned factors that are difficult to quantify and would also potentially provide relevant information about the interdependencies between different factors.

Finally, it is reasonable to expect that the costs of integrating electricity generated from fluctuating renewable energy sources (especially wind and solar) will play an increasingly important role in the coming years and decades in determining the overall costs of electricity supply. It could, therefore, be worthwhile for future research to focus on better understanding the historical and potential future cost developments of technologies such as batteries and fuel cells or of measures aiming to shave or shift demand peaks.

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5. The Experience Curve Theory and its Application in the Field of Electricity Generation Technologies – A Literature Review

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The experience curve theory and its application in the field of electricity generation technologies – A literature review

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ABSTRACT

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

1. Introduction

Access to electricity is widely regarded as a prerequisite for ensuring a high standard of living, yet more than one billion people globally still lack access to electricity [1]. One of the targets of the Sustainable Development Goals (SDGs) is, therefore, to "ensure universal access to affordable, reliable and modern energy services" by 2030 [2]. At the same time, decarbonisation scenarios for many different countries agree that substituting fossil fuel use with electricity in final energy demand (e.g. switching from conventional to electric vehicles) is a key element of decarbonisation strategies [3]. Electricity demand is, consequently, expected to continue to increase globally in the decades to come, while electricity supply will simultaneously need to undergo a transformation towards low or zero-carbon technologies.

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

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

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

- providing a systematic overview of the differences in the characteristics of experience curves for electricity generation technologies;

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

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

2. The experience curve theory

2.1. Deployment-induced learning and the experience curve theory

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

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

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

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

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

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

$$PR = 1–LR$$

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

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

2.2. Different characteristics

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

2.2.1. Methodological issues

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

Most of the available empirical studies that construct experience curves for electricity generation technologies do not use technology costs as the dependent variable – as would be theoretically preferable – but instead use a technology's market price. Market prices are frequently used as a proxy for market costs, as the former are more

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

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

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

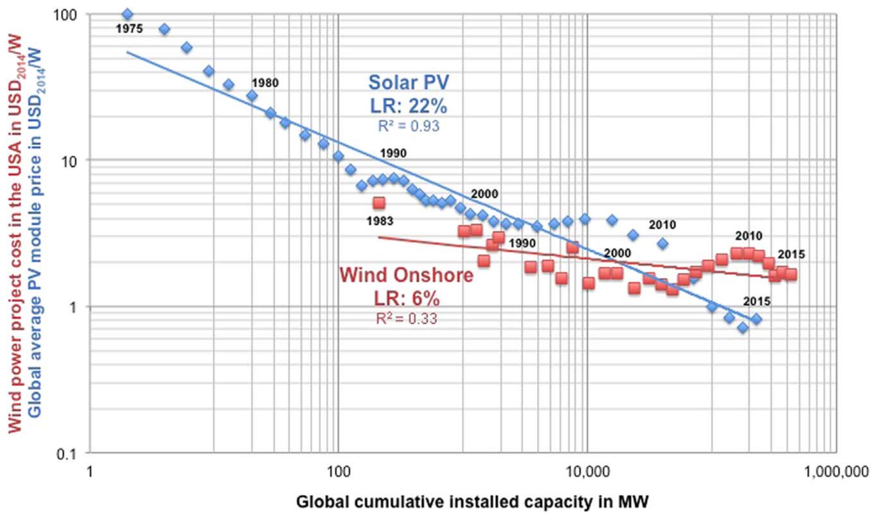

Fig. 1. Experience curves for global solar PV module manufacturing (1975–2015) and for wind power projects in the USA (1983–2015). Data sources: [33–39].

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

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

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

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

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

readily available [22]. See Section 2.3 for a discussion of the problems associated with using price data instead of cost data.

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

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

Criticism of the theoretical concept
- Concept implies that experience is the only driver of technology cost changes
- Effect of experience tends to be overestimated (omitted variable bias)
- Concept cannot prove that experience is indeed the *cause* of observed cost changes
- High level of aggregation does not allow for a deeper understanding of cost drivers
- Aspects of technological change that have no impact on market costs are neglected

Criticism of the empirical data
- Frequently used prices are often an inadequate proxy for costs
- Uncertainty in historic cost data can lead to substantive learning rate uncertainty

Criticism of the use of learning rates
- Learning rates are often uncritically assumed to remain constant in the future
- Uncertainties are frequently neglected when using learning rates in energy models

2.2.2. Learning system boundaries

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

When power plant technologies consist of different parts that are assumed to exhibit distinct learning rates or different deployment curves, it is more consistent to construct separate learning rates for these individual parts instead of a single learning rate for the entire technology [53]. For example, it has been suggested that separate experience curves should be constructed for the main elements of concentrating solar thermal power plants [54]. For these plants, three main components can be differentiated: the collector field, the thermal storage system and

Table 3
Overview of the reviewed experience curve studies and their associated learning rates as listed in Tables A1–A8 in the Appendix A.

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

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

the power block. All three elements of the power plant are distinct technologies and none of them share the same development of experience.

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

2.2.3. Definition of specific costs

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

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

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

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

2.2.4. Definition of experience

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

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

2.3. Limitations of the experience curve concept

The literature on experience curves widely acknowledges and

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

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

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

2.3.1. Criticism of the theoretical concept

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

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

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

Omitted variable bias occurs when neglected additional independent variables are correlated not only with technology costs but also with experience [65]. Experience, for example, usually has a strong correlation with time, as may be the case for other relevant variables such as knowledge stock (gained through R & D), economies of manufacturing scale or the suspected influence of inter-industry spillovers [57,62,63]. As a result, the high correlation between experience and technology costs, as suggested by many experience curves derived from historic data, may actually be (to some extent) a misrepresentation caused by the correlation between experience and other key cost-influencing factors omitted from the analysis. Based on a literature review of studies deriving learning rates for PV technology, de la Tour et al. [41] find that PV learning rates based on multi-factor experience curves are considerably lower than PV learning rates based on models with experience only. They conclude: "This suggests that the experience parameter is seriously biased when it is the only explanatory variable as it captures the influence of other drivers." [41]

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

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

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

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

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

2.3.2. Criticism of the empirical data used

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

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

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

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

2.3.3. Criticism of the use of learning rates

A key objective of deriving historic experience curves for individual technologies is to gain information about their possible future experience/cost relationship. In this regard, it is often assumed that learning rates observed in the past will remain constant in the future. Critics of this approach emphasise that it should not be taken for granted that past experience curves can simply be extrapolated [53,65,72]. Since simple experience curve analysis does not provide details about the deeper cost drivers (see above), it is considered problematic to simply assume that the relationship between experience and cost will remain constant in the future. For example, assuming constant learning rates does not take into

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

account possible future constraints to learning; for example, in the form of physical limits to conversion efficiency improvements or to material reductions. Equally, it does not allow for the consideration of possible future technological breakthroughs, which would manifest themselves in experience curve discontinuities [22,29,73].

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

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

- critically reflecting whether observed learning rates in the past can reasonably be expected to remain stable in the future, especially in the medium to long term [4,54,74,75];
- and performing several model runs when modelling the future costs of individual electricity generation technologies, using ranges of plausible future learning rate values in order to reflect the associated uncertainties [17,76].

3. Observed experience curves for electricity generation technologies

3.1. General observations

As part of this review, 67 studies with empirical observations of experience curves and associated learning rates for eight different types of electricity generation technologies have been identified. Tables A1 to A8 in the Appendix A list the observed learning rates and associated relevant information from these studies. The following table provides an overview of the reviewed studies included in Tables A1 to A8 (Table 3).

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

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

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

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

3.2. Renewable energy power plants

3.2.1. Onshore wind power plants

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

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

- Rising commodity prices
  Prices for commodities (including steel and copper, which are both relevant cost factors in wind turbines) increased considerably during the first decade of the century and were especially high between 2005 and 2008 [22,82,83].
- Supply constraints due to strong market growth
  Throughout the first decade of the century, global demand for wind turbines grew strongly as global annual installed wind capacity grew more than tenfold between 2000 and 2009, from 3760 MW to 38,478 MW [84]. This led to supply constraints, allowing turbine manufacturers and component suppliers to charge higher prices and increase their profits [22,38].
- Limits to learning
  Some authors expect a technology's learning rate to decline as the technology becomes more mature. For example, McDonald and Schrattenholzer [85] argue that mature technologies typically require more time until they reach doublings in cumulative capacity, leading to a higher risk of knowledge depreciation. Another explanation [44] is that as technologies become more mature, their inherent cost reduction potentials are increasingly exploited. To the extent that the previously discussed factors cannot fully explain recent reductions in the learning rate, this may be an indication that such a “flattening” of the experience curve for wind power plants is indeed taking place.

It is important to keep in mind that for wind power there is not necessarily a linear relationship between rated capacity and electricity generation. Instead, changes in turbine design, such as higher towers, longer rotor blades and improved control electronics, tend to lead to

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

higher capacity factors by allowing relatively weak and erratic wind resources to be captured. Such design changes were observed over the years for new wind power plants as these plants were increasingly optimised for use at sites with non-optimal wind conditions. However, when deriving experience curves based on turbine prices or investment costs, as most studies do, only the *costs* associated with these design changes are taken into account, while the *benefits* in the form of additional electricity generation are not captured [86,87].[8]

As a consequence, and as Neij [60] points out, wind power learning rates expressed in terms of the levelized production cost of electricity are generally higher than learning rates expressed in terms of turbine prices or investment costs. This is illustrated by the results of a limited number of studies in Table A1 [87–89], which derive experience curves for both turbine prices or investment costs, as well as for electricity generation costs, using the same region and the same or very similar time period.

3.2.2. Offshore wind power plants

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

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

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

3.2.3. Solar PV power plants

The PV learning rates listed in Table A3 are either for all types of PV systems on the market (a market which has always been dominated by PV systems using silicon modules), or specifically for PV systems using silicon modules. Only a few studies have looked at learning rates for non-silicon PV technology, such as cadmium-telluride thin film modules [92], or for concentrating PV systems [93].

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

3.2.4. Solar thermal power plants

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

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

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

3.2.5. Biomass power plants

Experience curves for biomass power plants are difficult to construct as there are variations in the characteristics of such plants, concerning the type of technology used, plant size and the type of biomass feedstock used. Perhaps as a consequence, only a few literature sources derive experience curves for biomass power plants. The three studies identified [23,59,69] provide learning rates for the specific generation costs in the European Union, Sweden and China, respectively. They find learning rates of between 2% and 15%. For biomass feedstock (not shown in Table A5), learning rates of about 10–45% have been found in the literature [23,100,101].

3.3. Nuclear power plants

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

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

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

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

- Continuous changes and tightening of regulations

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

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

3.4. Fossil fuel power plants

3.4.1. Coal power plants

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

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

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

3.4.2. Natural gas power plants

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

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

4. Deriving plausible future learning rates for electricity generation technologies

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

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

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

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

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

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

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

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

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

5. Conclusion

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

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

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

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

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

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

Overall, however, the empirical and theoretical insights from the reviewed literature suggest that learning does indeed take place as experience is accumulated by a technology. It is important to note that not only can experience directly reduce costs through experience-induced learning, but it can also indirectly reduce costs through its potential effects on other cost-influencing factors. These include both private and public RD & D expenses, as well as the potential for realising economies of manufacturing and unit scale (upsizing), all of which are likely to be

[9] If it is assumed that the average size of PV manufacturing plants will stop increasing once the global PV market is no longer growing, looking at global energy scenarios can shed light on how much longer PV manufacturing plants could continue to grow in size. The annual global demand for PV modules was around 50 GW in 2015 [114]. In the 2DS scenario of the IEA's Energy Technology Perspectives 2015 study [115], global PV capacity reaches 2755 GW by 2050, while it reaches 9295 GW in the Advanced Energy [R]evolution scenario commissioned by Greenpeace International, Global Wind Energy Council and SolarPower Europe [116]. Assuming that the PV capacity in 2050 is the long-term capacity required for a sustainable energy system and further assuming a 25 year lifespan for PV systems [96], this would mean that the global PV market will grow until it reaches 110 GW annually in the 2DS scenario and 372 GW annually in the Advanced Energy [R]evolution scenario.

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

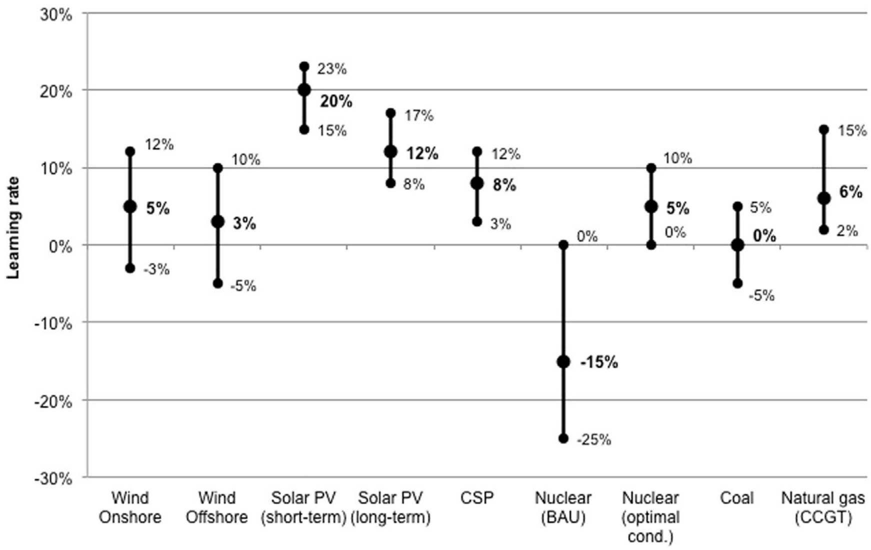

Fig. 2. Estimates of plausible future learning rate ranges for several important electricity generation technologies.

positively related to a technology's experience. This consideration also puts into perspective the findings stressed by some authors that not only experience, but also other factors such as RD & D and economies of scale, can considerably influence technology costs. This is probably true, but it does not necessarily mean that focusing primarily on experience as the variable for informing about costs is unjustified.

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

5.2. Suggestions for further research

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

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

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Appendix A

Note: In the following tables, learning rates provided by the original studies that refer to a limited part of the whole time period considered in the respective studies are indicated in italics (Tables A1–A8).

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

Table A1
Learning rates found in the literature for *onshore wind power plants*.

Literature source	Geographical domain	Experience (in cumulative terms)	Costs or prices [a] (in specific terms)	Period	Learning rate (%)	R2	Number of doublings of experience	Additional independent variable(s) controlled for
[87]	Denmark	Capacity sales	Wind turbine prices	1982-1995	4	0.83	10	
	Denmark	Capacity sales	Generation costs	1980-1991	9	n.s.	n.s.	
[86]	Global/USA [c]	Number of turbines installed	Generation costs	1985-1995	18	0.99 [b]	1	R & D
[49]	Denmark	Capacity sales	Wind turbine prices	1982-1997	8	n.s.	n.s.	
[59]	USA	Electricity generation	Generation costs	1985-1994	32	n.s.	4	
	EU	Electricity generation	Generation costs	1980-1995	18	n.s.	10	
[44]	Denmark	Installed capacity	Generation costs	1984-1999	8	n.s.	6	
	Denmark	*Installed capacity*	*Generation costs*	*1984-1988*	*12*	*n.s.*	*3*	
	Denmark	*Installed capacity*	*Generation costs*	*1988-1999*	*7*	*n.s.*	*3*	
	UK	Installed capacity	Generation costs	1991-1999	25	n.s.	4	
[122]	Germany	Installed capacity	Wind turbine prices	1990-2001	6	n.s.	7	
	Germany	*Installed capacity*	*Wind turbine prices*	*1990-1992*	*-2*	*n.s.*	*1*	
	Germany	*Installed capacity*	*Wind turbine prices*	*1992-1996*	*11*	*n.s.*	*3*	
	Germany	*Installed capacity*	*Wind turbine prices*	*1996-2001*	*-3*	*n.s.*	*3*	
	Germany	Electricity generation	Wind turbine prices	1990-2001	9	n.s.	8	
[123]	Denmark	Number of turbines produced	Wind turbine prices	1983-1998	18	0.82 [b]	4	
	Denmark	Produced capacity	Wind turbine prices	1983-1998	9	0.95 [b]	7	Time trend and annual export share
	Denmark	Number of turbines produced	Wind turbine prices	1983-1998	11	0.94 [b]	4	Time trend and annual export share
	Denmark	Number of turbines produced	Wind turbine prices	1983-1998	9	0.95 [b]	4	Time trend, annual export share and project scale
[42]	Global	Installed capacity	Investment costs	1971-1997	10	0.8	n.s.	R & D
[88]	Denmark	Installed capacity	Investment costs	1981-2000	10	0.92	8	
	Denmark	Installed capacity	Wind turbine prices	1981-2000	9	0.94	8	
	Denmark	Produced capacity	Wind turbine prices	1981-2000	8	0.84	10	
	Denmark	Produced capacity	Generation costs	1981-2000	17	0.97	10	
	Germany	Installed capacity	Wind turbine prices	1987-2000	6	0.88	11	
	Germany	Produced capacity	Wind turbine prices	1987-2000	6	0.74	8	
	Spain	Installed capacity	Investment costs	1984-2000	9	0.85	15	
	Sweden	Installed capacity	Investment costs	1994-2000	4	0.32	5	
[14]	Global/Spain [c]	Installed capacity	Investment costs	1990-2001	15	0.89	4	
	Global/UK [c]	Installed capacity	Investment costs	1992-2001	19	0.98	3	
[124]	Germany, Denmark, UK	Installed capacity	Investment costs	1986-2000	5	0.72 [b]	7	R & D
[125]	Japan	Installed capacity	Investment costs	1990-2003	11	0.42	8	
	Japan	*Installed capacity*	*Investment costs*	*2000-2003*	*8*	*0.59*	*2*	
[80]	Global/ Germany [c]	Installed capacity	Wind turbine prices	1991-2003	11	n.s.	4	
	Global/ Germany [c]	Installed capacity	Wind turbine prices	1991-2003	13	n.s.	4	Turbine scale and higher wind speeds at higher tower heights
	Germany	Installed capacity	Wind turbine prices	1991-2003	7	n.s.	7	
[126]	Germany, Denmark, UK	Installed capacity	Investment costs	1986-2000	5	0.72 [b]	n.s	R & D
	Germany, Denmark, UK, Spain	Installed capacity	Investment costs	1986-2000	7	0.83 [b]	n.s	R & D
	Germany, Denmark, UK, USA	Installed capacity	Investment costs	1986-2002	7	0.50 [b]	n.s	R & D
	Germany, Denmark, UK, Spain, USA	Installed capacity	Investment costs	1986-2002	7	0.65 [b]	n.s	R & D
[81]	Global	Installed capacity	Investment costs	1981-1997	14	0.95 [b]	n.s.	R & D
[58]	Germany	Installed capacity	Wind turbine prices	1987-2000	5	0.71 [b]	n.s	
	Germany	Electricity generation	Wind turbine prices	1987-2000	7	0.76 [b]	n.s	
	Denmark	Installed capacity	Wind turbine prices	1987-2000	11	0.83 [b]	n.s	
	Denmark	Electricity generation	Wind turbine prices	1987-2000	13	0.96 [b]	n.s	
[127]	Germany, UK, Denmark, Spain	Installed capacity	Investment costs	1986-2000	3	0.81	7	R & D, turbine scale and feed-in tariff level
[65]	Germany, UK, Denmark, Spain	Installed capacity	Investment costs	1986-2000	5	0.64 [b]	7	

(continued on next page)

Table A1 *(continued)*

Literature source	Geographical domain	Experience (in cumulative terms)	Costs or prices [a] (in specific terms)	Period	Learning rate (%)	R2	Number of doublings of experience	Additional independent variable(s) controlled for
	Germany, UK, Denmark, Spain	*Installed capacity*	*Investment costs*	*1992-2000*	*8*	*0.67* [b]	*4*	
	Germany, UK, Denmark, Spain	Electricity generation	Investment costs	1986-2000	6	0.67 [b]	n.s.	
	Germany, UK, Denmark, Spain	Installed capacity	Investment costs	1986-2000	4	0.73 [b]	7	R & D
	Germany, UK, Denmark, Spain	Installed capacity	Investment costs	1986-2000	2	0.74 [b]	7	R & D and turbine scale
	Germany, UK, Denmark, Spain	Installed capacity	Investment costs	1986-2000	8	0.96 [b]	7	R & D and identified endogeneity between cost and deployment
[72]	Global/ California c	Installed capacity	Wind turbine prices	1981-2004	11	0.75	12	
[128]	EU/Denmark	Installed capacity	Wind turbine prices	1990-2009	7	0.65	7	
	EU/Denmark	*Installed capacity*	*Wind turbine prices*	*1990-2001*	*9*	*0.95*	*5*	
	EU/Denmark	Installed capacity	Price of electricity	1998-2009	10	0.97	3	
[57]	Global/ Germany, Denmark, Spain, Sweden, UK c	Installed capacity	Investment costs	1986-2002	17	0.88	4	R & D and turbine scale
[129]	China	Installed capacity	Price of electricity	2003-2007	8	0.44	3	
	China	Installed capacity	Price of electricity	2003-2007	4	0.63	3	Steel price, project size, wind quality and localisation rate
[89]	India	Installed capacity	Investment costs	2006-2011	17	0.56 [b]	n.s.	Project size, capacity factor, steel price, exchange rate, time trend and region
	India	Installed capacity	Generation costs	2006-2011	18	0.67	n.s.	Project size, capacity factor, steel price, exchange rate, time trend and region
[38,130]	Global/USA c	Installed capacity	Investment costs	1982-2014	7	n.s.	12	
	Global/USA c	*Installed capacity*	*Investment costs*	*1982-2004*	*14*	*n.s.*	*9*	
[11]	Global	Installed capacity	Wind turbine prices	1990-2012	4	0.80	7	
	Global	Installed capacity	Wind turbine prices	1990-2012	2	0.84 [b]	7	R & D
[131]	China	Installed capacity	Generation costs	2004-2011	4	0.65	6	
[132]	China	Installed capacity	Generation costs	1997-2012	5	n.s.	n.s.	
[15]	China	Installed capacity	Wind turbine prices	1998-2012	8	0.80 [b]	8	
	China	Installed capacity	Wind turbine prices	1998-2012	9	0.99	8	R & D, turbine scale, labour price, cost of capital, steel price, fibre/resin price
[67]	Global/Eight EU countries	Installed capacity	Investment costs	1991-2008	8	0.37 [b]	6	Steel price
	Global/Eight EU countries	Installed capacity	Investment costs	1991-2008	7	0.36 [b]	6	Steel price, cumulative installed national capacity
	Global/Eight EU countries	Installed capacity	Investment costs	1991-2008	6	0.39 [b]	6	Steel price, R & D
	Global/Eight EU countries	Installed capacity	Investment costs	1991-2008	5	0.43 [b]	6	Steel price, R & D, feed-in-tariff level

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

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

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

Table A2
Learning rates found in the literature for *offshore wind power plants*.

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

[a] For reasons of clarity, the term "investment costs" as used in this table covers the dependent variables referred to in the literature sources as "total installation cost" [45] or "turbine production plus installation cost" [90]. The (limited) information provided by the studies in relation to the cost elements included suggests that there are no major differences between their respective cost definitions.
[b] This source includes mostly historic cost data, but also a few data sources based on the forecast costs for offshore wind farm projects that had not been realised at the time of writing.

Table A3
Learning rates found in the literature for *solar photovoltaic (PV) technology*.

Literature source	**Geographical domain**	**Experience** (in cumulative terms)	**Costs or prices** (in specific terms)	**Period**	**Learning rate (%)**	**R^2**	**Number of doublings of experience**	**Additional independent variable(s) controlled for**
[133]	Global	Produced capacity	Module prices	1976-1992	**18**	n.s.	10	
[134]	USA	Sold capacity	Module prices	1976-1988	**22**	0.98	9	
[59]	European Union	Electricity generation	Generation costs	1985-1995	**35**	n.s.	5	
	Global	Produced capacity	Module prices	1976-1984	**16**	n.s.	7	
	Global	Produced capacity	Module prices	1987-1996	**21**	n.s.	2	
[135]	Global	Produced capacity	Module prices	1968-1998	**20**	n.s.	13	
[136]	Global	Produced capacity	Module prices	1976-2000	**20**	0.99	12	
[137]	Global	Produced capacity	Module prices	1981-2000	**23**	0.99	7	
	Global	*Produced capacity*	*Module prices*	*1981-1990*	***20***	*0.98*	*4*	
	Global	*Produced capacity*	*Module prices*	*1991-2000*	***23***	*0.98*	*2*	
[138]	Global	Produced capacity	Module prices	1976-2002	**25**	n.s.	9	
	Global	*Produced capacity*	*Module prices*	*1989-2002*	***19***	*n.s.*	*3*	
[19]	Global	Produced capacity	Module prices	1976-2001	**20**	0.99	12	
	Global	*Produced capacity*	*Module prices*	*1987-2001*	***23***	*0.93*	*4*	
	Europe	Installed capacity	Balance of system prices	1992-2001	**21**	0.78	5	
	The Netherlands	Installed capacity	Balance of system prices	1992-2001	**19**	0.93	9	
[139]	Global	Produced capacity	Module prices	1976-2003	**20**	n.s.	13	
[94]	Global/ Germany [d]	Produced capacity	Module prices	1992-2002	**16**	0.73	3	
	Global/ Germany [d]	Produced capacity	Generation costs	1992-2002	**35**	0.95	3	
	Germany	Installed capacity	Generation costs	1992-2002	**19**	0.97	6	
	Germany	Installed capacity	System prices	1992-2002	**24**	0.92	3	
[81]	Global	Produced capacity	Module prices	1975-2000	**18**	0.99	10	R & D
[29] [a]	Global	Produced capacity	Module prices	1978-2001	**26**	n.s.	11	
	Global	Produced capacity	Module prices	1976-2001	**17**	n.s.	10	
[140]	Global	Produced capacity	Module prices	1979-2005	**19**	n.s.	7	
[58]	USA	Produced capacity	Module costs	1990-2000	**23**	0.97 [b]	n.s.	
	USA	Produced capacity	Module prices	1990-2000	**20**	0.95 [b]	n.s.	
	USA	Installed capacity	Module prices	1992-2000	**32**	0.93 [b]	2	
	Germany	Installed capacity	Module prices	1992-2000	**15**	0.95 [b]	5	
	Switzerland	Installed capacity	Module prices	1992-2000	**10**	0.82 [b]	2	
	USA, Germany, Switzerland	Installed capacity	Module prices	1992-2000	**17**	0.82 [b]	2	
	USA, Germany, Switzerland	Installed capacity	Module prices	1992-2000	**10**	0.84 [b]	2	Time trend
[95]	Global	Installed capacity	Module prices	1975-2003	**23**	0.99	12	
	Global	Installed capacity	System prices	1991-2004	**27**	0.88	4	
[71]	Global	Produced capacity	Module prices	1976-2006	**21**	0.99	15	
	Global	*Produced capacity*	*Module prices*	*1991-2000*	***30***	*0.98*	*2*	
	Global	*Produced capacity*	Module prices	*1997-2006*	***12***	*n.s.*	*4*	
[141]	Global	Produced capacity	Module prices	1976-2010	**19**	n.s.	16	
	Global	*Produced capacity*	*Module prices*	*1976-2003*	***23***	*n.s.*	*12*	
[92]	Global	Produced capacity	Module prices	1976-2010	**23**	n.s.	14	
	Global	*Produced capacity*	*Module prices*	*1976-1988*	***30***	*n.s.*	*6*	
	Global	*Produced capacity*	*Module prices*	*1988-2010*	***17***	*n.s.*	*8*	
	Global	Produced capacity	Module prices	1988-2010	**14**	n.s.	8	PV module efficiency
[24]	Global	Produced capacity	Module prices	1976-2006	**20**	0.98	15	
	Global	Produced capacity	Module prices	1976-2006	**14**	0.99	15	Economies of manufacturing scale, silver and silicon prices, R & D
[41]	Global	Produced capacity	Module prices	1990-2011	**20**	n.s.	9	Silicon prices [c]
[142]	Global	Installed capacity	Module prices	1976-2010	**21**	0.91	13	
	Global	*Installed capacity*	*Module prices*	*1991-2010*	***15***	*0.84*	*9*	
[35]	Global	Installed capacity	Module prices	1988-2006	**14**	0.87	5	
	Global	Installed capacity	Module prices	1988-2006	**8**	0.97	5	Silicon prices
[143]	South Korea	Electricity generation	Generation costs	2004-2011	**3**	0.93	n.s.	
	South Korea	Electricity generation	Generation costs	2004-2011	**2**	0.96 [b]	n.s.	R & D
[11]	Global	Installed capacity	Module prices	1992-2012	**17**	0.78	8	
	Global	Installed capacity	Module prices	1992-2012	**10**	0.82 [b]	8	R & D, PV module overcapacities (2011, 2012)
	Germany	Installed capacity	System costs	1991-2012	**13**	0.75	15	
[132]	China	Installed capacity	Generation costs	1976-2009	**25**	n.s.	n.s.	
[144]	Taiwan	Installed capacity	Installation costs	2000-2014	**10**	0.87 [b]	n.s.	
	Taiwan	Installed capacity	Installation costs	2000-2014	**12**	0.97 [b]	n.s.	Silicon prices
[99]	Global	Installed capacity	Module prices	1976-2014	**21**	n.s.	19	
[17]	Global	Installed capacity	Module prices	1981-2013	**24**	0.97 [e]	12	

(continued on next page)

Table A3 *(continued)*

Literature source	Geographical domain	Experience (in cumulative terms)	Costs or prices (in specific terms)	Period	Learning rate (%)	R^2	Number of doublings of experience	Additional independent variable(s) controlled for
	Global	Installed capacity	Module prices	1981-2013	**23**	0.98 [e]	12	Silicon prices
	Global	Installed capacity	Module prices	1993-2013	**25**	0.98 [e]	8	Silicon prices
	Global	Installed capacity	Module prices	1993-2013	**35**	n.a. [e]	8	Silicon prices, fossil fuel energy prices

[a] The two different learning rates provided by this source are based on two different sets of historic data on cost and experience.
[b] Numbers refer to the *adjusted* R^2. Unlike R^2, the adjusted R^2 does not automatically increase as more explanatory variables are added. Instead, the adjusted R^2 only increases when additional explanatory variables improve the R^2 more than would be expected by chance.
[c] The study tests the explanatory power of three additional variables (silver prices, economies of scale in manufacturing and R & D) in various combinations but finds the specification with only experience and silicon prices as the independent variables to be the best.
[d] The geographical domains of the dependent and the independent variables differ in these experience curves. The region named first refers to the independent variable, while the country named after the slash refers to the geographical domain of the dependent variable.
[e] These R^2 values were kindly provided by the author of the article [17], Ignacio Mauleón, based on personal communication in February 2017. In his article, Mauleón does not report any R^2 values, but instead reports for each of his models the sum of squared residuals and the standard deviation of the errors. These are more meaningful indicators of the goodness of fit of each model than the R^2, according to Mauleón. However, in this table only the values for R^2 are reported, as R^2 is the value that is by far the most common in the reviewed literature sources. The fourth model listed here from [17] does not have a proper R^2, since it is the reduced form of a two equations structural model.

Table A4
Learning rates found in the literature for *concentrating solar thermal power (CSP) plants.*

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

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

Table A5
Learning rates found in the literature for *biomass power plants.*

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

Table A6
Learning rates found in the literature for *nuclear power plants*.

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

[a] As in the other tables, the term “investment costs” covers the dependent variables referred to in the literature sources that relate to the costs of power plant projects. Ostwald and Reisdorf [46] and Komanoff [102] use the term “capital costs”, while Rangel and Lévêque [68] use the term “construction cost”.
[b] Number refers to the *adjusted* R^2. Unlike R^2, the adjusted R^2 does not automatically increase as more explanatory variables are added. Instead, the adjusted R^2 only increases when additional explanatory variables improve the R^2 more than would be expected by chance.
[c] The study tests the explanatory power of five additional variables (reactor type (boiling or pressurised water reactor), reactor manufacturer, regional seismic potential, proximity to centres and licensing time) but does not find any of these to correlate significantly with nuclear costs.

Table A7
Learning rates found in the literature for *coal power plants*.

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

[a] As in the other tables, the term “investment costs” covers the dependent variables referred to in the literature sources that relate to the costs of power plant projects. The two literature sources listed here that refer to project costs use the terms “capital costs” [46] or “construction costs” [107].
[b] The Mountain States of the USA consist of Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah and Wyoming.
[c] In deriving this learning rate, the study neglects the experience gained from coal power plants built prior to 1957.
[d] The geographical domains of the dependent and the independent variables differ in these experience curves. The region named first refers to the independent variable, while the country named after the slash refers to the geographical domain of the dependent variable.
[e] Cost data is taken from 12 actual US plants constructed between 1942 and 1973 and from one hypothetical plant described in a 1999 study by the U.S. Department of Energy.

Table A8
Learning rates found in the literature for *natural gas power plants.*

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

[a] As in the other tables, the term "investment costs" covers the dependent variables referred to in the literature sources that relate to the costs of power plant projects. The two literature sources listed here use the terms "capital costs" [46] or "investment prices" [108].
[b] The Mountain States of the USA consist of Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah and Wyoming.
[c] In deriving this learning rate, the study neglects the experience gained from natural gas power plants built prior to 1949.
[d] The geographical domains of the dependent and the independent variables differ in these experience curves. The region named first refers to the independent variable, while the regions named after the slash refer to the geographical domain of the dependent variable.

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6. Treatment of Electricity Supply Costs in Energy Models

This final Chapter draws mainly on the findings from Chapter 3 (Article 2) and Chapter 4 (Article 3) of this thesis to gain insights into how energy models treat electricity supply costs. The investigations focus specifically on the societal costs related to electricity supply and factors affecting the generation costs of electricity generation technologies over time that are typically taken into account by energy models, as well as considering to what extent the treatment of costs differs between energy model types. To this end, an online survey was developed and conducted among researchers who use different types of energy models. The survey answers were evaluated and are presented and discussed in this chapter.

The first section (Section 6.1) discusses the motivation for conducting the survey and outlines the expected added value for research. Section 6.2 then provides a brief definition and classification of energy models appropriate for the analysis, before Section 6.3 describes the survey that was conducted, including its structure, the selection of recipients, its implementation and the response rate. Section 6.4 describes and discusses the survey results, examining the respondents' observations about how the models can take types of costs and cost-influencing factors into account. Finally, Section 6.5 discusses the key insights gained from the survey, including a brief evaluation of the advantages and disadvantages of the survey methodology as a means of answering the research questions.

6.1. Motivation for conducting the survey

The findings from Chapter 3 (Article 2) and Chapter 4 (Article 3) illustrate that the total social costs of electricity supply are made up of a number of different types of costs and that several factors play a role in influencing plant-level electricity generation costs over time. As various types of energy models are frequently used with the intention of providing advice on the possible future evolution of a low-cost energy system, it is clearly valuable to understand which of the identified types of costs and cost dynamics are typically taken into account in energy models – and which ones are not. Firstly, such an analysis can help policymakers, researchers and interested stakeholders to obtain a better understanding of the significance and the limitations associated with energy modelling results. Secondly, the analysis may provide support to energy model developers in their efforts to improve their models. Model developers may use the analysis to check whether their respective models can and should treat different types of electricity supply costs and cost dynamics more comprehensively.

To the best of the author of this thesis' knowledge, no studies currently exist that provide an overview of how different types of energy models take into consideration different types of electricity supply costs and cost dynamics. This chapter intends to fill this gap and aims to provide such an overview by answering Research Question 3: "What relevant types of social costs of electricity generation and what factors affecting plant-level electricity generation costs over time are taken into account in different kinds of energy models?" One focus of the investigation is on identifying whether certain types of costs and cost dynamics are typically not represented in energy models and, if so, why not. Another emphasis is on identifying the typical differences in the consideration of types of costs and cost dynamics between different *types* of energy models and understanding the reasons why these differences exist.

6.2. Definition and classification of energy models

An energy model can be defined as a simplified mathematical description of a real energy system and the ways in which phenomena occur within that system (based on van Beeck 2000). Many different energy models with varying characteristics and purposes exist and are used by research institutes, government agencies and companies around the world.

There is no uniform and commonly accepted approach for classifying the many different types of energy models. However, recent literature (e.g. Bhattacharyya and Timilsina 2010; Després et al. 2015; Herbst et al. 2012; Pfenninger et al. 2014) typically differentiates models based on their sectoral coverage, their analytical approach and/or their underlying methodology. While additional criteria can be used to differentiate energy models, including mathematical approach, geographical coverage and time span, these are less commonly used in the literature and will not be discussed here. Interested readers are referred to van Beeck (2000).

Table 7 presents a classification for energy models which is similar to classifications found in the literature and is appropriate for the purpose of this chapter. This classification differentiates energy models based on a combination of their sectoral coverage, analytical approach and underlying methodology. It should be noted that, due to the many differences between energy models, not all existing energy models fit neatly into one of the eight categories presented in the table. Nonetheless, this classification appears to be reasonable for the analysis at hand, as most of the energy models used at present can fit relatively well into one of these categories and the classification should help to explain some of the key differences in how electricity supply costs are treated (see Section 6.4).

Table 7: Classification of energy models chosen for this chapter

Analytical approach	Sectoral coverage	Underlying methodology	Model category
Bottom-up	Power system	Optimisation (typically)	**Power system model**
	Energy system	Accounting	**Energy system accounting model**
		Simulation	**Energy system simulation model**
		Optimisation	**Energy system optimisation model**
Top-down	Overall economy	Economic equilibrium	**Computable general equilibrium (CGE) model**
		Demand-driven economy	**Macro-econometric model**
Hybrid	Overall economy, often including sub-systems of the environment	Simulation	**Energy-economy (-environment) simulation model**
		Optimisation	**Energy-economy (-environment) optimisation model**

Bottom-up energy models describe individual technologies on the demand and supply sides in detail. Power system models do so exclusively for the power sector (sometimes focusing only on the supply side), while energy system models also include a representation of the rest of the energy system. For energy system models, further differentiation between accounting, simulation and optimisation models is usually made.

Accounting models calculate physical flows of energy carriers based entirely on exogenous assumptions about the interrelations within the energy system. Simulation models aim to reproduce a simplified operation of the energy system by simulating the expected behaviour of market actors. Finally, optimisation models calculate system investments and operations by maximising or minimising an objective function (such as overall system costs), subject to a set of constraints.

Top-down models include a representation of the overall economy. Energy demand and supply and their changes over time depend on aggregate economic variables, such as economic output, energy prices and price elasticities. In these models, energy technologies are typically represented in a more aggregate form compared to bottom-up models. Frequently differentiated categories in top-down models include computable general equilibrium (CGE) models and macro-econometric models.[13] CGE models equalise supply and demand across all the interconnected markets in an economy by adjusting relative prices while assuming agents always make the best decisions and have access to perfect information. They provide a framework for studying price-dependent interactions between the energy system and the rest of the economy (Löschel 2002). In macro-econometric models, relationships between variables are estimated based on long-run time series data. These models attempt to represent the real-life behaviour of agents by using econometrically estimated equations without equilibrium assumptions (Löschel 2002).

Hybrid models combine elements of both the top-down and bottom-up approaches. In many of these models, a top-down representation of the overall economy is combined with a technologically more detailed representation of the energy system. Integrated Assessment Models (IAMs), which offer an integrated assessment of human activities and environmental systems (such as the climate system), also typically exhibit a hybrid structure in their representation of the energy system and the overall economy. Therefore, most IAMs can also be grouped into this category (Després et al. 2015). Within hybrid models, simulation and optimisation approaches can be differentiated, with the former attempting to simulate market actors' behaviour and the latter aiming to optimise a system-wide objective, such as maximising consumer welfare (van Beeck 2000; Welsch 2013).

In the following analysis of the treatment of electricity supply costs in energy models, the classification depicted in Table 7 is adopted to differentiate between model types. As the differences between these model types can be expected to influence the way in which electricity supply costs are treated within the models, such a classification is helpful for gaining a more nuanced understanding of this treatment.

[13] Input-output models, optimal growth models and dynamic stochastic general equilibrium (DSGE) models are additional categories that are sometimes differentiated within top-down models. However, they are not included in this chapter as, for various reasons, these types of models are rarely used in the literature to gain insights into long-term and technology-specific energy or power sector developments. For example, input-output models build on a set of linear equations to represent and assess the interdependencies between the various sectors of the economy and rely on a large amount of empirical data (Welsch 2013). As these interdependencies can change radically over longer time horizons (e.g. as combustion engines in vehicles may be largely substituted by electric engines over the course of several decades), the potential for long-term analysis using these models is restricted. On the other hand, input-output models can be applied to analyse issues such as the short to medium-term sector-specific employment effects of certain policy measures or energy scenarios (Hienuki et al. 2015; Markaki et al. 2013). It should be noted that CGE or macro-econometric models, such as the PANTA RHEI model (Lutz et al. 2014), also often use an input-output accounting framework, but do so as part of a broader modelling framework.

6.3. Description of the survey

This section describes the online survey that was conducted as part of this thesis to understand how energy supply costs are treated in various energy models. An overview of key information about the survey is provided in Table 8, while the subsequent subsections provide additional detail. Subsection 6.3.1 outlines the survey structure, Subsection 6.3.2 describes how the survey recipients were selected and Subsection 6.3.3 provides information about the survey implementation and the responses received.

Table 8: Overview of key information about the survey

General information	
Type of survey	Self-administered online survey of experts
Online survey provider	umfrageonline.com
How the survey was carried out	
How recipients were contacted	By email
Execution phase	April and May 2017
Issue date	April 5th, 2017
Reminder date	April 21st, 2017
Recipients	
Number of recipients	66
Number of institutions represented by the recipients	48
Number of energy models covered by the recipients	35
Number of responses and response rates	
Number of (complete) responses received	24 [a]
Response rate relative to number of survey recipients	36 %
Response rate relative to institutions contacted	50 %
Response rate relative to number of models covered	66 %

[a] *Each response came from a participant from a unique institution and, apart from two separate responses that referred to the same model, each response related to a different energy model.*

6.3.1. Survey structure

The survey consisted of three sections for completion by the survey participants.[14] These three sections were complemented by an introductory page and an end page. The introductory page thanked the participants for their willingness to take part in the survey, briefly introduced the three sections and clarified what energy models the participants were asked to base their answers on. The end page simply informed participants that they had completed the survey and thanked them for their participation.

The first section of the survey consisted of general questions about the participants and the models they would refer to when answering the questions. The second section asked questions about the types of cost – as identified by Samadi (2017) – that are taken into account by the respective models. Finally, the third section of the survey asked which factors influencing plant-level electricity costs over time – as identified by Samadi (2016) – are endogenously represented by the respective models.

[14] The full survey is documented in Annex E.

6.3.2. Selection of energy models and survey recipients

The objective of the survey was to find out how the costs of electricity supply are represented in various types of energy models currently used by researchers around the world. Therefore, as a first step, it was necessary to identify which energy models to examine. To this end, several recent literature reviews of energy models were assessed (Bhattacharyya and Timilsina 2010; Després et al. 2015; Herbst et al. 2012; Pfenninger et al. 2014) and all models discussed or listed in these reviews were included on an initial list of potential models for inclusion in the survey. Several energy models used by German research teams, with which the author of this thesis is familiar based on his previous work, were also added to the list.

The next step was to assess whether the models on this initial list could fit into the categories differentiated in Table 7. Models that did not fit into these categories, such as pure input-output models, were not included in the survey. The remaining models were then reviewed to determine whether they featured in at least one peer-reviewed publication published in 2013 or later. This criterion was applied to ensure that the models examined in the survey were still actively used and relevant; consequently, models for which no recent peer-reviewed study could be identified were not included in the survey.[15]

Table 9 provides an overview of the thirty-five models that met the criteria listed above and were included in the survey. The models are grouped into the categories differentiated in Table 7. For each model, one study released in recent years making use of the model is also provided.

[15] One exception to this is the dynELMOD model, which was included in the survey despite the fact that, at the time of model selection, no peer-reviewed study applying this model was available. However, the author was informed about a dynELMOD-based manuscript that was to be submitted shortly to a peer-reviewed journal, so the decision was made to include this model in the survey.

Table 9: Overview of the thirty-five models that were included in the survey

Model type		Model name	Model developer / administrator	Example of a study in which the model was used
Bottom-up	Power system model	WASP	IAEA	Malik and Kuba 2013
		dynELMOD	DIW	Gerbaulet et al. 2014
		PLEXOS	Energy Exemplar	Deane et al. 2014
		AURORAxmp	EPIS	Gülen and Soni 2013
		DIMENSION	EWI	Bertsch et al. 2016
		SWITCH	RAEL, UC Berkeley	Solomon et al. 2014
		ReEDS	NREL	Cole et al. 2016
		E2M2s	IER	Spiecker and Weber 2014
	Energy system simulation / accounting model	PRIMES	NTUA/E3MLab	Fragkos et al. 2017
		Green-X	EEG/TU Wien	Capros et al. 2014
		WEM	IEA	Kesicki and Yanagisawa 2015
		LEAP	SEI	Park et al. 2013
		POLES	LEPII	Criqui et al. 2015
	Energy system optimisation model	TIMES [a]	IEA	Vaillancourt et al. 2017
		ETSAP-TIAM	IEA	Morfeldt et al. 2015
		MESSAGE	IIASA	Sullivan et al. 2013
		OSeMOSYS	dESA/KTH	Lyseng et al. 2016
		REMix	DLR	Scholz et al. 2017
Top-down	CGE model	GEM-E3	NTUA/E3MLab	Fragkos et al. 2017
		WorldScan	CPB	Bollen 2015
		GTAP-E	Purdue University	Gerlagh and Kuik 2014
		EPPA	MIT	Octaviano et al. 2016
	CGE model / Macro-econometric model	G-Cubed [b]	McKibbin/Wilcoxen	McKibbin and Wilcoxen 2013
	Macro-econometric model	PANTA RHEI	GWS	Lutz et al. 2014
		NEMESIS	ERASME	Capros et al. 2014
Hybrid	Energy-economy (-environment) simulation model	IMACLIM-R world	CIRED	Edelenbosch et al. 2017
		AIM/CGE	NIES	Thepkhun et al. 2013
		GCAM	JGCRI	Davies et al. 2013
		IMAGE/TIMER	PBL	Gernaat et al. 2014
		E3ME/G-FTT	CE	Mercure et al. 2016
	Energy-economy (-environment) optimisation model	MERGE	Stanford University	Blanford et al. 2014
		MARKAL-MACRO	IEA	Kumar 2017
		MESSAGE-MACRO	IIASA	McCollum et al. 2013
		WITCH	FEEM	Carrara and Marangoni 2017
		REMIND	PIK	Luderer et al. 2013

[a] *It should be noted that many different versions of TIMES exist and are used by multiple research groups around the world. There may be considerable differences in terms of how each version of TIMES treats the costs of electricity supply.*

[b] *The G-Cubed model can be regarded as a hybrid between a CGE model and a macro-econometric model.*

It should be emphasised that the initial list of energy models compiled cannot be considered either exhaustive or representative. Consequently, the thirty-five models included in the survey (see Table 9) cannot be deemed to be representative of all energy models that are currently employed. However, for the purpose of this analysis, it is not essential for the sample to be fully representative as the analysis aims to derive insights into the treatment of electricity supply costs in energy models rather than trying to produce conclusive evidence supporting or refuting certain hypotheses. Furthermore, as the selected models include some of the most prominent and frequently used energy, energy-economy and energy-economy-environment models and they cover a range of different model types, it is assumed here that the results obtained from the survey analysis are significant in terms of the overall energy modelling landscape.

Once it was determined which models to include in the survey, the next step was to identify individual researchers with experience in applying the respective models so they could be asked to participate. In many cases, authors of the model-specific peer-reviewed literature previously identified were selected as contacts for their respective models. In other cases, information about the models available on the internet was used, as sometimes this information specifically referred to the individual researcher(s) mainly responsible for developing and/or using the models.

Wherever possible, two different researchers using a certain model were selected for the survey to increase the chances of receiving answers for that model. If these researchers belonged to the same institution, they were contacted together. As some participants requested anonymity, a list of the researchers included in the survey is not provided.

6.3.3. Survey implementation and responses

The online survey was constructed using the website umfrageonline.com.

Before asking the identified researchers to participate in the survey, the decision was taken to issue a pilot survey to a limited number of recipients asking them to provide feedback about the survey design - particularly whether the questions could be clearly understood. In late March 2017, several researchers from three institutions were asked to take part in this pilot. One response was received within a week and provided helpful suggestions that were subsequently used to modify the survey. Specifically, it was recommended to increase the size of the input fields for the open answer categories to make them easier to complete and to modify the phrasing of the survey's question about the use of resource classes in models.

Subsequently, an email was sent to all the identified researchers (except for the one who took part in the pilot) on 5 April 2017. This email briefly introduced the background and motivation for the survey, included a link to the online survey site and stressed that the survey, consisting mostly of multiple-choice questions, should only take about ten minutes to complete. Recipients were asked to respond to the survey by 21 April 2017.

The email was sent out by Prof. Manfred Fischedick, Vice President of the Wuppertal Institute and one of the two supervisors of this thesis. As Prof. Fischedick is internationally prominent in the energy research community and knows several of the survey's recipients personally, it was decided that sending out the emails in his name was likely to lead to a higher response rate than if the emails were sent out by the author of this thesis.

By 21 April 2017, fifteen complete responses to the survey had been received. On that day, an email reminder was sent out by the author of the thesis to survey recipients who had not yet responded and whose model was not covered by the fifteen initial responses. By 10 May 2017, nine additional complete responses were received, bringing the total number of complete responses to twenty-four. No more responses were received by the time the survey closed at the end of May. As noted in Table 8, the twenty-four complete responses are equivalent to a response rate of 50 % when counting each institution as one recipient.[16] For a few widely used models, two different institutions were contacted separately and, consequently, the response rate relative to the number of energy models covered by the survey was higher, at 66 %.

As two responses referred to the same model, the number of different models for which answers were received is not twenty-four but twenty-three. The two responses referring to the same model were largely identical but did include some differences. These differences needed to be reconciled and this was done by checking with one of the two respondents and by referring to literature sources describing the model.

As a way of potentially increasing the survey's response rate, participants were promised that in the published analysis specific answers would not be able to be traced back to individual models. Therefore, in the following analysis, the answers will not be discussed in relation to individual models, but rather in relation to the four following aggregated model types:

- Bottom-up energy system models
- Bottom-up power system models
- Top-down models
- Hybrid models

As a further step to ensure that specific answers cannot be traced back to individual models, it is not disclosed whether responses were or were not received for each of the models. However, Table 10 provides an overview of the number of responses received for each of the four types of models differentiated. The table shows that for all these four model types, a similar number of responses (ranging from five to seven) were received.

Table 10: Number of individual models by model type for which responses were received (in parenthesis: number of models which are global in scale)

Bottom-up models		Top-down models	Hybrid models	ALL MODELS
Energy system models	Power system models			
7 (3)	5 (0)	5 (4)	6 (6)	**23 (13)**

After a participant completed the survey, an email thanking that person was sent. In many cases, a few customised follow-up questions were also sent to the participants. These follow-up questions related to answers that appeared to be of particular interest for understanding the respective models and their differences. Slightly more than half of the participants who were asked follow-up questions responded to these. Many of the responses received were very helpful for gaining a better understanding of how specific models treat electricity supply costs and for learning about relevant differences between the models. In some cases, the responses received to these follow-up questions led to changes in the answers, as it transpired that a mistake had been made by the respondent when completing the survey or the question had been misunderstood by the respondent. Furthermore, some changes to the answers were also made when the available literature clearly indicated that a different answer was accurate for a certain

[16] As mentioned earlier, for several institutions two researchers using a certain model were identified and contacted with one email. Obviously, and as was intended, for all institutions that responded, only one contact filled out the survey. Consequently, the response rate in relation to the total number of researchers contacted was lower (36 %).

model, perhaps because more advanced versions of a model (than available to a particular survey participant) included more nuanced options for modelling the costs of electricity supply.

6.4. Description and discussion of survey results

This section describes and discusses the survey results by examining the respondents' observations about how their models can take into account different types of costs (Subsection 6.4.1) and cost-influencing factors (Subsection 6.4.2). The discussion of the survey results is complemented where appropriate by insights from recent literature on the treatment of electricity supply costs and cost dynamics in energy models.

6.4.1. Findings on how societal cost types are taken into account in energy models

Figure 6 shows the survey answers for the twenty-three different energy models to the question: "Which of the following types of costs can be taken into account by the model you use?". The respondents were asked about each of the thirteen different types of costs associated with electricity supply as identified in Article 2 of this thesis (Samadi 2017). Modellers taking part in the survey could indicate that their model can take specific cost types into account endogenously, exogenously, or not at all. Two additional answer options were "Don't know" and "Other". Where modellers indicated "Other", they were asked to specify the way in which a certain type of cost can be taken into account in their model. These "Other" answers were subsequently assessed by the author of this thesis and in many cases the modeller's remarks made it possible to allocate the answer to one of the three main answer categories ("Yes, endogenously", "Yes, exogenously" or "No"). It was not appropriate to allocate three of the "Other" answers to one of these three categories and these three answers are – along with two "Don't know" answers – included in Figure 6 in the "Don't know/Other" category.

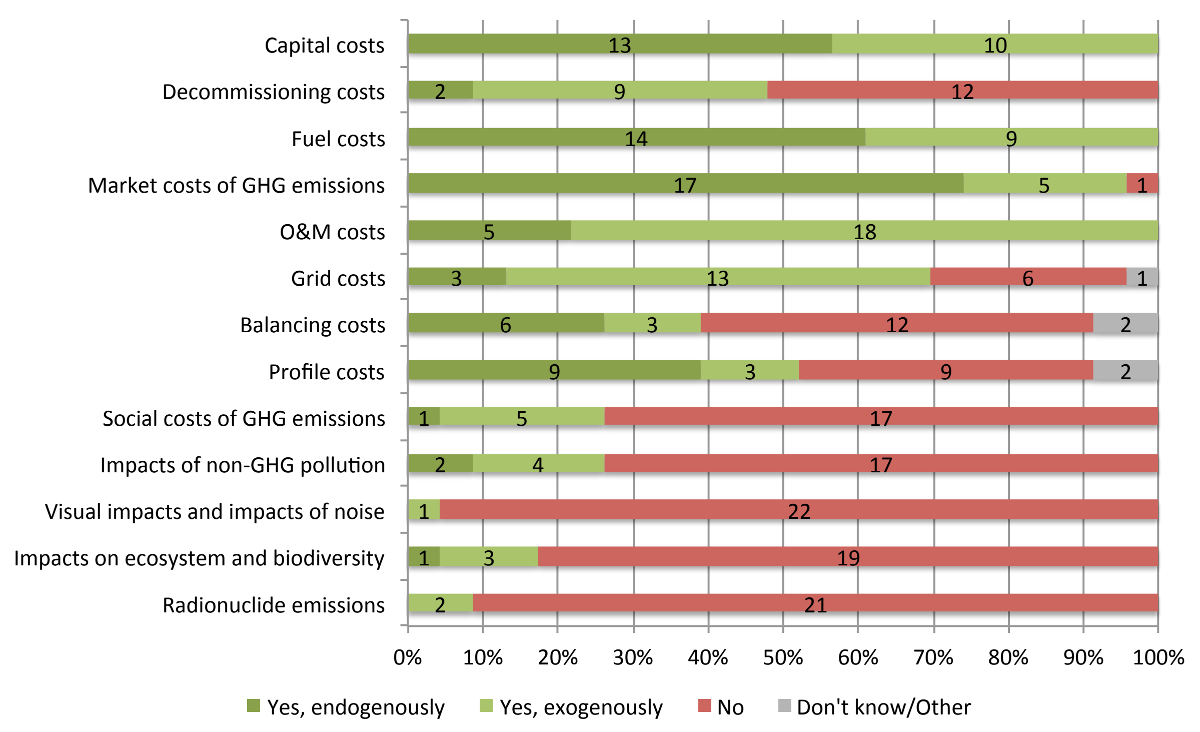

Figure 6: Survey answers to the question: "Which of the following types of costs can be taken into account by the model you use?"

In the following, the answers for each of the thirteen types of costs are briefly discussed.

Capital costs of electricity generation technologies are taken into account in all of the models surveyed. This is not surprising given the important role of these costs in the total social costs of electricity generation for all technologies, as well as the relatively good availability of capital cost data (Samadi 2017). In over half of the models (thirteen out of twenty-three), changes in capital costs over time can be modelled endogenously. There are different ways in which models can endogenise capital costs, and these are discussed in more detail in the following subsection.

Concerning model types, differences in the endogenisation of capital costs are most pronounced between the power system models and the hybrid models. In the latter, capital costs are treated endogenously in most cases (in five out of six models), while in the power system models they are modelled endogenously in only one case (in one out of five models). It is likely that one of the main reasons for this difference is that power system models are not typically used on a global scale, while hybrid models typically are. As technological learning is – for the most part – assumed to be a global phenomenon (depending, for example, on global cumulative investments or on global RD&D expenses), it is more likely that capital costs are endogenised in models that take global developments into account. Of all the model types surveyed, 85 % (eleven out of thirteen) of those that are typically or often applied on a global scale include an endogenous representation of capital cost changes, while only 20 % (two out of ten) of those that are typically applied at country or world region level do so.

According to the survey results, about half of the models can take **decommissioning costs** into account. These costs are sometimes included in models within capital costs; this was explicitly noted by several respondents. It can be assumed that such an approach might also be feasible for the models for which respondents stated that decommissioning costs cannot be taken into account. Respondents using bottom-up energy system and power system models were much more likely to indicate that this type of cost can be taken into account in their respective models (in eight out of twelve cases), compared with respondents using top-down or hybrid models (in three out of eleven cases).

Fuel costs, a highly relevant cost category especially for fossil fuel and biomass power plants, are taken into account in all of the models. Most of the models determine fuel cost changes endogenously. There is, again, a clear difference between bottom-up models on the one hand, and top-down and hybrid models on the other hand. While only four out of twelve bottom-up models endogenously represent fuel costs, almost all (ten out of eleven) of the top-down and hybrid models do so. A key reason for this difference may be (as in the case of capital costs) that unlike most of the bottom-up models surveyed, the top-down and hybrid models tend to cover the global energy system and economy. These models can capture global demand for fossil fuels and, by also including assumptions about supply costs (e.g. in the form of extraction cost curves, see Luderer et al. (2012)), they are able to endogenously determine the costs of internationally traded fossil fuels.

Market costs of GHG emissions can be taken into account in all but one model (a power system model). In most models, the costs of GHG emissions can be determined endogenously, by setting an emission constraint and letting the model determine the respective emission price. Seven of the modellers explicitly noted in the survey that their models can treat the market costs of GHG emissions either exogenously, by specifying a certain CO_2 or CO_2-equivalent tax level, or endogenously. (In the cases where both endogenous and exogenous options were possible, the answers were classified as "Yes, endogenously" in Figure 6.) While all respondents for the eleven top-down and hybrid models indicated that their models can treat market costs of GHG emissions endogenously, this was the case for only half of the twelve respondents for the bottom-up energy system and power system models.

Operation and maintenance (O&M) costs are taken into account in all models; in most cases as an exogenous variable. Noticeably, most of the survey participants answering for CGE models indicated that their respective models take O&M costs into account endogenously. This is likely to be the case because CGE models include labour market representations and can, therefore, model the development of wages, which are a key element of O&M costs.

Grid costs are taken into account in just over two thirds of the models surveyed.[17] These costs seem less likely to be taken into account in the more aggregated top-down models (three "No" and two "Yes, exogenously" responses). According to the survey results, hybrid models tend to provide the most sophisticated representation of grid costs, with three of the six participating modellers indicating that their respective models take grid costs into account endogenously, while the other three responded "Yes, exogenously" for their respective models. Somewhat surprisingly, the survey results indicated that grid costs do not tend to be treated in a very sophisticated way in the technologically and geographically detailed power sector models. For these models, two "No" and three "Yes, exogenously" responses were received in relation to the treatment of grid costs.

In a recent study, Pietzcker et al. (2017) examined new approaches in energy models to improve the representation of power sector dynamics and the integration of electricity generation from variable renewable energy sources. The authors also include a discussion of how transmission grid costs are taken into account in six different energy models. They note, for example, that the hybrid models IMAGE and WITCH take into consideration the fact that solar PV and wind power – with their generally low capacity factors – automatically require more grid capital per produced kWh than the average and, consequently, that these models implicitly include additional grid costs for solar PV and wind power technologies.

Balancing costs are taken into account by less than half the models. The survey results indicate that power system models, which tend to possess a relatively high temporal resolution, are more likely than other types of model to include balancing costs. Of the power system models surveyed, four out of five take balancing costs into account; three of these endogenously. However, some energy system models and hybrid models also take balancing costs into account endogenously; for example, by linking an increase in the use of electricity generation from variable sources to an increased need for flexibility in the conventional power generation system (Pietzcker et al. 2017; Sullivan et al. 2013).

Profile costs are defined here as the additional specific capital and operational costs that electricity generation from a new plant may cause in the residual electricity system, plus overproduction costs of electricity generation from variable renewable energy sources. According to the survey, these costs are taken into account by about half the models, in most cases in an endogenous form. The "No" answers are dominated by top-down models, as respondents for all five macro-econometric and CGE models indicated

[17] In one of the models (an energy system model), the survey respondent indicated that grid costs are not yet included, but that future inclusion is planned. This is the "Other" answer seen in Figure 6 for grid costs.

that profile costs are not taken into account in their respective models. Not representing these costs is likely to significantly skew overall system costs in scenarios with a high penetration of electricity generation from renewable energy sources (Sullivan et al. 2013). Sullivan et al. (2013) and Pietzcker et al. (2017) discuss different ways in which energy models can be configured to represent electricity sector variability and reliability, which is a prerequisite for accounting for both profile costs and balancing costs.

The survey also asked whether any additional **social costs of GHG emissions** can be considered in the respective models. The term “additional” intended to imply costs associated with GHG emissions that are not fully included in the market costs of GHG emissions. This question mainly sought to discover whether the social costs of GHG emissions can be determined endogenously in any of the models, through an incorporated climate change damage function. According to the survey results, such an endogenous representation of GHG emission costs can be found in only one of the models, a hybrid model. Respondents for most other models answered “No” to this question. “No” applied to all simulation models, reflecting the fact that market actors in these models do not take non-market costs into account. For optimisation models, differentiation between the market and non-market costs of GHG emissions is in some sense futile, as the societal optimisation sought by these models means that only the social costs of GHG emissions are considered relevant. In model runs this is often done by setting an emissions cap according to a social target and having the model endogenously determine the corresponding specific emission costs.

The **costs of non-GHG emissions** mainly relate to health impacts and can be considerable for fossil fuel and biomass power plants, especially for those plants which are not equipped with sophisticated emission control technology. Most of the models surveyed (seventeen out of twenty-three) do not take these costs into account. As anticipated, none of the energy system simulation models take these costs into consideration, reflecting the fact that market actors in these models are not expected to include non-market costs in their decision-making. Respondents for one energy system optimisation model, two power system models and one hybrid model indicated that the costs of non-GHG emissions can be taken into account exogenously in their respective models. Two respondents, one for a CGE model and the other for a hybrid optimisation model, indicated that their respective models take these costs into account endogenously. The CGE model does so by including damage functions that link the concentration of pollutants to health damage. Health damage is then translated as a loss of human capital or a reduction in working hours. Klaassen and Riahi (2007) present an approach to internalise these externalities of electricity generation in the hybrid MESSAGE-MACRO model.

One respondent for an energy system optimisation model noted that while the model she uses cannot take into account the costs of non-GHG emissions, the model can be combined with other models to enable the consideration of these costs. Furthermore, two additional respondents for hybrid models pointed out that while no such costs are modelled, the pollution itself is accounted for by the model.

Almost none of the survey models take **costs associated with the visual and/or noise impacts** of individual power plants into account. However, the respondent for one of the energy system optimisation models noted that this type of cost can, in principle, be exogenously included in the model’s “externalities” cost category, like any other type of external cost. One respondent for an energy system optimisation model noted (again) that combination with other models is possible to enable the consideration of this type of cost.

The costs of impacts on the ecosystem and on biodiversity cannot be taken into account in most of the models (nineteen out of twenty-three). Respondents for one of the energy system optimisation models and two of the power system models indicated that such costs can be taken into account exogenously by their respective models. According to the survey, only one of the models – a hybrid optimisation model – endogenously takes ecosystem and biodiversity costs into account, at least to the extent that such costs are caused by airborne emissions.

As with the previous types of external costs mentioned, potential **costs caused by radionuclide emissions**, especially costs associated with large-scale accidents at nuclear facilities, cannot be taken into account by most of the models (twenty-one out of twenty-three). Only two respondents, one for an energy system optimisation model and the other for a power system model, indicated that this type of cost can generally be taken into account exogenously in their respective models. It should be noted that the quantification of the external costs of nuclear power is highly contentious in the literature (see discussion in Samadi 2017) and rather than trying to quantify these costs, several modelling studies instead develop and compare energy scenarios with and without constraints on the future role of nuclear power (e.g. Luderer et al. 2014; Riahi et al. 2012; Vaillancourt et al. 2008). Such an approach reflects uncertainties related to the future social acceptance of this technology and, in doing so, implicitly assumes different nuclear power externality costs.

6.4.2. Findings on how factors determining electricity generation cost changes over time are taken into account in energy models

Figure 7 shows the survey answers for the twenty-three different energy models to the question: "Which of the following factors influencing plant-level electricity costs over time are endogenously represented by the model you use?". The respondents were asked about each of the ten different factors identified in Article 3 of this thesis (Samadi 2016). Modellers taking part in the survey could indicate whether a certain factor is endogenously represented in their respective model ("Yes") or not ("No"). Two additional answer options were "Don't know" and "Other". The "Other" answers were subsequently assessed by the author of this thesis and in many cases the modeller's remarks made it possible to allocate the answer to one of the two main answer categories ("Yes" or "No"). One "Other" answer could not be clearly allocated to either of these two categories and this answer is – along with three "Don't know" answers – included in Figure 7 in the "Don't know/Other" category.

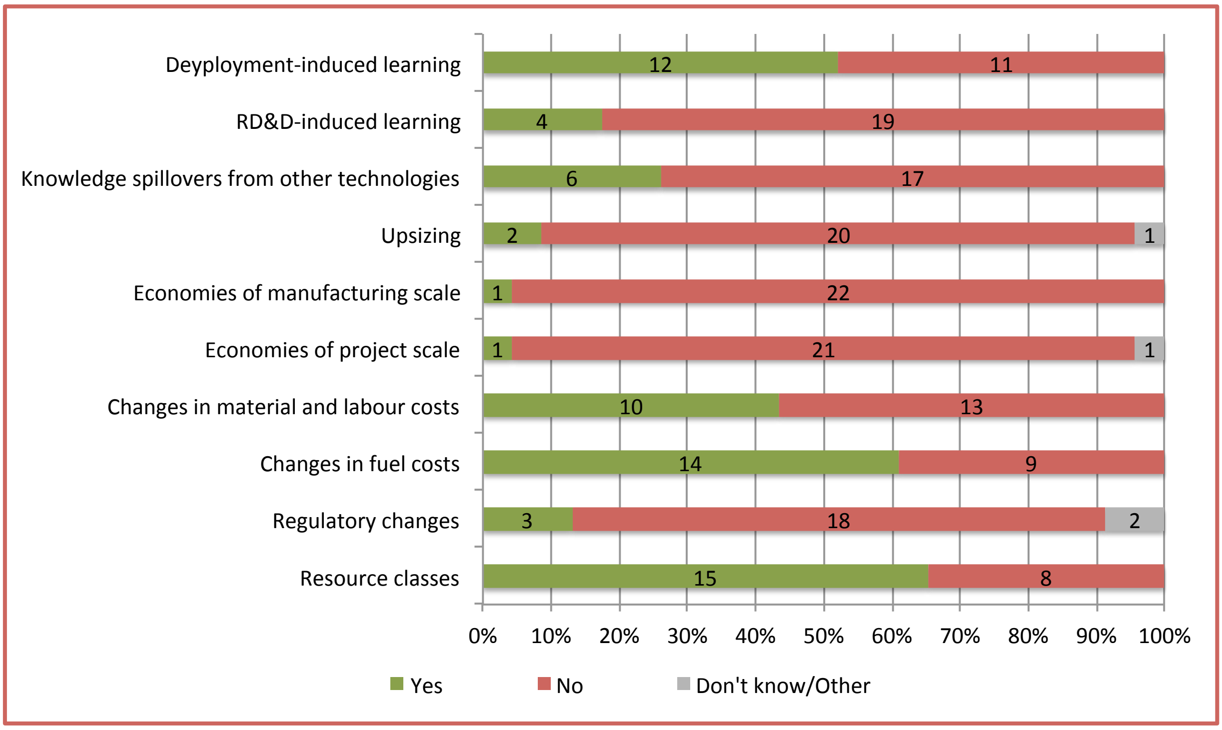

Figure 7: Survey answers to the question: "Which of the following factors influencing plant-level electricity costs over time are endogenously represented by the model you use?"

In the following, the answers for each of the ten factors influencing plant-level electricity costs over time are briefly discussed.

Deployment-induced learning is taken into account endogenously in just over half of all the models surveyed (twelve out of twenty-three). The survey shows that all but one model for which respondents specified in the previous question that capital costs are modelled endogenously do so at least[18] via deployment-induced learning. This also means that the considerable difference between models applied globally and models not applied globally also holds true for the treatment of deployment-induced learning: global models typically include an endogenous representation of related cost reductions, while country or region-specific models typically do not. Likewise, according to the survey, hybrid models typically include an endogenous representation of this factor, while power system models typically do not.

Over the past two decades in particular, growing recognition of the strong correlation in many electricity generation technologies between installed capacity on the one hand and cost reductions on the other has led to widespread efforts by energy system modellers to endogenously account for this relationship in their models (Berglund and Söderholm 2006; Criqui et al. 2015; Gillingham et al. 2008; Gritsevskyi and Nakićenovi 2000; Grubb et al. 2002; Grubler and Gritsevskii 1997; Kahouli-Brahmi 2008; Köhler et al. 2006; Mattsson and Wene 1997; Messner 1997). The considerable improvement in computer processing power during this period has undoubtedly also helped to enable deployment-induced learning (as well as other types of so-called "induced technological change") to be endogenously considered in many energy models today, given that such endogenous representations tend to be computationally demanding.

[18] In some models, additional factors – such as RD&D-induced learning – also endogenously influence capital costs.

RD&D-induced learning is endogenously represented in only four of the twenty-three models surveyed, suggesting that this type of endogenous technological change is less widely considered in energy models than deployment-induced learning. This may come as a surprise, as RD&D-induced learning has a long-established theoretical foundation (e.g. Binswanger et al. 1978; Kamien and Schwartz 1968; Kennedy 1964) and arguments for including RD&D-induced learning in energy models have been discussed extensively in the literature for at least two decades (see e.g. Grübler et al. 1999; Grubler and Gritsevskii 1997; Weyant and Olavson 1999). However, the apparently minor role occupied by this type of induced learning in current energy models may be due to the fact that the empirical correlation between RD&D and cost reductions is more uncertain and controversial than the correlation between a technology's cumulative investments and its cost reductions (Samadi 2016). Thus, defining model parameters for RD&D-induced learning can be particularly difficult. Another reason why most models that include an endogenous representation of capital costs do so only via deployment-induced learning may be due to the computational difficulties associated with implementing two-factor learning, i.e. both deployment-induced learning and RD&D-induced learning.

Knowledge spillovers from other technologies refer to cost reductions stemming from advances in other energy or non-energy technologies. Such spillovers can be endogenously represented in energy models by defining learning "clusters" made up of a number of interdependent energy technologies (Gritsevskyi and Nakićenovi 2000; Seebregts et al. 2000). One example is a wind turbine cluster, which benefits from learning in both the onshore and offshore wind sector. Another example is a gas turbine cluster, which benefits from learning at (inter alia) integrated coal gasification power plants, gas turbine peaking plants and biomass gasification plants (Seebregts et al. 2000). These – or similar – knowledge spillovers are endogenously represented in six of the twenty-three models surveyed. All these six models are global in scope. While the majority (four out of six) of the hybrid models endogenously represent such spillovers, only one of the six bottom-up energy system models, none of the five power system models and one of the five top-down models surveyed do so.

According to the survey results, only two of the twenty-three models endogenously take into account cost changes caused by technology **upsizing**. This cost-influencing factor refers to the empirical observation that many technologies exhibit economies of plant scale until certain plant sizes are reached (Samadi 2016). The two models for which "Yes" was answered are a top-down model and a hybrid optimisation model. However, no information could be obtained about the exact method these two models – or other models discussed in the literature – use to take upsizing into account. While upsizing can be an important explanation for the cost changes in technologies, this tends to be the case only in the early phases of a technology's diffusion. This limited relevance of upsizing, together with the fact that for new technologies the exact cost reduction potential of upsizing (along with the "optimal" plant size of these technologies), is very difficult to predict, may be reasons why upsizing is typically not taken into account endogenously in energy models.

The survey results suggest that **economies of manufacturing scale** are typically not taken into account endogenously in energy models. Only one respondent indicated that the model he uses (a top-down model) endogenously takes into account the fact that larger manufacturing plants can reduce specific technology costs. As in the case of upsizing, however, no further information about precisely how this relationship between manufacturing scale and technology cost is implemented in the model could be obtained - neither from the modeller nor from literature sources. Some empirical studies suggest that, particularly for solar PV technology, the steadily increasing size of module manufacturing plants may have played a relevant role in reducing the cost of this technology over past decades (Nemet 2006; Watanabe et al. 2000; Yu et al. 2011). However, the magnitude of this effect is difficult to quantify reliably and for other electricity generation technologies – especially for those which are not mass-manufactured – the effect is likely to be small. This may be a reason why almost none of the models surveyed endogenously represent economies of manufacturing scale.

Similarly, according to the survey results, **economies of project scale** are only taken into account endogenously in one of the twenty-three models. Correlation between specific capital costs and the number of plants built at a certain site has been found by several studies for some electricity generation technologies, such as nuclear, solar PV and wind (Samadi 2016). However, economies of project scale only become a relevant factor in explaining cost changes *over time* if significant changes in the typical sizes of projects occur over time. Model and/or scenario developers may assume that no such changes will occur in the future or may decide that such changes are difficult to model, which might explain why this factor is typically not represented endogenously in current energy models.

Changes in material and/or labour costs are taken into account endogenously in ten of the twenty-three models surveyed. Interestingly, all five top-down models (i.e. all the macro-econometric and CGE models) are among these ten models. Top-down models typically include labour market representations, so they can model the development of wages. Some top-down models also account for material costs, for example by making assumptions about the relationship between the price level in relevant sectors (such as non-energy mining) and the price of certain materials (Cambridge Econometrics 2014). Three respondents for power system models also indicated that changes in material and/or labour costs are taken into account in their models. In at least two of these models, such cost changes are taken into account by assuming that labour and/or material costs for certain technologies increase (to a certain extent) when these technologies are deployed in relatively large numbers over a relatively short period of time.

According to the survey results, **changes in fuel costs** can be taken into account endogenously in the majority of the models, specifically in fourteen out of twenty-three.[19] Respondents for all five top-down models indicated that their model is capable of representing fuel cost changes endogenously. Similar to “deployment-induced learning” and “knowledge spillovers from other technologies” (see above), the endogenous representation of this factor in an energy model appears to correlate to its geographical scope; while respondents for almost all (eleven out of thirteen) of the global models indicated that changes in fuel costs are represented endogenously in their respective models, this was the case for only three out of ten of the country or region-specific models surveyed. As previously mentioned, global models are principally able to endogenously determine the costs of internationally traded fossil fuels.

[19] The information obtained from this question is, in fact, identical to the information already obtained from one of the other questions in the survey, which asked respondents to indicate whether fuel costs are taken into account by their respective models and, if so, whether endogenously or exogenously (see previous subsection). However, as fuel costs are not only an important cost category but also highly relevant for influencing electricity generation costs over time for many technologies, fuel costs are – for the sake of completeness – included in both parts of the survey.

Regulatory changes, such as stricter environmental standards for coal plants or stricter safety standards for nuclear power plants, have been found to be relevant in explaining past cost changes over time for certain technologies (Samadi 2016). However, anticipating and modelling future regulatory changes is very challenging and such efforts are typically not made in energy models, as the survey results suggest. While nine respondents initially indicated that that their respective models were capable of taking regulatory changes into account, the responses by the respective respondents to the follow-up questions led to subsequent changes in these answers from "Yes" to "No" for six of these models. In two cases, the follow-up conversation revealed that errors had been made in responding to this question, while in four cases it turned out that the question had been misunderstood, indicating that the intention of this question was not expressed sufficiently clearly in the survey.

For example, one respondent noted in the follow-up conversation that his model endogenously adjusts RD&D expenses and subsidies for technologies for which a constraint, such as a CO_2 standard, is imposed. While this can be understood as an endogenous representation of regulatory changes, the question intended to refer to regulatory changes that either directly impact the technological characteristics of electricity generation technologies, for example through new safety or environmental standards, or impose spatial restrictions on the installation of certain technologies, as in the case of stricter minimum distance standards for new wind power plants. For the three models for which a "Yes" answer remains (two hybrid models and one top-down model), the respective survey participants did not respond to follow-up questions so there is the possibility that in these cases, too, the respondents did not fully understand the question.

The final cost-influencing factor in the survey was **limits to the availability of suitable sites**. Taking such limits into account requires models to differentiate between different resource classes with varying electricity generation costs. Resource classes can be differentiated inter alia in terms of a site's variation in wind quality or insolation and/or in terms of a site's access to transmission (Baker et al. 2013). As resource classes need to be defined exogenously, it would not have been accurate to ask participants whether their respective models could *endogenously* take limits to the availability of suitable sites into account.[20] Therefore, in order to find out how this cost-influencing factor is taken into account in energy models, the question was asked: "Does the model differentiate between resource classes, so that a scarcity of suitable sites can lead to higher marginal generation costs?"

Survey respondents for two thirds of the models (fifteen out of twenty-three) indicated that their respective models differentiate between resource classes. Except for the pure top-down models (two out of five), differentiation between resource classes was reported for the majority of models in all the categories. In the bottom-up energy system model MESSAGE, for example, solar and wind deployment potential "is characterized as a supply curve of resource quantity (EJ/year) at quality level, where higher quality resource costs less (on an energy basis) and provides higher energy output for capacity installed" (Sullivan et al. 2013). Energy system models are reported to "have more detailed supply curves for wind and solar power than IAMs, allowing estimating their [levelized electricity costs] quite accurately at a finer geographic resolution" (Hirth 2015).

[20] This was helpfully pointed out to the author by the participant of the pilot survey.

6.5. Key insights gained from the survey

This section discusses the key insights gained from the survey. Subsection 6.5.1 focuses on learning relating to the survey methodology. It does so by mirroring the experiences faced in administering the survey with the general characteristics ascribed to the survey method in the qualitative social research literature. Subsection 6.5.2 then derives the key insights gained in terms of how electricity supply costs are taken into account in different types of energy models currently in use. Finally, Subsection 6.5.3 discusses relevant implications of the survey insights for developers and users of energy models.

6.5.1. Insights into the survey methodology

The method used in this chapter to gain insights into the treatment of electricity supply costs in energy models was a self-administered online survey of experts. Compared to structured interviews (in person or by phone), self-administered surveys have several advantages – but also certain disadvantages (Bryman 2015). Two of the most important general advantages for choosing the survey method in the context of this work were that surveys are cheap and quick to administer and are also convenient for respondents. These advantages mean it is relatively easy to contact a large number of experts in a limited period of time and still produce a good response rate. The fact that twenty-four complete responses and a response rate of 50 % (relative to the number of institutions contacted) were obtained within eight weeks suggests that the survey did benefit from these general advantages.

On the other hand, a key disadvantage of self-administered surveys is that no-one is present to help respondents with questions they find difficult to understand. While survey respondents could, in principle, contact the author of this thesis (and were encouraged to do so) if they had any questions about the survey, respondents are probably less likely to ask about the meaning of a specific question via email (and interrupt the completion of the survey) than if they were in an interview situation. Of the twenty-four respondents, only one took a break from filling out the survey to inquire about the meaning of several of the questions. However, as respondents to this survey could complete a blank response field for each question, they were able to provide nuanced answers in cases where they were not entirely sure of the meaning of certain questions. This blank response field was used occasionally for that purpose.

However, during the evaluation of the survey results it became clear that, for certain questions, a more detailed explanation of the question's meaning would have been beneficial and could have been more easily provided in an interview situation. This type of detailed explanation would have been beneficial for the question on regulatory changes (see discussion in Subsection 6.4.2 above). Furthermore, during a follow-up email conversation with a modeller, it became clear that the modeller was answering the questions in relation to how he typically uses the model, even though the questions intended to elicit what the models were capable of, irrespective of whether certain functions were frequently used by the respondent or not. While this intention was outlined at the beginning of the survey, it may not have been sufficiently clear for all the participants and an interview would probably have helped to avoid such misunderstandings.

A further disadvantage of the self-administered survey is that follow-up questions cannot easily be put to the experts. This also means that the level of detail gained by such surveys is limited or, in other words, only rather general information can be elicited. In the survey conducted for this chapter, the problem was compounded by the fact that the number of questions was intentionally limited and the questions were posed in such a way to allow for pre-defined answers, in order to keep the time required to fill out the survey to a minimum (an estimated 10 minutes). This was intended to contribute to a high response rate and apparently achieved this aim, but it also contributed to a limited level of detail in the information elicited. During the assessment of the survey results it became clear, for example, that more in-depth follow-up questions would have been especially pertinent with respect to the treatment in energy models of the complex concept of "profile costs".

In general, the approach of conducting an online survey was successful in achieving a broad overview of the different types of costs and cost-influencing factors that are typically taken into account by different types of energy models. The survey, combined with the follow-up questions and insights from the relevant literature, also provided some information about *how* these costs and cost-influencing factors are modelled, what different approaches exist and what key reasons there are (or may be) to explain why certain costs and cost-factors are *not* included in certain energy models. However, this kind of information was inevitably limited due to the general characteristics of the self-administered online survey, as explained above.

Therefore, a potentially successful next step for gaining a deeper understanding of how different models or types of models treat electricity supply costs would be to conduct expert interviews with selected modellers. Such interviews, which could build on the general overview and aggregate insights gained by the survey described in this chapter, could focus on specific issues of special interest and would provide much deeper insights into these issues. Specific issues of interest could include the treatment of profile costs in different energy model types or the question of whether individual cost-influencing factors such as RD&D, economies of manufacturing scale or upsizing can and should ideally be modelled endogenously, or whether such factors should be accounted for exogenously, either explicitly or as part of an experience curve assumed to include the combined effects of these factors. Several model comparison studies performed in recent years had similar intentions, i.e. to learn more about how energy models treat profile costs and how this treatment can be improved in the future (Connolly et al. 2010; González et al. 2015; Luderer et al. 2012, 2014; Pietzcker et al. 2017).

6.5.2. Insights into the treatment of electricity supply costs in energy models

In terms of the treatment of different types of electricity supply costs in energy models, the following key insights were obtained from the survey results:

- The different types of plant-level costs (such as investment, fuel and O&M costs), which are all relatively well understood and important, can be taken into account by virtually all models.
- Different types of system and external costs tend to be less frequently taken into account in energy models.
- Although questions to understand the reasons for the inclusion or omission of certain types of costs in a model were not included in the survey, some of the open answer survey responses, email conversations with the participating modellers and information in the available literature suggest that the following three reasons are relevant in explaining why many models do not take all the socially relevant types of costs into account:
    - For some types of models, certain types of costs are simply not relevant. This is especially true for simulation models, which attempt to model the behaviour of market actors and, therefore, intentionally omit different types of external costs,

as these are considered irrelevant to the decision-making processes of individual market actors. Consequently, the survey responses indicated that none of the simulation models were able to take into account any of the external costs specified in the survey.
    - There are considerable uncertainties in the quantification of certain types of costs. This is especially true for external costs. External costs that are especially difficult to quantify and/or for which their relevance is contentious (such as impacts on ecosystems and biodiversity, as well as external costs associated with nuclear accidents) are, therefore, only taken into consideration by a few energy models.
    - Some types of costs (especially some system costs, such as grid costs, but also landscape and noise impacts) are highly location or context-specific and require high spatial and temporal resolution. Some models lack this high resolution and/or the associated data and computational requirements are considered to be too challenging to adequately include these types of costs.
- Among the types of costs that are seldom taken into account by energy models are air pollution costs, even though these costs are generally believed to be highly relevant to today's electricity systems. Air pollution costs may become less relevant in future electricity systems, as newly-built fossil fuel power plants with state-of-the-art pollution abatement technology emit considerably less pollutants than decade-old plants and fossil fuel plants are widely expected to become displaced by low-carbon technologies. However, it is important to note that in (optimisation) models that do not take the costs associated with this kind of pollution into account, CCS power plants can have a non-negligible advantage relative to low-carbon alternatives such as wind, solar or nuclear power.
- It also appears that profile costs are not taken into account by a relevant number of energy models. These costs are expected to become particularly relevant in future electricity systems with high shares of variable renewable energy sources and neglecting this type of cost would result in a benefit for electricity from these sources compared to other types of electricity generation.
- While the power system models surveyed that typically model the electricity system in great technological, geographical and temporal detail appear to be more likely to include an endogenous representation of balancing costs than the other types of models (which typically represent the electricity system in less detail), interestingly – and perhaps surprisingly – the same relationship was not found in relation to grid costs. In fact, grid costs were more likely to be able to be taken into account (either endogenously or exogenously) in energy system models and hybrid models than in power system models.

In terms of the endogenous representation of factors found by empirical studies to be key in explaining changes in electricity generation costs, the following main insights were obtained from the survey results:

- Several cost-influencing factors found by the empirical literature to be relevant in explaining past cost changes of electricity generation are not taken into account endogenously in the vast majority of the models surveyed. Specifically, RD&D-induced learning, upsizing, economies of manufacturing scale, economies of project scale and regulatory changes are taken into account endogenously in less than 20 % of the models.
- Although the survey did not attempt to discover the reasons for the inclusion or the omission of certain cost-influencing factors in an endogenous way in the models,

some of the open answer survey responses, email conversations with the participating modellers and the available literature suggest that the following three reasons are relevant in explaining why the models surveyed generally do not take into account many of the factors found to be relevant in explaining past cost changes:

  - Some cost-influencing factors cannot be endogenously taken into account by some models as the respective model scope does not allow for an endogenous representation. This is the case, for example, for global learning in a national or regional model or changes in labour costs in an energy system model that does not cover the rest of the economy.
  - There is a general desire to limit the complexity of models in order to promote their simplicity, limit their computational demands and/or make them as easy to use and understand as possible. An endogenous representation of individual cost-influencing factors can be complex and computationally very demanding.
  - There are considerable uncertainties in reproducing and parameterising the specific interactions of many of the cost-influencing factors.

- Deployment-induced learning and limits to the availability of suitable sites are the two factors that are most often endogenously accounted for in energy models, perhaps because future developments of these factors can be estimated and modelled relatively well.
- Several cost-influencing factors, specifically deployment-induced learning, knowledge spillovers and fuel cost changes, are found to be much more likely to be taken into account endogenously by global models than by models covering a limited geographical scope. This is not surprising, given that these three cost-influencing factors are largely determined by global inter-relationships and can, therefore, only be truly endogenised in models with a global scope.

6.5.3. Implications of the insights gained from the survey

The survey results illustrate that the well-known and frequently used energy models tend to neglect several types of electricity supply costs that are relevant to society. This is not only the case for energy models in general, but also for optimisation models which aim to inform policymakers and society about socially optimal future energy system developments. Furthermore, energy models do not endogenously account for several factors that are known to influence plant-level electricity generation costs over time. These limitations should be transparently communicated in studies that use these models and should be taken into account by policymakers and other interested stakeholders when interpreting energy modelling results.

A comprehensive representation in energy models of all socially relevant types of electricity supply costs and cost dynamics may be impossible, at least for the foreseeable future, for several reasons, including a lack of reliable data for some types of costs and computational restrictions. Nonetheless, energy model developers may wish to use this overview to consider whether it is possible to add certain relevant types of costs and cost dynamics into their energy models.

Finally, researchers applying energy models for their studies can use the information to improve their awareness of the possibilities and limitations of the models they use and they may attempt to reflect these limitations in their study approaches. For example, researchers using models that do not taken into account the (highly uncertain) costs associated with the specific risks of nuclear power may want to include scenarios which restrict the use of nuclear power. Similarly, researchers using models that do not (fully) take into account profile costs may, in their scenarios, introduce an upper limit on the share of electricity generation from variable renewable energy sources or may link the future deployment of wind and solar PV technologies to the sufficient availability of flexible electricity supply, storage technologies and/or demand response capacities. More generally, researchers should be aware that some models are more suitable for certain research questions than others. For example, models that do not account sufficiently for profile costs and/or neglect key cost-influencing factors (such as deployment induced learning or site-dependent variations in natural potential) should not be used to derive insights into long-term, cost-optimal pathways for electricity system decarbonisation.

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Annex A: Declaration of Authorship

Declaration of authorship

I hereby declare that I am the sole author of this doctoral thesis (with the exception of Chapter 2, see separate declaration of co-authorship for this chapter) and that I have not used any sources other than those listed in the bibliography and identified as references. I further declare that I have not submitted this thesis at any other institution in order to obtain a degree.

Ratingen, 25.09.2017
(place, date)

S. Samadi
(signature)

Annex B: Declaration of Co-Authorship (Chapter 2)

Declaration of co-authorship

One of the four articles on which this thesis is based ("Sufficiency in energy scenario studies: taking the potential benefits of lifestyle changes into account", also referred to in this thesis as "Article 1") was prepared in collaboration with five further authors from the Wuppertal Institute. These are Marie-Christine Gröne, Prof. Dr. Uwe Schneidewind, Dr. Hans-Jochen Luhmann, Dr. Johannes Venjakob and Benjamin Best.

As the article's lead author, my contribution to it consisted of writing the introduction (Section 1), differentiating between three types of sufficiency and preparing the respective figures (parts of Section 2), writing about the need for energy scenarios to consider sufficiency (Section 3), researching, analysing and summarising the available literature on sufficiency in global energy and emissions scenarios (Section 4), writing parts of the conclusion (parts of Section 5), coordinating the joint work and revising the text that was initially submitted based on the reviewers' comments.

My co-authors wrote the definitions of "sufficiency" and "energy scenarios", as well as parts of the concluding section. Furthermore, they contributed to the article through numerous discussions on the term "sufficiency" and by commenting on and amending draft sections of the paper.

The co-authors of this article and I hereby declare that the above statement is correct.

Marie-Christine Gröne:

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Annex C: Curriculum Vitae (CV)

Curriculum vitae

PERSONAL INFORMATION

Sascha Samadi

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Sex Male | Date of birth 04/02/1981 | Nationality German

WORK EXPERIENCE

03/2008–Present

Research Fellow and PhD student

Wuppertal Institute for Climate, Environment and Energy, Wuppertal (Germany)

- project work in national and international research projects focussing on developing and analyzing long-term energy scenarios

- project work in national research projects focussing on renewable energy support policies and - more generally - on energy system transition strategies

- work on PhD thesis on the costs of electricity generation technologies and their consideration in energy models

06/2005–09/2005

Internship

Institute for Ecological Economy Research (IÖW), Berlin (Germany)

- supporting research within various projects in the field of policy support for renewable energy sources and energy efficiency

EDUCATION AND TRAINING

10/2001–10/2007

Diplom-Ökonom

EQF level 7

University of Oldenburg, Oldenburg (Germany)

PERSONAL SKILLS

Mother tongue(s): German

Other language(s)

	UNDERSTANDING		SPEAKING		WRITING
	Listening	Reading	Spoken interaction	Spoken production	
English	C2	C2	C1	C1	C1
French	A1	A2	A1	A1	A1

Levels: A1 and A2: Basic user - B1 and B2: Independent user - C1 and C2: Proficient user
Common European Framework of Reference for Languages

Communication skills: - good communication skills and team spirit (acquired through team exercises during education at university and later through research projects at work)

Job-related skills: - extensive writing experience in English language

Digital competence: - good computer literacy, especially in Word, Excel and PowerPoint software

ADDITIONAL INFORMATION

Publications

Peer-reviewed articles:

- Samadi, S. (2017): The experience curve theory and its application in the field of electricity generation technologies – A literature review. Renewable and Sustainable Energy Reviews. doi: 10.1016/j.rser.2017.08.077
- Spencer, T., Pierfederici, R., Sartor, O., Berghmans, N., Samadi, S., Fischedick, M., Knoop, K., Pye, S., Criqui, P., Mathy, S., Capros, P., Fragkos, P., Bukowski, M., Śniegocki, A., Virdis, M. R., Gaeta, M., Pollier, K. Cassisa, C. (2017): Tracking sectoral progress in the deep decarbonisation of energy systems in Europe. Energy Policy 110, 509-517. doi: 10.1016/j.enpol.2017.08.053
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- Fischedick, M., Samadi, S. (2010): Die grundsätzliche wirtschaftstheoretische Kritik am Erneuerbare-Energien-Gesetz greift zu kurz, Energiewirtschaftliche Tagesfragen,1/2/2010, 122-128

Conference and book contributions:

- Lechtenböhmer, S., Schneider, C., Samadi, S. (2017): Energy efficiency quo vadis? – the role of energy efficiency in a 100% renewable future. ECEEE 2017 Summer Study.
- Lechtenböhmer, S., Samadi, S. (2015): The Power Sector: Pioneer and Workhorse of Decarbonization, in: Dupont, C. (Ed.): Decarbonization in the European Union: internal policies and external strategies
- Fischedick, M., Friege, J., Höller, S., Samadi, S. (2015): Energie- und Emissionsszenarien, in: Fischedick, M. (Ed.): CO_2: Abtrennung, Speicherung, Nutzung: ganzheitliche Bewertung im Bereich von Energiewirtschaft und Industrie
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Annex D: Supplementary Materials for Article 2

Supplementary Materials: The Social Costs of Electricity Generation—Categorising Different Types of Costs and Evaluating Their Respective

Sascha Samadi

File S1: Input parameters for plant-level LCOE calculations

This supplementary file provides detailed information about how the plant-level LCOE values (ranges and central values) in the article for selected types of newly-built power plants in Europe and the USA were derived. In the article, these LCOE values are depicted in Figure 2, discussed in Section 3.1.5 and used as input for the social cost overview in Section 4.

Plant-level LCOE values are calculated for the following technologies:

- Nuclear power plants;
- Hard coal power plants;
- Natural gas power plants (combined-cycle gas turbine, CCGT);
- Onshore wind turbines;
- Offshore wind turbines;
- Solar PV power plants (utility-scale).

LCOE values for both Europe and the USA are calculated for current newly-built power plants. For the renewable energy technologies (i.e. onshore wind, offshore wind and solar PV), plant-level LCOE values are also calculated for power plants to be built in the year 2040, based on projections of future capital and O&M costs found in the literature. For nuclear, coal and natural gas power plants, plant-level LCOE values are assumed to remain constant at current values, so for these technologies no additional calculations were made for the year 2040.

As explained in the article, a discount rate of 3% is generally used, with a sensitivity case analysis shown for nuclear power plants using a 6% discount rate, reflecting the assumption that these plants exhibit higher investments risks than other types of power plants (particularly renewable energy plants) and that these additional risks can be captured by the higher discount rate.

The publicly available spreadsheet calculator from the Danish Energy Agency (https://ens.dk/en/our-responsibilities/global-cooperation/levelized-cost-energy-calculator) was used as a tool to calculate the plant-level LCOE values. While this calculator includes default values for the technical and economic parameters required to calculate LCOE values for various electricity generation technologies, many of these default values were adjusted to take up-to-date values and estimates for Europe and the USA into account, as provided by several literature sources.

CO_2 costs and transmission costs are not included in the plant-level costs as defined in the article, but are considered as external costs (CO_2) and system costs (transmission costs). Therefore, these costs are not included in this paper's LCOE calculations. No other external or system costs are included either, although the LCOE generator from the Danish Energy Agency allows costs for various external and system costs to be assigned and taken into account.

While grid connection costs are included in the overnight investment costs of wind and solar PV technologies, they are not taken into account by [1], the primary source used for the investment costs of nuclear, hard coal and natural gas power plants. While this omission gives conventional plants a slight advantage over renewables, this is not deemed to be significant as grid connection costs for conventional plants are reported to make up less than 5% of investment costs [2].

For reasons of simplification it is assumed that none of the power plant technologies exhibit reductions in conversion efficiency or any other deteriorations in technical characteristics or operational costs over their technical lifetime. Furthermore, transport costs of fossil fuels from the point of import or extraction to the respective power plants are not included.

The following tables list the input values used for the key LCOE parameters and the sources of the respective values. Tables are shown separately for Europe and the USA for the current situation and for the year 2040. US Dollar values found in the literature are converted to Euros using a conversion rate of 1.1 US Dollar per Euro.

The central values represent plants with typical or median costs, while the ranges are derived by varying capital costs (all technologies), full load hours (onshore wind, offshore wind and solar PV), fuel costs (coal and natural gas) and technical lifetime (nuclear power) within typically observed ranges. These ranges are documented in the tables.

The tables with the relevant input parameters are grouped into the following three categories:

- A. Assumptions on future natural gas, hard coal and uranium price developments;
- B. Technology-specific assumptions for current newly-built power plants;
- C. Technology-specific assumptions for renewable energy power plants to be built in 2040.

A. Assumptions on future natural gas, hard coal and uranium price developments

Table A1: Natural gas price development assumed for low end of LCOE price range.

Year	Price (in EUR/GJ)		Source	Comment
	Europe	USA		
2015	6.0	2.2	[3]	Historic value
2020	5.9	3.4	[3]	450 Scenario
2030	8.1	4.1	[3]	450 Scenario
2040 and beyond	8.5	4.7	[3]	450 Scenario

Table A2: Natural gas price development assumed for central LCOE estimate.

Year	Price (in EUR/GJ)		Source	Comment
	Europe	USA		
2015	6.0	2.2	[3]	Historic value
2020	6.1	3.5	[3]	New Policies Scenario
2030	8.9	4.7	[3]	New Policies Scenario
2040 and beyond	9.9	5.9	[3]	New Policies Scenario

Table A3: Natural gas price development assumed for high end of LCOE price range.

Year	Price (in EUR/GJ)		Source	Comment
	Europe	USA		
2015	6.0	2.2	[3]	Historic value
2020	6.3	3.7	[3]	Current Policies Scenario
2030	9.6	5.1	[3]	Current Policies Scenario
2040 and beyond	11.2	6.8	[3]	Current Policies Scenario

Table A4: Hard coal price development assumed for low end of LCOE price range.

Year	Price (in EUR/GJ)		Source	Comment
	Europe	USA		
2015	2.0	1.8	[3]	Historic value
2020	2.0	1.9	[3]	450 Scenario
2030	2.0	1.8	[3]	450 Scenario
2040 and beyond	1.8	1.7	[3]	450 Scenario

Table A5: Hard coal price development assumed for central LCOE estimate.

Year	Price (in EUR/GJ)		Source	Comment
	Europe	USA		
2015	2.0	1.8	[3]	Historic value
2020	2.2	1.9	[3]	New Policies Scenario
2030	2.6	2.0	[3]	New Policies Scenario
2040 and beyond	2.7	2.1	[3]	New Policies Scenario

Table A6: Hard coal price development assumed for high end of LCOE price range

Year	Price (in EUR/GJ)		Source	Comment
	Europe	USA		
2015	2.0	1.8	[3]	Historic value
2020	2.3	2.0	[3]	Current Policies Scenario
2030	2.8	2.1	[3]	Current Policies Scenario
2040 and beyond	3.1	2.2	[3]	Current Policies Scenario

Table A7: Uranium price development assumed for full LCOE range

Year	Price (in EUR/GJ)		Source	Comment
	Europe	USA		
Entire period	2.4	2.4	[1]	Includes back-end fuel cycle costs

B. Technology-specific assumptions for current newly-built power plants

Table B1: Technological and economic assumptions for current new nuclear power plants in Europe and the USA.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	4000	Own assumption	Based on [1,4–7]
Overnight investment cost (central cost estimate)	Thousand €/MW	5500	Own assumption	
Overnight investment cost (high cost estimate)	Thousand €/MW	6500	Own assumption	
Fixed O&M	€/MW/a	62,545	[1]	Median values from all nuclear power plants listed
Variable O&M	€/MWh	6.3	[1]	
Net electrical efficiency	%	n. a.	-	-
Full load hours	Hours/year	7446	[1]	Capacity factor of 85%
Technical lifetime (low cost estimate)	Years	60	[1]	-
Technical lifetime (central cost estimate)	Years	50	Own assumption	Mean value of the values provided by [1] and [8]
Technical lifetime (high cost estimate)	Years	40	[8]	-
Construction time	Years	7	[1]	-

Table B2: Technological and economic assumptions for current new hard coal power plants in Europe.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	1470	[1]	Lowest value for new hard coal plants in Europe
Overnight investment cost (central cost estimate)	Thousand €/MW	2300	[1]	Median value for new hard coal plants in Europe
Overnight investment cost (high cost estimate)	Thousand €/MW	2790	[1]	Highest value for new hard coal plants in Europe
Fixed O&M	€/MW/a	34,221	[1]	Median values from all new hard coal plants
Variable O&M	€/MWh	3.1	[1]	
Net electrical efficiency	%	46	[1]	Median value for new hard

				coal plants in Europe
Full load hours	Hours/year	7446	[1]	Capacity factor of 85%
Technical lifetime (low cost estimate)	Years	40	[1]	-
Construction time	Years	4	[1]	-

Table B3: Technological and economic assumptions for current new hard coal power plants in the USA.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	2270	[1]	-
Overnight investment cost (central cost estimate)	Thousand €/MW	3310	[4]	-
Overnight investment cost (high cost estimate)	Thousand €/MW	4,490	[4]	-
Fixed O&M	€/MW/a	38,273	[4]	-
Variable O&M	€/MWh	4.2	[4]	
Net electrical efficiency	%	43		-
Full load hours	Hours/year	7446	[1]	Capacity factor of 85%
Technical lifetime (low cost estimate)	Years	40	[1]	-
Construction time	Years	4	[1]	-

Table B4: Technological and economic assumptions for current new natural gas power plants (CCGT) in Europe.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	860	[1]	Lowest value for new plants in Europe
Overnight investment cost (central cost estimate)	Thousand €/MW	890	[1]	Median value for new plants in Europe
Overnight investment cost (high cost estimate)	Thousand €/MW	1003	[1]	Highest value for new plants in Europe
Fixed O&M	€/MW/a	26,759	[1]	Median values from all new natural gas CCGT plants
Variable O&M	€/MWh	2.5	[1]	
Net electrical efficiency	%	60	[1]	Median value for new plants in Europe
Full load hours	Hours/year	7446	[1]	Capacity factor of 85%
Technical lifetime (low cost estimate)	Years	30	[1]	-
Construction time	Years	2	[1]	-

Table B5: Technological and economic assumptions for current new natural gas power plants (CCGT) in the USA.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	760	[1,4]	-
Overnight investment cost (central cost estimate)	Thousand €/MW	890	[1,4]	-
Overnight investment cost (high cost estimate)	Thousand €/MW	1.450	[1,4]	-
Fixed O&M	€/MW/a	10,000	[4]	-
Variable O&M	€/MWh	3.2	[4]	
Net electrical efficiency	%	60	[1]	-
Full load hours	Hours/year	7446	[1]	Capacity factor of 85%
Technical lifetime (low cost estimate)	Years	30	[1]	-
Construction time	Years	2	[1]	-

Table B6: Technological and economic assumptions for current new onshore wind turbines in Europe.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	1050	[9]	-
Overnight investment cost (central cost estimate)	Thousand €/MW	1660	[9]	-
Overnight investment cost (high cost estimate)	Thousand €/MW	2200	Own assumption	Value provided by [9] (3370) was adjusted downward [a]
Fixed O&M	€/MW/a	44,545	[1]	Median values from all new onshore wind turbines
Variable O&M	€/MWh	0	[1]	
Net electrical efficiency	%	n. a.		-
Full load hours (low cost estimate)	Hours/year	4468	[9]	-
Full load hours (central cost estimate)	Hours/year	2365	[9]	-
Full load hours (high cost estimate)	Hours/year	1900	Own assumption	Value provided by [9] (1226) was adjusted upward [a]
Technical lifetime (low cost estimate)	Years	25	[1]	-
Construction time	Years	1	[1]	-

[a] See footnote to Table B7.

Table B7: Technological and economic assumptions for current new onshore wind turbines in the USA.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	1150	[9]	-
Overnight investment cost (central cost estimate)	Thousand €/MW	1570	[9]	-
Overnight investment cost (high cost estimate)	Thousand €/MW	2400	Own assumption	Value provided by [9] (2560) was adjusted downward [a]
Fixed O&M	€/MW/a	46,364	[10]	-
Variable O&M	€/MWh	0	[10]	
Net electrical efficiency	%	n. a.	-	-
Full load hours (low cost estimate)	Hours/year	4468	[9]	-
Full load hours (central cost estimate)	Hours/year	3592	[9]	-
Full load hours (high cost estimate)	Hours/year	2200	Own assumption	Value provided by [9] (1927) was adjusted upward [a]
Technical lifetime (low cost estimate)	Years	25	[1]	-
Construction time	Years	1	[1]	-

[a] Values provided by [9] were adjusted to reflect the fact that the lowest full load hours and the highest overnight investment costs do not typically coincide at one power plant project. While the LCOE *range*, the overnight investment cost *range* and the full load hour *range* of the sum of all projects identified by [9] were available to the author, the respective *individual values* for each project were not. Therefore, the LCOE range provided by [9] was used to contain the high cost values for overnight investment costs and full load hours. A respective adjustment of the low cost values turned out to be unnecessary.

Table B8: Technological and economic assumptions for current new offshore wind turbines in Europe.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	2950	[11]	-
Overnight investment cost (central cost estimate)	Thousand €/MW	4460	[11]	-
Overnight investment cost (high cost estimate)	Thousand €/MW	5000	Own assumption	Value provided by [11] (5820) was adjusted downward so as to obtain a reasonable high cost LCOE estimate (in line with the one found in [11])
Fixed O&M	€/MW/a	125,455	[10]	-
Variable O&M	€/MWh	0	[10]	
Net electrical efficiency	%	n. a.	-	-
Full load hours (low cost estimate)	Hours/year	4786	Own assumption	Value for central cost estimate +30%
Full load hours (central cost estimate)	Hours/year	3682	[12]	-
Full load hours (high cost estimate)	Hours/year	3000	Own assumption	Value was chosen so as to obtain a reasonable high cost LCOE estimate (in line with the one found in [11])
Technical lifetime (low cost estimate)	Years	25	[1]	-
Construction time	Years	1	[1]	-

Table B9: Technological and economic assumptions for current new offshore wind turbines in the USA.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	2820	[8]	-
Overnight investment cost (central cost estimate)	Thousand €/MW	4400	[10]	-
Overnight investment cost (high cost estimate)	Thousand €/MW	5000	Own assumption	Value provided by [4] (5760) was adjusted downward so as to obtain a reasonable high cost LCOE estimate (in line with the one found in [11])
Fixed O&M	€/MW/a	125,455	[10]	-
Variable O&M	€/MWh	0	[10]	
Net electrical efficiency	%	n. a.		-
Full load hours (low cost estimate)	Hours/year	4829	Own assumption	Value for central cost estimate +30%
Full load hours (central cost estimate)	Hours/year	3714	[10]	-
Full load hours (high cost estimate)	Hours/year	3000	Own assumption	Value was chosen so as to obtain a reasonable high cost LCOE estimate (in line with the one found in [11])
Technical lifetime (low cost estimate)	Years	25	[1]	-
Construction time	Years	1	[1]	-

Table B10: Technological and economic assumptions for current new solar PV power plants (utility-scale) in Europe.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	1230	[8]	Data from the USA, but costs are here assumed to be identical in Europe
Overnight investment cost (central cost estimate)	Thousand €/MW	1360	[8]	
Overnight investment cost (high cost estimate)	Thousand €/MW	1590	[8]	
Fixed O&M	€/MW/a	22,557	[1]	-
Variable O&M	€/MWh	0	[1]	
Net electrical efficiency	%	n. a.		-
Full load hours (low cost estimate)	Hours/year	1680	[13]	-
Full load hours (central cost estimate)	Hours/year	1190	[13]	Median value of all values shown
Full load hours (high cost estimate)	Hours/year	960	[13]	-
Technical lifetime (low cost estimate)	Years	30	[13]	-
Construction time	Years	1	[1]	-

Table B11: Technological and economic assumptions for current new solar PV power plants (utility-scale) in the USA.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	1230	[8]	-
Overnight investment cost (central cost estimate)	Thousand €/MW	1360	[8]	-
Overnight investment cost (high cost estimate)	Thousand €/MW	1590	[8]	-
Fixed O&M	€/MW/a	19,818	[4]	-
Variable O&M	€/MWh	0	[4]	
Net electrical efficiency	%	n. a.		-
Full load hours (low cost estimate)	Hours/year	3066	[14]	-
Full load hours (central cost estimate)	Hours/year	2260	[15]	Average value for the year 2015
Full load hours (high cost estimate)	Hours/year	1752	[14]	-
Technical lifetime (low cost estimate)	Years	30	[13]	-
Construction time	Years	1	[1]	-

C. Technology-specific assumptions for new renewable energy power plants to be built in 2040

Table C1: Technological and economic assumptions for new onshore wind turbines built in 2040 in Europe.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	1025	Own assumption	Assumes that the lowest overnight investment costs will be 30% lower than central value
Overnight investment cost (central cost estimate)	Thousand €/MW	1464	[16]	-
Overnight investment cost (high cost estimate)	Thousand €/MW	1903	Own assumption	Assumes that the highest overnight investment costs

				will be 30% higher than central value
Fixed O&M	€/MW/a	37,273	[16]	-
Variable O&M	€/MWh	0	[16]	-
Net electrical efficiency	%	n. a.		-
Full load hours (low cost estimate)	Hours/year	4468	[9]	-
Full load hours (central cost estimate)	Hours/year	2365	[9]	
Full load hours (high cost estimate)	Hours/year	1900	Own assumption	-
Technical lifetime (low cost estimate)	Years	25	[1]	-
Construction time	Years	1	[1]	-

Table C2: Technological and economic assumptions for new onshore wind turbines built in 2040 in the USA.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand $€_{2015}$/MW	1025	Own assumption	Assumes that the lowest overnight investment costs will be 30% lower than central value
Overnight investment cost (central cost estimate)	Thousand $€_{2015}$/MW	1464	[16]	-
Overnight investment cost (high cost estimate)	Thousand $€_{2015}$/MW	1903	Own assumption	Assumes that the highest overnight investment costs will be 30% higher than central value
Fixed O&M	€/MW/a	37,273	[16]	-
Variable O&M	€/MWh	0	[16]	-
Net electrical efficiency	%	n. a.		-
Full load hours (low cost estimate)	Hours/year	4468	[9]	-
Full load hours (central cost estimate)	Hours/year	3592	[9]	-
Full load hours (high cost estimate)	Hours/year	2200	Own assumption	-
Technical lifetime (low cost estimate)	Years	25	[1]	-
Construction time	Years	1	[1]	-

Table C3: Technological and economic assumptions for new offshore wind turbines built in 2040 in Europe.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	1973	[11]	Assumes that the lowest overnight investment costs will be 30% lower than central value
Overnight investment cost (central cost estimate)	Thousand €/MW	2818	[16]	-
Overnight investment cost (high cost estimate)	Thousand €/MW	3664	Own assumption	Assumes that the highest overnight investment costs will be 30% higher than central value
Fixed O&M	€/MW/a	98,182	[16]	-
Variable O&M	€/MWh	0	[16]	-
Net electrical efficiency	%	n. a.	-	-
Full load hours	Hours/year	4786	Own assumption	Value for central cost

(low cost estimate)				estimate +30%
Full load hours (central cost estimate)	Hours/year	3682	[12]	-
Full load hours (high cost estimate)	Hours/year	3000	Own assumption	-
Technical lifetime (low cost estimate)	Years	25	[1]	-
Construction time	Years	1	[1]	-

Table C4: Technological and economic assumptions for new offshore wind turbines built in 2040 in the USA.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	1973	[11]	Assumes that the lowest overnight investment costs will be 30% lower than the central value
Overnight investment cost (central cost estimate)	Thousand €/MW	2818	[16]	-
Overnight investment cost (high cost estimate)	Thousand €/MW	3664	Own assumption	Assumes that the highest overnight investment costs will be 30% higher than the central value
Fixed O&M	€/MW/a	98,182	[16]	-
Variable O&M	€/MWh	0	[16]	-
Net electrical efficiency	%	n. a.	-	-
Full load hours (low cost estimate)	Hours/year	4829	Own assumption	Value for central cost estimate +30%
Full load hours (central cost estimate)	Hours/year	3714	[10]	-
Full load hours (high cost estimate)	Hours/year	3000	Own assumption	-
Technical lifetime (low cost estimate)	Years	25	[1]	-
Construction time	Years	1	[1]	-

Table C5: Technological and economic assumptions for new solar PV power plants (utility-scale) built in 2040 in Europe.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	750	Own assumption	Assumes that the lowest overnight investment costs will be 10% lower than the central value
Overnight investment cost (central cost estimate)	Thousand €/MW	840	[16]	-
Overnight investment cost (high cost estimate)	Thousand €/MW	920	Own assumption	Assumes that the highest overnight investment costs will be 10% higher than the central value
Fixed O&M	€/MW/a	8182	[16]	-
Variable O&M	€/MWh	0	[16]	-
Net electrical efficiency	%	n. a.	-	-
Full load hours (low cost estimate)	Hours/year	1680	[13]	-
Full load hours (central cost estimate)	Hours/year	1190	[13]	Median value of all values shown
Full load hours (high cost estimate)	Hours/year	960	[13]	-

Technical lifetime (low cost estimate)	Years	30	[13]	-
Construction time	Years	1	[1]	-

Table C6: Technological and economic assumptions for new solar PV power plants (utility-scale) built in 2040 in the USA.

Parameter	Unit	Value	Source	Comment
Overnight investment cost (low cost estimate)	Thousand €/MW	750	Own assumption	Assumes that the lowest overnight investment costs will be 10% lower than the central value
Overnight investment cost (central cost estimate)	Thousand €/MW	840	[16]	-
Overnight investment cost (high cost estimate)	Thousand €/MW	920	Own assumption	Assumes that the highest overnight investment costs will be 10% higher than the central value
Fixed O&M	€/MW/a	8182	[16]	-
Variable O&M	€/MWh	0	[16]	-
Net electrical efficiency	%	n. a.	-	-
Full load hours (low cost estimate)	Hours/year	3066	[14]	-
Full load hours (central cost estimate)	Hours/year	2260	[15]	-
Full load hours (high cost estimate)	Hours/year	1752	[14]	-
Technical lifetime (low cost estimate)	Years	30	[13]	-
Construction time	Years	1	[1]	-

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Annex E: Documentation of the Online Survey on the Treatment of Electricity Supply Costs in Energy Models

Survey: Electricity generation costs in energy models

Dear survey participant,

Thank you very much for your willingness to participate in this short survey on how the costs of electricity supply are taken into account in different energy and energy-economy (environment) models.

The survey consists of three sections:
- General questions about you and your model
- Questions about the types of costs considered by the model
- Questions about the dynamics of plant-level costs considered by the model

Most questions simply ask you to select from predefined answers (e.g. “yes” or “no”), but if you feel a more nuanced answer is needed you will also have the opportunity to give an alternative answer.

I kindly ask you to complete the questionnaire in relation to the model for which I have identified you as the expert (see email). However, if you feel more qualified to respond for a different model, or if you can complete the survey for more than one model, you are welcome to do so. Please refer to the latest version of the model or the latest version of the model that you are familiar with. Where different specifications of a model exist, please refer to the specification (if you are familiar with it) that most comprehensively models the electricity supply costs.

Participant *

First name	
Last name	
Affiliation	
Would you be happy to be identified in any future publication(s) as a modeler who participated in this questionnaire?	

Name of the model that is referred to *

Details about the model that is referred to (optional)

Type of model (e.g. energy system optimization, CGE, ...)	
Additional comment on the model	

Which of the following types of costs can be taken into account by the model you use?

Note:
- "Yes, endogenously" means the model endogenously determines the development of a certain type of cost over time (e.g. fuel costs as a function of fuel demand, resource availability and/or other factors included in the model).
- "Yes, as an exogenous input" means that while the model does take a certain cost into account, its level either doesn't change or the change is based on an exogenous input (e.g. exogenous fuel cost assumptions).
- "Other answer" may be used to provide a more nuanced answer, e.g. if another model is typically used and is hard or soft linked with the model discussed here to take into account a certain type of cost.

PLANT-LEVEL COSTS

Investment costs *

- [ ] Yes, endogenously
- [ ] Yes, as an exogenous input
- [ ] No
- [ ] Don't know
- [ ] Other answer:

Fuel costs *

- [ ] Yes, endogenously
- [ ] Yes, as an exogenous input
- [ ] No
- [ ] Don't know
- [ ] Other answer:

Market costs of GHG emissions *

- [ ] Yes, endogenously
- [ ] Yes, as an exogenous input
- [ ] No
- [ ] Don't know
- [ ] Other answer:

Operation and maintenance costs (other than fuel) *

- [ ] Yes, endogenously
- [ ] Yes, as an exogenous input
- [ ] No
- [ ] Don't know
- [ ] Other answer:

Decommissioning costs *

- [ ] Yes, endogenously
- [ ] Yes, as an exogenous input
- [ ] No
- [ ] Don't know
- [ ] Other answer:

SYSTEM COSTS

Grid reinforcement and extension costs *

- [ ] Yes, endogenously
- [ ] Yes, as an exogenous input
- [ ] No
- [ ] Don't know
- [ ] Other answer:

Balancing costs *

Note: Balancing costs are all types of costs that accrue to ensure that unplanned short-term fluctuations in both electricity demand and supply can be compensated.

- [ ] Yes, endogenously
- [ ] Yes, as an exogenous input
- [ ] No
- [ ] Don't know
- [ ] Other answer:

Profile costs *

Note: Profile costs are the additional specific capital and operational costs that electricity generation from a new plant may cause in the residual electricity system, plus overproduction costs of electricity generation from variable renewable energy sources.

- [ ] Yes, endogenously
- [ ] Yes, as an exogenous input
- [ ] No
- [ ] Don't know
- [ ] Other answer:

EXTERNAL COSTS

Social costs of GHG emissions (beyond market costs of GHG emissions) *

- [ ] Yes, endogenously
- [ ] Yes, as an exogenous input
- [ ] No
- [ ] Don't know
- [ ] Other answer:

Impacts of non-GHG pollution (especially health costs of air pollution) *

- [ ] Yes, endogenously
- [ ] Yes, as an exogenous input
- [ ] No
- [ ] Don't know

Other answer:

- [ ]

Visual impacts and impacts of noise *

E.g. disamenity costs of wind turbines built close to houses.

- [ ] Yes, endogenously
- [ ] Yes, as an exogenous input
- [ ] No
- [ ] Don't know

Other answer:

- [ ]

Impacts on ecosystem and biodiversity (beyond those related to climate change) *

- [ ] Yes, endogenously
- [ ] Yes, as an exogenous input
- [ ] No
- [ ] Don't know

Other answer:

- [ ]

External costs associated with radionuclide emissions *

Note: Mainly concerns the risks of major accidents at nuclear power facilities.

- [ ] Yes, endogenously
- [ ] Yes, as an exogenous input
- [ ] No
- [ ] Don't know

Other answer:

- [ ]

General comment (optional)

E.g. any additional type of cost taken into account by the model.

Which of the following factors influencing plant-level electricity costs over time are endogenously represented by the model you use?

Note:
"Other answer" may be used if a more nuanced answer than a simple "yes" or "no" needs to be given.

LEARNING AND TECHNOLOGICAL IMPROVEMENTS

Deployment-induced learning *

Refers to cost reductions as a function of installed capacity.

- [ ] Yes
- [ ] No
- [ ] Don't know
- [ ] Other answer:

RD&D-induced learning *

Refers to cost reductions as a function of RD&D spending.

- [ ] Yes
- [ ] No
- [ ] Don't know
- [ ] Other answer:

Knowledge spillovers from other technologies *

Refers to cost reductions for one type of technology stemming from advances in other energy or non-energy technologies.

- [ ] Yes
- [ ] No
- [ ] Don't know
- [ ] Other answer:

Upsizing *

Refers to cost changes as a function of the typical size of one unit of a technology.

- [ ] Yes
- [ ] No
- [ ] Don't know
- [ ] Other answer:

ECONOMIES OF SCALE

Economies of manufacturing scale *

Refers to cost changes as a function of the typical size of the plants manufacturing a technology.

- [ ] Yes
- [ ] No
- [ ] Don't know
- [ ] Other answer:

Economies of project scale *

Refers to cost changes as a function of the number of plants built at a certain site.

- [ ] Yes
- [ ] No
- [ ] Don't know
- [ ] Other answer:

CHANGES IN INPUT FACTOR PRICES

Changes in material and labour costs *

- Yes
- No
- Don't know
- Other answer:

Changes in fuel costs *

- Yes
- No
- Don't know
- Other answer:

SOCIAL AND GEOGRAPHICAL FACTORS

Regulatory changes *

E.g. tighter emission control standards.

- Yes
- No
- Don't know
- Other answer:

Does the model differentiate between resource classes, so that a scarcitiy of suitable sites can lead to higher marginal generation costs? *

E.g. lack of good sites for wind power.

- [ ] Yes
- [ ] No
- [ ] Don't know
- [ ] Other answer: