Coupling life cycle assessment with energy system analysis

Zur Erlangung des akademischen Grades eines

Doktors der Ingenieurwissenschaften

(Dr.-Ing.)

von der KIT-Fakultät für Wirtschaftswissenschaften

des Karlsruher Instituts für Technologie (KIT)

genehmigte

Dissertation

von

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Tag der mündlichen Prüfung:	12.12.2022
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Acknowledgments

This thesis was written during my time as a research associate at the Institute for Technology Assessment and Systems Analysis (ITAS) and the Chair of Energy Economics (Institute for Industrial Production (IIP)) of the Karlsruhe Institute of Technology (KIT). During this period, I was honored to be awarded a doctoral scholarship by China Scholarship Council (CSC) and had the chance to contribute to research projects funded by the European Union's Horizon 2020 research and innovation program.

While working on the thesis, I have received support from many people, for which I would like to express my sincere gratitude.

First and foremost, I would like to thank my doctoral father PD Dr. Patrick Jochem and the second reviewer of my thesis Prof. Dr. Wolf Fichtner for their valuable guidance and support throughout the thesis process. I would also greatly appreciate the inspiration they gave me to pursue my research interest. I would also like to thank my group leader Dr. Witold-Roger Poganietz, who played a large part in the successful publication of my contributed papers, for his trust in me and his encouragement. Moreover, I am grateful to Prof. Dr. Kay Mitusch and Prof. Dr. Oliver Stein for serving as committee members.

I also owe a big thank you to all my colleagues from ITAS and IIP for the great working atmosphere, the inspiring discussions and the valuable friendship. I would also like to thank all the cooperators in research. Here, I would like to give special recognition to Thomas Dengiz, Maryegli Fuss, Manuel Ruppert, Zongfei Wang, and Hasan Ümitcan Yilmaz.

More importantly, I am very grateful to my family and friends who have always been there to support me, especially my husband Bo Wang who gave me continuous company and encouragement. During my PhD, we had our first daughter, Stella, and we are looking forward to our second daughter. Thank you all.

Karlsruhe, March 2023

Lei Xu

Abstract

One of the main drivers for switching the current energy system from a conventional fossil-base to one dominated by renewable technologies is climate change. However, energy system transformation aiming at reducing greenhouse gas (GHG) emissions may lead to increases in other types of environmental impacts. Incorporating environmental impacts beyond climate change into future energy systems is required, in order to develop energy policies that do not, or at least can reduce, conflict with other goals.

With this as the background, this thesis couples life cycle assessment (LCA) with energy system analysis, to broaden the scope by including additional environmental impacts, and to switch from a direct emissions perspective to a life cycle perspective. For this purpose, a standard LCA approach is applied to assess energy technologies. Subsequently, the standard LCA is extended to couple with energy system models (ESM) for the assessment of multi-technological energy systems, from both life cycle and energy system perspectives. Considering the methodological challenges that occur due to differences between the models resulting from their different system boundaries, databases, and the levels of detail of their input data, the thesis introduces the Environmental Assessment Framework for Energy System Analysis (EAFESA) as a guideline for studies to cope with model coupling between LCA and ESM.

This thesis includes four papers with different study aims. Paper A applies the standard LCA approach for technological assessment. As wind power is one of the most promising renewable energy sources worldwide, a case study assessing the environmental impacts of wind power technologies is conducted. Paper B develops the EAFESA framework and includes a case study to elaborate how to use the framework. Paper C and Paper D are two additional case studies applying the EAFESA framework for model coupling between LCA and ESM, considering, respectively, one of the two model coupling directions. The applications of the EAFESA framework in the case studies confirms the importance and benefits of "integrated thinking" as proposed by EAFESA, which allows minimizing the pitfalls of combining both models comprehensively. At the same time, EAFESA has the potential to raise awareness of issues not often discussed among policymakers. As shown, for example, the decarbonized electricity system will be accompanied by increased metal demand and urban land occupation. Nevertheless, metal demand could be decreased slightly, together with the decrease of GHG emissions, when the system expenditure increases insignificantly.

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Part I: Overview

1 Introduction

1.1 Background and motivation

Energy systems across the world are undergoing a fundamental transformation driven mainly by climate considerations. A good example is the European Commission, that has announced the European Green Deal, aiming to ensure no net greenhouse gas (GHG) emissions, such as carbon dioxide (CO_2) and methane (CH_4), by 2050 (Fetting, 2020). As the production and use of energy account for over 75% of the GHG emissions in Europe, decarbonizing the European energy system is critical to achieve carbon neutrality by 2050. As instruments to drive the energy system transformation, energy policy generally uses energy system models (ESM) for advice regarding the adequate shape of the future energy system (Bhattacharyya and Timilsina, 2010). The mainstream approach of modeling energy systems is to minimize the total system expenditure while constraining CO_2 or GHG emissions. In this context, the share of the low-carbon renewable energy sources (RES) for electricity generation has been continually increasing in European countries as well as other countries in the world, e.g., China, during recent years (Cozzi et al., 2020). Wind power and photovoltaics (PV) are amongst those considered the most promising renewable technologies, and are usually considered emission-free as there is no fossil consumption in the generation process (e.g., Jochem et al. 2015).

However, their indirect emissions, i.e., emissions from upstream, downstream, and auxiliary processes are not included in these considerations. Taking into account the entire life cycle, which would include, the combustion of fossil fuels, the production and provision of construction materials and electric generation equipment, some negative impacts of energy technologies, in particular of wind power and PV, can be revealed. These negative impacts include not only climate aspects, but also non-climate environmental and resource-related aspects, e.g., freshwater eutrophication or metal depletion. These above-mentioned impacts that a typical ESM does not consider arise mainly because the predominant objective of the optimization is system expenditure. System expenditure is only constrained by direct GHG emissions, i.e., emissions during the electricity generation process, and is not affected by indirect GHG emissions or other direct and indirect environmental factors.

Life cycle assessment (LCA), as an operationalization of the idea of Life cycle Thinking (LCT), is thus of importance to energy systems, as it is useful to avoid burden-shifting when only the electricity generation process is evaluated. LCA is an approach to consider the environmental impacts throughout the entire process chain, starting from the extraction and processing of raw materials, through the processes of production, utilization, recycling, and disposal (i.e., the so-called “cradle to grave”) (Finnveden et al., 2009; ISO, 2006). Additionally, LCA is a useful tool to assess diverse environmental impacts beyond climate change. Over the past two decades, LCA has been widely applied to assess the life cycle impacts of energy-related technologies worldwide, including wind technologies (e.g., Xue et al., 2015), PV (e.g., Sherwani and Usmani, 2010) and electric vehicles (EV) (e.g., Qiao et al., 2019), even though GHG emissions are still the main focus.

Both ESM and LCA have their own unique advantages for policymaking. Coupling ESM and LCA offers the possibility and potential to take advantage of both models and raise policymakers awareness of problems that cannot be identified by applying only one of the two models. For the model development, the coupling of one model with the other provides a possibility for model extension, i.e., both ESM and LCA are able to obtain a wider perspective from the model coupling. Specifically, for ESM, the coupling with LCA provides a life cycle perspective and a possibility to consider diverse environmental impacts beyond climate change. For LCA, the coupling with ESM provides an energy system perspective and a possibility to extend the model from a single-technology assessment to a multi-technological energy system assessment. Consequently, new insights could be gained from both life cycle and energy system perspectives for policymakers.

Recent literature has performed the model coupling approach between ESM and LCA to broaden the scope of the analyses. Some of the studies conduct ex-post LCA analysis to assess the trade-offs in terms of environmental, resources, and other aspects connected to the shaped energy systems pathways, calculated by ESM (Berrill et al., 2016; García-Gusano et al., 2016a; García-Gusano et al., 2016b; Hertwich et al., 2015; Igos et al., 2015; Junne et al., 2020a; Luderer et al., 2019; Viebahn et al., 2011). Others focus on integrating LCA indicators to ESM, in order to research the possible cost-effective pathways in energy systems to reduce GHG emissions and other pollutants (Fernández Astudillo et al., 2019; Junne et al., 2021; Rauner and Budzinski, 2017; Vandepaer et al., 2020; Volkart et al., 2018). These studies are good examples to demonstrate the advantages of applying the model coupling approach. However, methodological challenges arise in the model coupling between LCA and ESM, mainly due to their different characteristics (e.g., different system boundaries, differences in databases, diverging assumptions, etc.). These methodological challenges could be summarized into two aspects: (1) how to identify elements in a systematic way in both models, which have to be harmonized, or at least matched, and (2) how to conduct a prospective LCA model which needs to consider technological progress in both market-proved technologies and emerging technologies. To the best knowledge of the author, few studies have systematically discussed the methodological challenges which occur in the model coupling processes, and their discussions as well as their consideration to overcome the challenges are insufficient. The extent of the considerations varies from study to study, and a detailed comparison and explanation are provided in Section 3.2.1. Briefly speaking, no studies consider the data harmonization related to energy mix in the background system (the background system means the upstream and auxiliary processes, i.e., non-energy sectors), nor the development of prospective LCA for future emerging technological markets. A methodological framework is thus required to standardize the model coupling between ESM and LCA and to reduce the associated challenges as far as possible. This thesis fills in the gap by introducing the Environmental Assessment Framework for Energy System Analysis (EAFESA) as a guideline for studies to cope with the challenges in the model coupling between LCA and ESM.

The motivation of this thesis comes from the coexistence of both opportunities and challenges in the model coupling between ESM and LCA. Against this background, the overarching objectives are distinguished into two parts; from a methodological perspective and from a policymaking perspective. These are: (1) to develop a methodological framework to overcome the challenges in the model coupling between ESM and LCA models; and (2) to include the consideration of the life cycle non-climate environmental impacts besides GHG emissions in the energy system transformation, and to give possible solutions for policymakers for the trade-offs caused by mitigating climate change.

1.2 Research questions

To achieve the objectives, four research questions are central to the discussion. Fig.1 provides an overview of the research questions as well as the scope of their focus related to energy systems. From a structural perspective, an energy system is primarily designed to supply energy services to final demand sectors, including all technologies related to transforming energy, carriers, and providing end-use of energy. As a starting point, the first research question is concentrated on the technological level: how to assess promising renewable technologies, e.g., wind power, from a life cycle perspective? On this basis, the second research question focuses on the level of the entire energy system: How to assess energy systems from a life cycle perspective? How to overcome the challenges in the model coupling between LCA and ESM? For this purpose, a methodological framework (i.e., EAFESA) is developed for the model coupling.

The final two research questions are proposed as case studies aiming to demonstrate the applicability and effectiveness of the EAFESA framework for political recommendations. The case studies are selected with the consideration of different model coupling directions, i.e., to integrate ESM output to LCA, and to integrate LCA indicators to ESM, respectively. The focus of the third research question is on the electricity system: How to consider the impacts of trade-offs (e.g., metal depletion) on the electricity system transformation? The fourth research question considers the sector coupling between electricity and transport sectors by integrating EV into the electricity system: How to assess the GHG emissions of EV in Europe by 2050, considering different charging strategies?

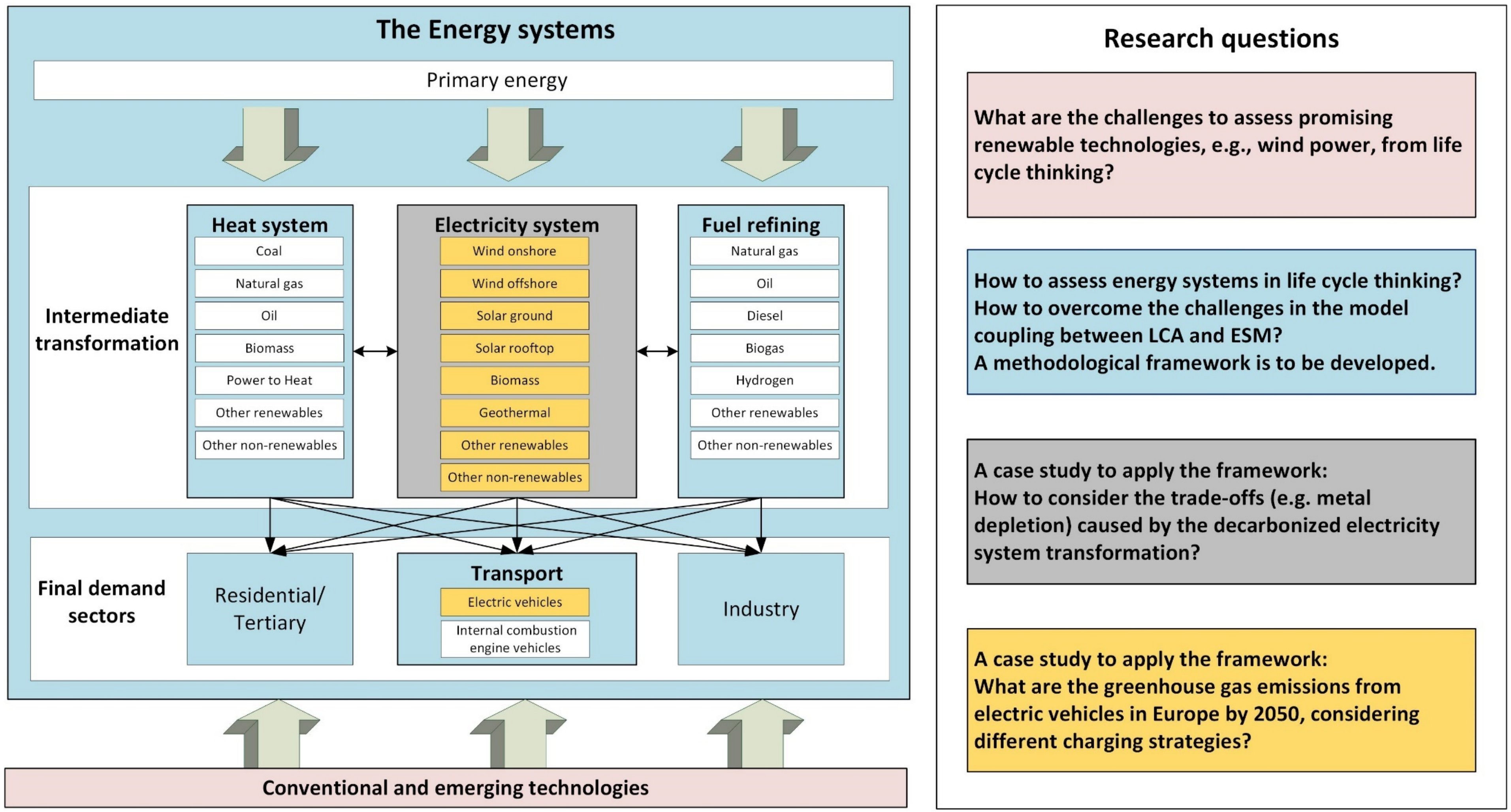

Fig. 1: Overview of the research questions and their specific scopes with regard to energy systems

1.3 Structure of the thesis

The thesis consists of two parts. Part I provides an overview of the background, challenges, methods and applications of model coupling between ESM and LCA. Section 1 of Part I introduces the motivation and research questions. Section 2 provides the basic information for LCA and ESM, and highlights the importance and challenges of the model coupling between LCA and ESM. Section 3 introduces the methodologies, including a standard LCA model for a single technology assessment, a methodological framework as a general guideline for model coupling between LCA and ESM, and model extensions of LCA and/or ESM to be used for case studies. Section 4 summarizes the background, methodologies, and the main results of the appended papers with case studies. Section 5 concludes the overview.

Part II includes the four appended papers constituting the research of the thesis (see Fig. 2).

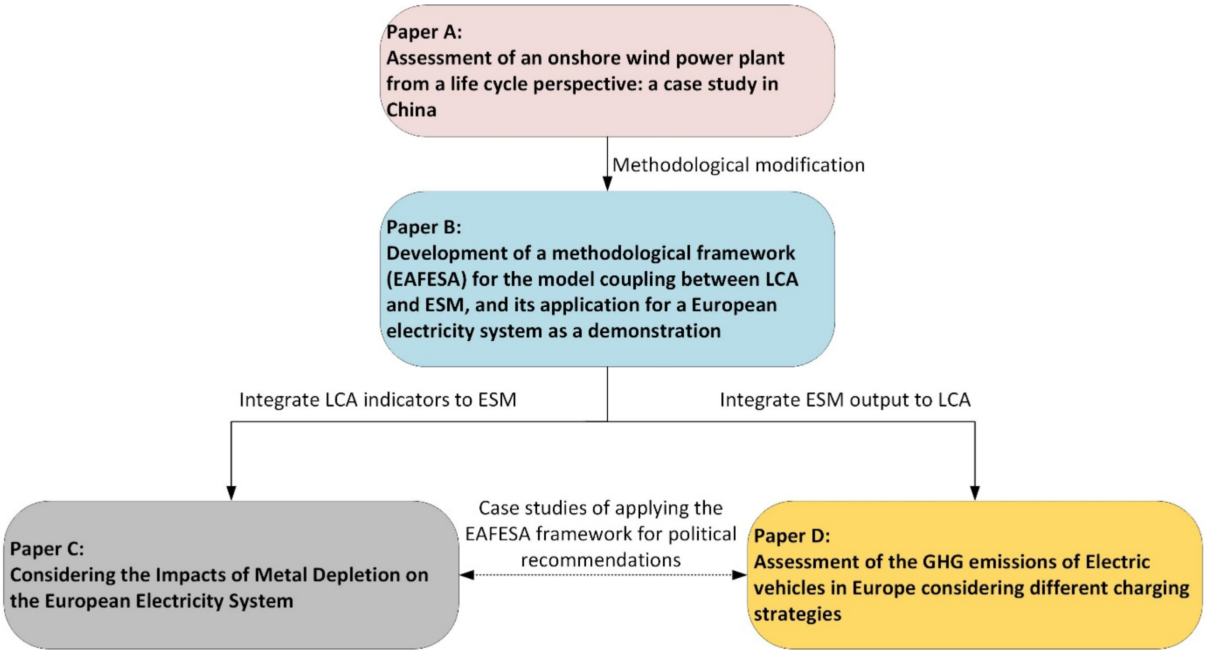

Fig. 2: Structure of the appended papers

The list of appended papers is as follows:

Paper A (Xu et al., 2018): Life cycle assessment of onshore wind power systems in China

Paper A is published in the journal, *Resources, Conservation and Recycling*. It focuses on the environmental assessment of an onshore wind power plant in China from a life cycle perspective. A standard LCA model is applied, which is the basis for the methodological extension on LCA in Papers B-D.

Paper B (Xu et al., 2020a): An Environmental Assessment Framework for Energy System Analysis (EAFESA): The method and its application to the European energy system transformation

Paper B is published in the *Journal of Cleaner Production*. A methodological framework as a guideline for coupling LCA and ESM is developed, which is proposed to be applicable in cases regardless of the various scopes and study aims. A case study applying the methodological framework is performed, to analyze the environmental impacts of the future decarbonized European electricity system. For the analysis, an extended LCA model is used. The case study serves as an example to test the applicability of the framework.

Paper C (Xu et al., 2021): Considering the Impacts of Metal Depletion on the European Electricity System

Paper C is published in the journal, *Energies*, and is a case study to apply the methodological framework for coupling LCA and ESM developed in Paper B. It considers the impacts of metal depletion, a trade-off of climate change, on the European electricity system. For the analysis, an extended LCA model and an extended ESM model with a multi-criteria formulation are developed.

Paper D (Xu et al., 2020b): Greenhouse gas emissions of electric vehicles in Europe considering different charging strategies

Paper D is published in the journal, *Transportation Research Part D: Transport and Environment*. Like Paper C, it is also a case study to apply the methodological framework developed in Paper B. It investigates the GHG emissions from electricity generation and EV batteries in Europe in 2050 considering different EV charging strategies. For the analysis, the LCA model is extended to integrate ESM output, while ESM is extended to integrate EV charging strategies, i.e., uncontrolled, unidirectional controlled, and bidirectional controlled charging.

2 Life cycle assessment in energy systems

2.1 The role of energy system models in energy system transformation

Global warming is considered to increase the risk of extreme climate (floods, droughts, and storms), which will threaten the health and safety of life. From an economic point of view, it could also reduce the world per capita output by 15% to 40%, although these economic effects are still uncertain (Duan et al., 2021). Based on this, the necessity to mitigate climate change has been widely recognized. Climate change is mainly caused by human activity, primarily from the burning of fossil fuels that emit CO_2, CH_4 and other GHG emissions into the atmosphere (Trenberth, 2018). Almost all countries have announced a series of long-term climate change mitigation policies and have explored pathways for key sectors, such as energy and transport, to limit the increase of the global average surface temperature to less than 2℃ or even 1.5℃ compared with preindustrial levels (Stocker, 2014).

The transformation to a low-carbon energy system has been put into practice, from fossil-based to renewable-dominated ones (International Energy Agency, 2016). ESM, mathematical representations of energy systems, are widely used to investigate how the future energy system could look in scenario analyses, thereby helping to shape the future energy system to achieve specific aims, such as decarbonization. Numerous ESM are available to represent a more or less simplified picture of the energy system or sub-system for different technical, methodological, as well as political considerations (Bhattacharyya and Timilsina, 2010). Energy system optimization models (ESOM) are amongst others widely used for climate change mitigation targets, which are developed to define the optimal set of technology choices to achieve a specific target at minimized cost.

An ESOM usually minimizes total system-relevant costs to satisfy the exogenously given electricity demand, under a set of technical, ecological and political constraints. The costs are composed of the fuel costs, the costs for emitting CO_2, other operating costs as well as investment costs of electricity generation units. Some ESOM are implemented in GAMS (e.g., PERSEUS-EU (Heinrichs, 2014) and ELTRAMOD (Anke, 2019; Müller et al., 2013)), the programming language for writing mathematical optimization problems, and are solved with the CPLEX solver, a solution algorithm for large-scale mixed integer linear programming (MILP) problems.

Both PERSEUS-EU and ELTRAMOD are designed as a long-term bottom-up ESOM of the European electricity system. A time horizon begins from the base year to a year in the future. For example, a time horizon beginning from the base year 2015 until the year 2050 is chosen for PERSEUS-EU. The base year 2015 is especially used for model calibration with the help of historical data. Due to the computational restrictions, not all chosen years are modeled, but the characteristic years of 2015, 2020, 2030, 2040 and 2050 are calculated. A European ESOM is focusing on the European energy system. The regional scope of ELTRAMOD, for example, consists of the 27 European countries, Norway, Switzerland, United Kingdom and the Balkan region (see Fig. 3).

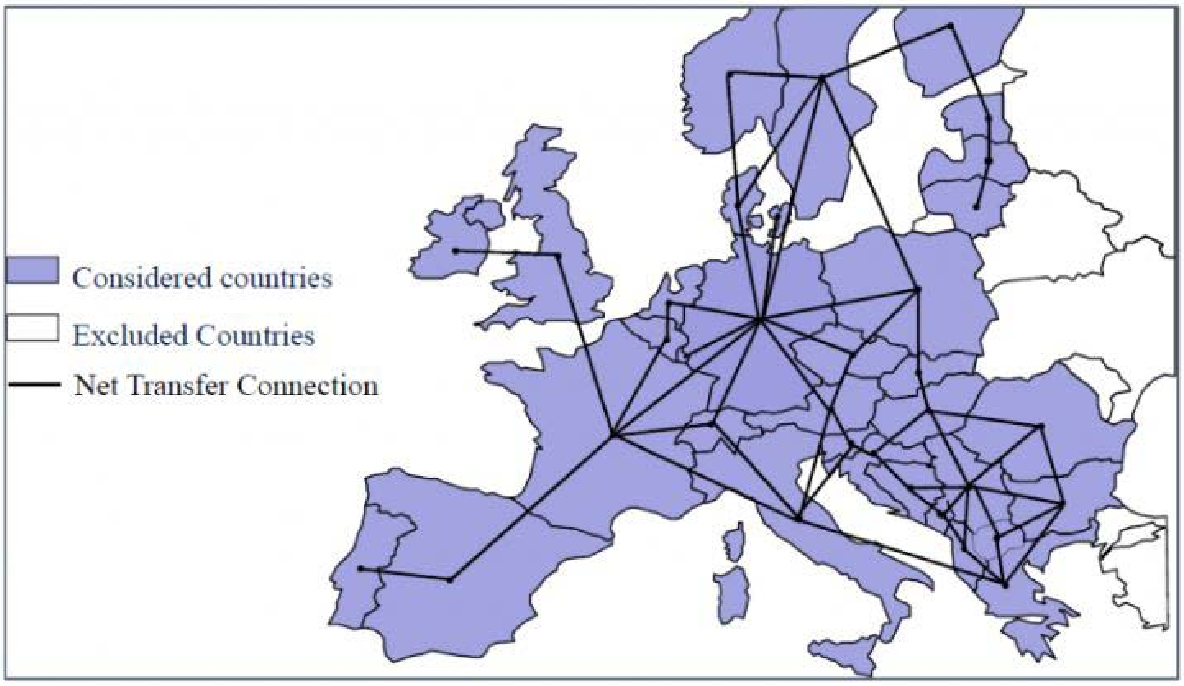

Fig. 3: Regional scope of a European ESOM taken from ELTRAMOD (TUD (Energy Economics), 2017)

The countries are modeled as one electricity system with their own electricity demand, their existing power plant fleet and their future possible investment options. The hierarchical structure of the PERSEUS-EU model, for example, relies on a flow graph (see Fig. 4). The countries are represented as nodes which are connected to one another through energy flows and gather several energy conversion units. The physical limitation of power exchange capacities between the countries is modeled by putting a restriction on the maximum amount of electricity which can be exchanged between the model nodes in each time interval. The extension of interconnector capacities and transmission losses are also considered.

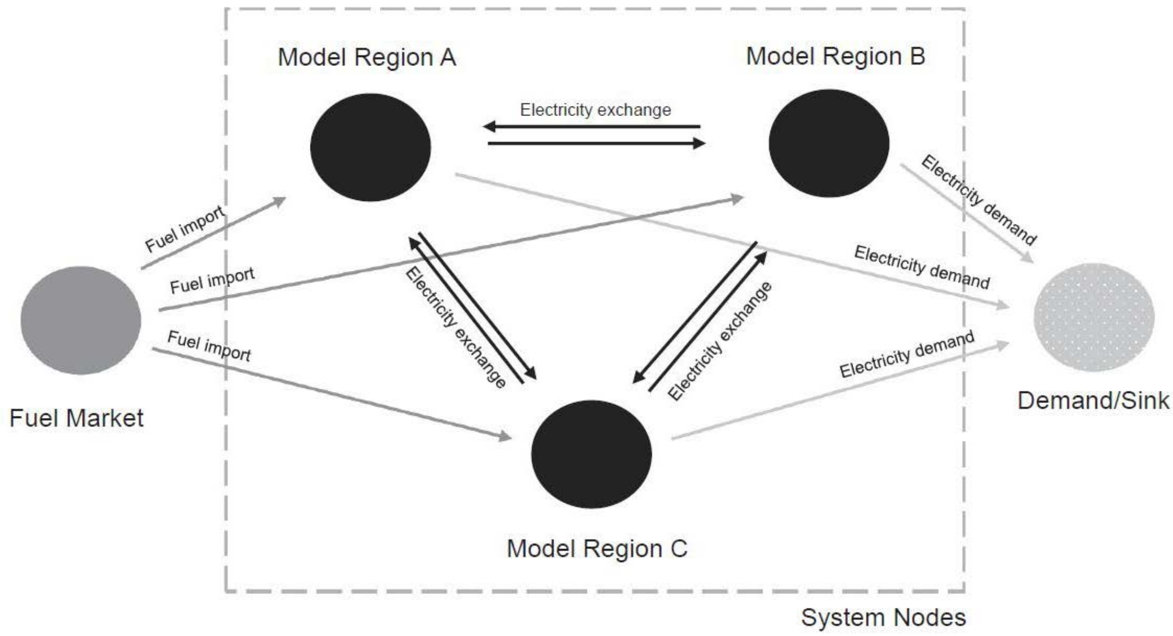

Fig. 4: Model structure of an ESOM on the basis of the PERSEUS-EU model (Paper D, Xu et al., 2020b)

PERSEUS-EU is part of the PERSEUS (Program package for Emission Reduction Strategies in Energy Use and Supply) model family, which constitutes numerous models according to their different scope and preset targets (Babrowski et al., 2014; Fichtner, 1999; Fichtner et al., 1999; Fichtner et al., 2013; Heinrichs et al., 2014; Jochem et al., 2015; Möst and Fichtner, 2010; Wietschel et al., 1997). PERSEUS is particularly used for different scenario analyses, especially the impact analysis of changing framework conditions due to political or environmental reasons. Several applications of the PERSEUS model family have been developed to answer various energy-related questions from a political or an environmental perspective.

Similarly, ELTRAMOD allows an in-depth analysis with various targets of the future European electricity system. For example, it can be used to analyze the penetration of different flexibility options and their contribution to RES integration, as well as the interdependencies among various flexibility options in the European electricity system, taking existing regulatory frameworks into account. The model has been applied for numerous national as well as EU-wide studies (Anke, 2019; Anke and Möst, 2021; Klingler et al., 2019; Müller et al., 2013).

In addition to the PERSEUS and ELTRAMOD models, alternative models have been developed to analyze energy systems with different characteristics in e.g., space, sector and time (Bhattacharyya and Timilsina, 2010; Chang et al., 2021). Each model has its strengths to address different specific challenges. The purpose of this thesis is not to compare the different ESM models, but to apply an appropriate model to a practical problem. Learning from literature, ESOM are appropriate to integrate LCA indicators.

Although well-developed, ESM need to evolve (or extend) to cope with the emerging challenges and new technological breakthroughs in the energy system transformation (Chang et al., 2021; Ellenbeck and Lilliestam, 2019; Pfenninger et al., 2014). As shown in this thesis, the applied ESM models are extended for the case studies.

2.2 Life cycle assessment and its importance

There is clearly no doubt on the importance of climate change in the future energy system transformation. Nevertheless, other environmental threats have come more into focus, e.g., air pollutant emissions (Masanet et al., 2013), material and resource demand (Piasecka et al., 2020), ozone depletion (Rasheed et al., 2021), human toxicity (Zang et al., 2020), etc. How decision-makers can integrate other potential environmental considerations beyond climate change into the shape of future energy systems is a huge challenge. In order to meet the challenge, information on different environmental impacts of energy systems is thus needed as a critical step. Effective and robust analytical and assessment methods or tools are required.

LCA is such a tool to assess the potential environmental impacts throughout the life cycle of a product (or technology), i.e., from raw material acquisition, via production, transportation and use phase, to waste management (ISO, 2006). The unique feature of LCA is the focus on a product system from a life cycle perspective, which compensates for ESM that do not generally include a systematic approach for environmental assessment. The comprehensive scope of LCA is able to avoid burden-shifting, for example, from one phase of the life cycle to another, or from one environmental impact to another.

There are four phases in an LCA: goal and scope definition, life cycle inventory analysis (LCI), life cycle impact assessment (LCIA), and interpretation, as illustrated in Fig. 5.

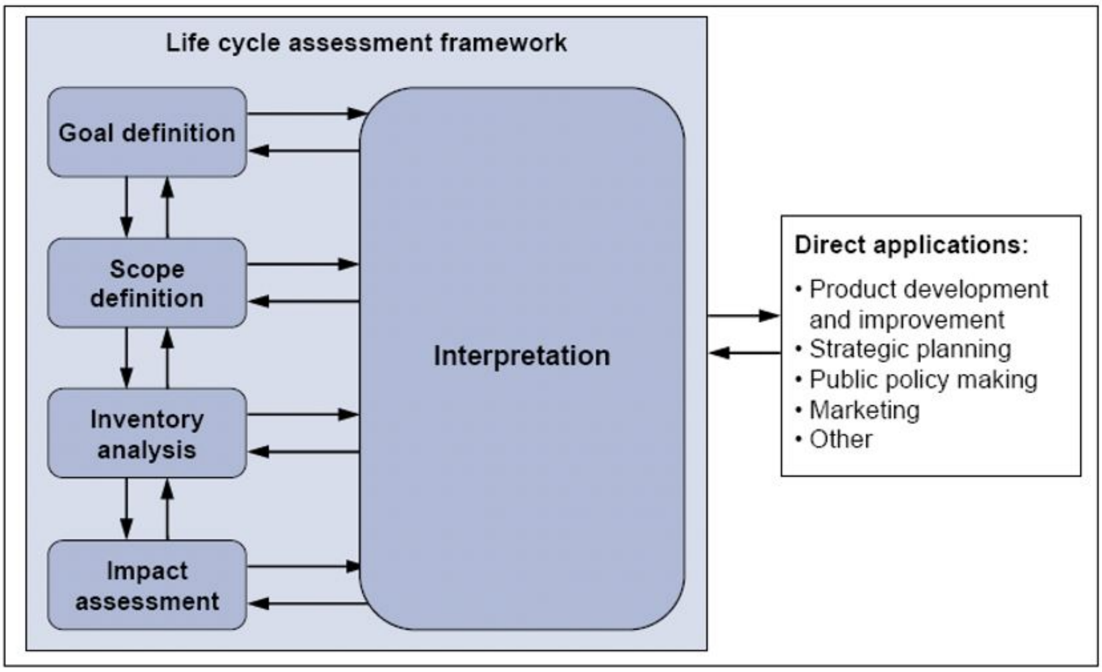

Fig. 5: Life cycle assessment framework and its applications (ISO, 2006)

In the phase of the goal and scope definition, the reasons for carrying out the study, the intended application and audience are explained. Meanwhile, the scope, including the product system, functional units, system boundaries, etc., is described. The functional unit provides a quantitative reference that can correlate the inputs and outputs of the system, which could reflect the benefit of a product. Therefore, when choosing an appropriate functional unit, the benefit of the products should be the relevant criterion. The functional unit is used as a basis for selecting one or more product systems that can provide the function, so that it enables different systems to be treated as functionally equivalent.

The LCI involves an inventory of the inputs (resources) and the outputs (emissions) for a product system over its life cycle in relation to the functional unit. Data collection to set up the LCI is one of the most time-consuming stages of an LCA study. Fig. 6 shows an effective process of data collection and calculation of an LCI. In the data collection parts, data requirements and limitations might be changed in order to meet the aim of the study. In order to manage the LCI and avoid duplication, the inventory databases have been developed in the last decades, a good example of which is the Ecoinvent database (Wernet et al., 2016). This is process-based, and contains around 18,000 LCI datasets. It covers a range of sectors, including energy, metals, forestry and wood, agriculture and animal husbandry, building and construction, waste treatments and recycling, as well as other industrial sectors.

Fig. 6: An effective process of setting up a life cycle inventory (GaBi Education, 2009)

The phase of LCIA is aimed at evaluating the potential environmental impacts of the studied system. According to the ISO standard on LCA, LCIA involves the following compulsory steps: selection of impact categories, classification and characterization (ISO, 2006). Common impact categories include climate change, ozone depletion, acidification, human toxicity, metal depletion, etc. (Lee and Inaba, 2004). The classification assigns emissions in the inventory to these chosen impact categories based on the substance's ability to contribute to different environmental issues. Characterization transforms the environmental emissions quantitatively expressed as a common unit for all contributors within each impact category, applying the concept of characterization factors to create impact category indicators (Michael et al., 2018). For example, for climate change the global warming potential is an often-used characterization factor. The unit is generally defined as CO_2-eq. where CO_2 is given a value of 1 and all other units are converted respective to their related contribution. The ISO standard on LCA also provides some optional steps to be considered in addition to the aforementioned mandatory steps: normalization, grouping or weighting (Michael et al., 2018). Normalization aims to explain the LCIA results in respect to reference values in order to express the magnitudes of the impact categories. Grouping or weighting reflects the relative importance of the chosen environmental impact categories assigned in the study.

The phase of interpretation is to identify, quantify and evaluate the results from the LCI and LCIA in order to conclude the study and give recommendations.

Depending on the purpose of the individual study, the LCA methods can be distinguished into two types: attributional and consequential LCA (Finnveden et al., 2009). Attributional LCA is defined by its aim to describe the environmentally relevant flows from and to the life cycle as well as its subsystems (Ekvall et al., 2016). Consequential LCA is defined by describing how the environmentally relevant flows will change as a response to possible decisions (Curran et al., 2005; Ekvall et al., 2016; Velez Henao, 2021). The different focuses of attributional and consequential LCA can be reflected in the choice between average and marginal data used in the modeling of the life cycle (Curran et al., 2005; Finnveden et al., 2009). Average data are those representing the average environmental impacts of a unit process in the life cycle system. Marginal data are those representing the influence of a small change in the inputs and outputs of a system on the environmental impacts of its life cycle. Attributional LCA typically uses average data, but excludes the use of marginal data. Instead, consequential LCA uses marginal data which are relevant to the purpose of assessing the consequences (Curran et al., 2005; Moretti et al., 2022).

The standard LCA is based on process-based LCI databases, which has the limitation that an LCI is not able to include all processes due to practical reasons, e.g., missing data or missing knowledge. As supplementary to a standard LCA, Input-Output Tables (IOT) become a tool for LCA practitioners when information on environmental emissions and average resource use from each sector are added. IOT state the inputs and outputs between each economic sector in average monetary terms (Dietzenbacher et al., 2013). This is called an Input-Output (IO) LCA (Nakamura and Nansai, 2016). Combining the process-based LCA and IO LCA forms a so-called hybrid LCA that takes advantage of both types of database (Nakamura and Nansai, 2016; Nikkhah and Van Haute, 2022; Peters and Hertwich, 2006; Suh, 2006). At the present stage, the use of IO data has a certain controversy. While it could assist in expanding the system boundary to consider more comprehensive input and output flows to and from a life cycle, its sector resolution is too coarse. The estimation of environmental impacts is based on the data for the “average product” from each sector. These data are used as approximations for specific products under study, which can cause a low precision and a weak robustness (Yang et al., 2017). Uncertainty emerges as to whether the insights gained from the expanded system boundaries are reliable.

The standard LCA faces challenges in assessing emerging technologies, leading to the development of prospective LCA. An LCA is prospective when the emerging technology studies are in an early phase of development, but the technology is modeled at a future more-developed phase (Arvidsson et al., 2018). How to conduct such prospective assessments in a relevant manner is a challenge for LCA practitioners, which is also one of the challenges in the model coupling between LCA and ESM for the assessment of future energy systems.

Sustainability assessment of products or technologies is normally viewed as covering impacts in three dimensions: social, environmental, and economic (Kaur and Garg, 2019). With inspiration from environmental LCA, social LCA (cf. Schlör et al., 2018; Suski et al., 2021) and life cycle costing (LCC) (cf. Mondello et al., 2021; Naves et al., 2019) are being developed. Focus on all the three dimensions from a life cycle perspective would avoid problem-shifting in a product system comprehensively. This thesis, however, focuses on environmental LCA.

2.3 Challenges of applying LCA in energy system analysis

2.3.1 Applying LCA to assess an individual technology

LCA practitioners face multiple challenges when conducting research to assess an individual technology, despite the development of an international standard.

One of the challenges is to define the system boundaries. There are three main types of system boundary in the LCI (Guinée and Lindeijer, 2002): between the technical system and the environment; between significant and insignificant processes; and between the technological system under study and other product systems. The system boundary between the technical system and the environment is obvious. However, it needs to be explicitly defined when forestry, agriculture, emissions to external wastewater systems, and landfills are involved in the life cycle (Dijkman et al., 2018; Finnveden et al., 2009; Obersteiner et al., 2007). To define the system boundary between the significant and insignificant processes is a challenge, as it is generally not clear beforehand which processes are significant and should be included, and which processes are insignificant and could be excluded. Ideally, the processes that are left out should have an insignificant contribution to the results (Finnveden et al., 2009). The system boundary between the technological system under study and other product systems has to be clarified, especially regarding multi-functional processes (Ekvall and Tillman, 1997). A multi-functional process is shared among several product systems, and it is necessary to clarify to which product system the environmental impacts should be allocated. Guidelines are available to provide several allocation recommendations, e.g., system expansion, cut-off or substitution. However, the selection of a suitable allocation procedure is challenging, as all allocation procedures seem to be reasonable and are in line with the LCA international standards. The choices of allocation methods may potentially influence the results of an LCA study. Therefore, the selected allocation procedure should be determined in line with the goal of a specific LCA study (Schrijvers et al., 2016).

Data collection is intensive in an LCA. This is often challenging due to the lack of appropriate data for the product system under study. Lack of data or low-quality data can influence the quality of the assessment results and therefore restrict the insights gained from a specific study. A discussion about data quality and uncertainty is often done with the use of sensitivity analysis and uncertainty analysis (Groen et al., 2017; Groen et al., 2014; Guo and Murphy, 2012; Heijungs and Huijbregts, 2004; Huang et al., 2013; Shimako et al., 2018; Wei et al., 2015).

2.3.2 Model coupling between ESM and LCA

The methodological challenges in the model coupling between ESM and LCA arise due to their different characteristics caused by their different explanatory aims. In detail, the models differ with respect to:

- The system's boundaries

ESM focuses on energy carriers without considering non-energy material flows and non-energy-related upstream and downstream sectors, while LCA considers the whole life cycle (i.e., from cradle to grave) of technologies to avoid burden shifting.

- The scale of technology description

ESM tends to describe conventional technologies in depth from a techno-economic perspective, whereas innovative technologies or technologies with non-standardized feedstocks are recognized as aggregated. For example, in the PERSEUS model, biomass, wind and solar technologies are highly aggregated without detailed technical breakdown. On the contrary, LCA considers the energy and material flows of technologies in as detailed a way as possible, however, it does not consider the relevance to the energy system as a whole.

- The temporal and spatial scales

ESM clarifies its specific temporal and spatial scales. The temporal and spatial coverage of different studies could be quite different according to their specific research aims. From a temporal perspective, typical LCA is a steady-state approach. As for the spatial scale, the majority of LCA models have global coverage (Mutel et al., 2019). Typical LCA is normally not focused on the local impacts for a product system (Hauschild, 2006), but the regionalization of LCA results from generic into smaller spatial units could be accomplished by applying other analytic tools such as a geographic information system (GIS) (Liu et al., 2014).

- Model logics

ESM is based on the logic of linked technologies (typically, but not only, via markets): to model the entire energy system or large chunks of the energy system, trying to derive a mix of energy technologies based on some specific objectives. LCA focuses on assessing single technologies, without modeling the connection to competing technologies. Therefore, typical LCA does not consider the possible interlinked impacts due to e.g., changes of the composition of materials or changing efficiencies. LCA considers the relationship between competing technologies in a different way, generally aiming to compare their environmental chains.

The different characteristics mean the two models differ in their data requirements, which leads to the fact that data from ESM databases and LCA databases are seldom directly comparable.

Based on the above discussion, the first challenge to overcome is to identify elements (variables, parameters, etc.) in both models which should be interlinked and harmonized in the model coupling in a systematic way. The prima facie interaction between ESM and LCA seems to be quite un-challenging. The common parameters or variables related to the energy sectors are relatively straightforward to identify, including technical parameters such as energy conversion efficiency, life time of energy technologies, etc., as well as energy mix. However, energy mix used for non-energy sectors is often overlooked and no consideration is given to the harmonization of relevant data. The consideration of energy mix in non-energy sectors requires a precise understanding of all upstream sectors as well as the trade flows of the materials: the life cycle environmental impacts of single technologies, or a set of technologies, depend crucially on the chosen energy mix in the upstream sectors. For example, the life cycle environmental burdens of wind power technologies depend partly on the upstream electricity mix that was used to produce wind turbines, while the installed capacity of wind technologies in ESM will in turn influence the electricity mix. A feedback loop thus exists between energy sectors and non-energy sectors. As shown in Fig. 7, non-energy sectors work as upstream sectors to provide non-energy product mix (e.g., metals) for energy systems and vice versa. This implies that a simple connection of ESM and LCA does not consider the possible feedback loops, which potentially leads to an over- or underestimation of the environmental impacts.

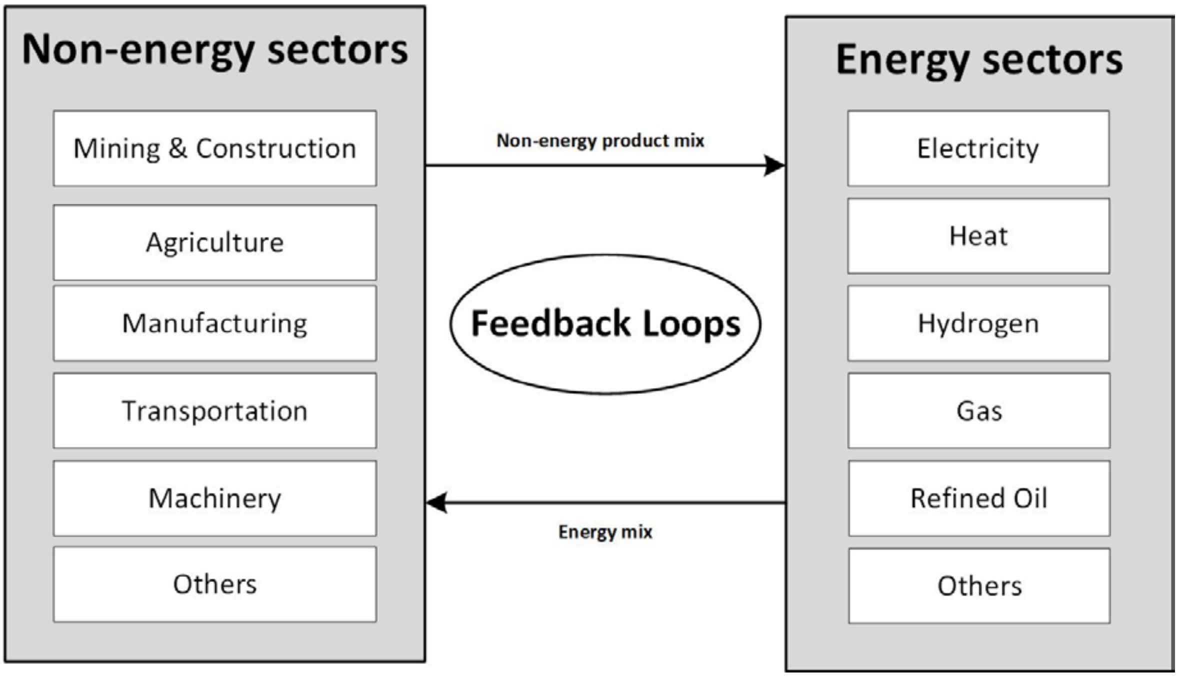

Fig. 7: Feedback loops between the life cycle processes for energy systems

The second challenge to overcome is to conduct a prospective LCA model. An important driver for the energy transition is technical progress, i.e., innovation to improve energy efficiency while reducing, in particular, the resource requirements. Typically, ESM implements technical progress by changing energy conversion efficiencies or by implementing new technologies. However, in general LCA does not take into account technical progress by considering learning curves when analyzing a particular technology. Technical progress is considered only by analyzing "new" (non-mature) technologies. Thus, a prospective (dynamic) LCA model is required. Such a model needs to consider technological progress in both the market-proved technologies and emerging technologies. Additionally, the assumptions with regard to technical progress should match those used in the coupled ESM.

3 Methodology

3.1 Applying LCA for an individual technology assessment (the basic LCA model)

LCA converts material and energy inputs into environmentally relevant outputs per functional unit associated with all stages of the life cycle of an individual technology (product or service). The general formulation of an LCA model on the technological scale is described in Eq. (1):

$$h_l = \sum_{k \in K} \sum_{i \in I} \sum_{i' \in I} Q_{l,k} B_{k,i'} A_{i',i} f_i \tag{1}$$

$$\forall\, l \in L$$

Where h_l represents the potential environmental impact of impact category l over the life cycle of the technology under study per functional unit, $Q_{l,k}$ is the characterization factor which reflects the relative contribution of emission k to the environmental impact in category l for the technology under study. $B_{k,i'}$ represents the environmental output of emission k by process i' for technology under study. $A_{i',i}$ represents the linkage between the processes i' and i that shows how many products from the process i' are required in process i for the technology under study. f_i denotes the final demand in process i which specifies the functional unit for the technology under study. Typically, the functional unit is set to one mass of product produced by the technology under study. K represents the set of all emissions within one impact category, while I is the set of all processes.

There are several LCIA methods available. The ReCiPe method is one of the most recent and comprehensive methods and is widely used by LCA practitioners in many scientific studies (Huijbregts et al., 2016; Zelm, 2009). It provides harmonized characterization factors at midpoint and endpoint levels. Characterization factors at the midpoint level indicate impacts along the impact pathway, typically at the point after which the emissions are assigned to each impact category. Characterization factors at the endpoint level correspond to impacts on areas of protection. Fig. 8 provides an overview of the impact categories that are covered in the ReCiPe methodology and their relation to the areas of protection. It involves 18 midpoint impact categories and 3 endpoint areas of protection, i.e., human health, ecosystem quality and resource availability. The midpoint characterization has a stronger relation to the environmental flows and a relatively low uncertainty, while the endpoint characterization provides better information on the environmental relevance of the environmental flows, but also increases uncertainty in the results due to a further aggregation across mid-point categories (Bare et al., 2000; Huijbregts et al., 2016).

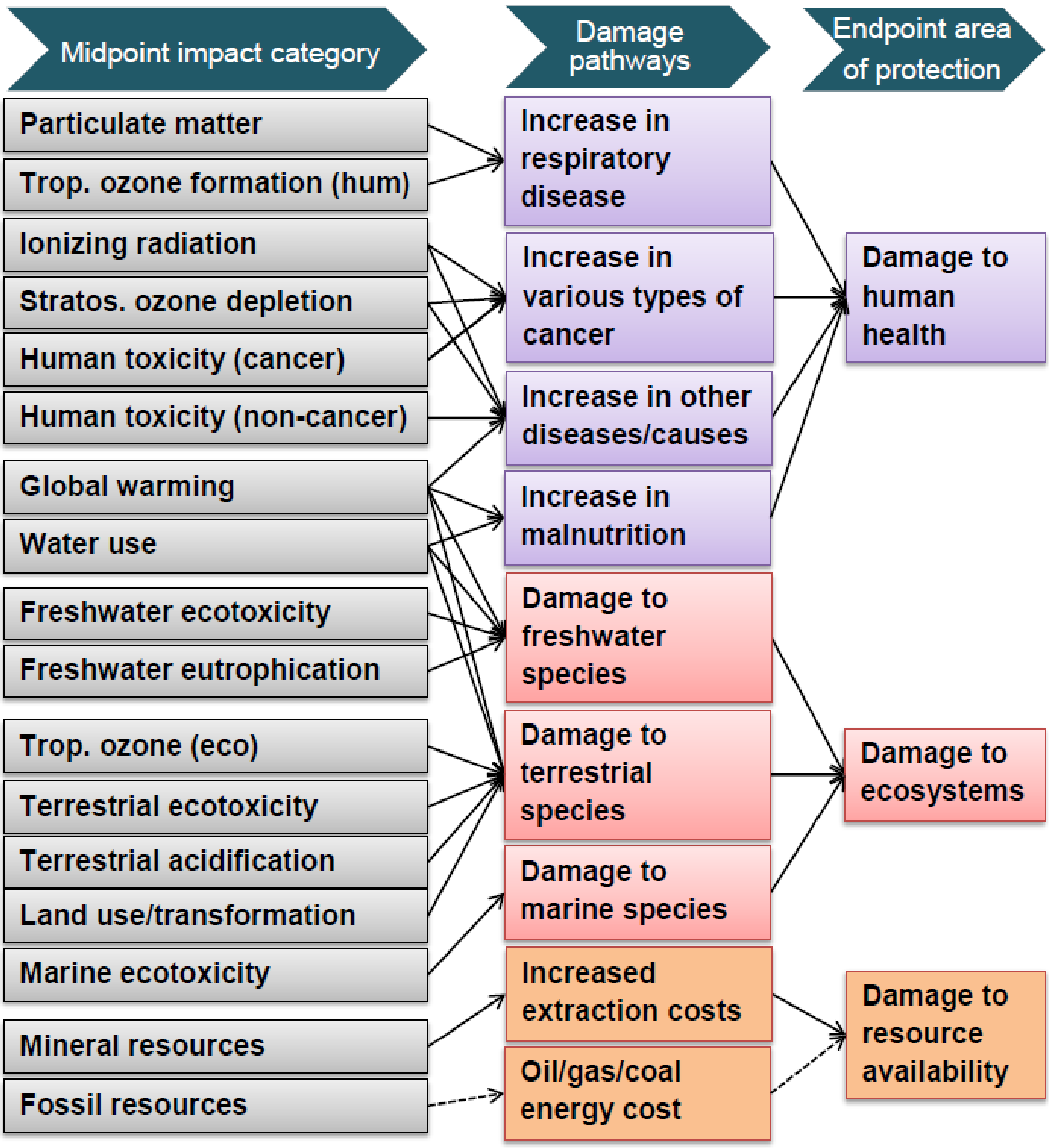

Fig. 8: Overview of the impact categories covered in the ReCiPe methodology and their relation to the areas of protection (Huijbregts et al., 2016). The dotted line means there is no constant mid-to-endpoint factor for fossil resources.

3.2 Development of a framework for model coupling

3.2.1 The development of the EAFESA framework

The EAFESA framework was developed as a guideline for the model coupling between LCA and ESM. The idea of the EAFESA Framework is to use the most promising methodological advantages from the coupling approaches based in either LCT or energy system thinking, and merge them into one holistic methodology, making use of the lessons learned from recent studies.

Current research on coupling ESM with LCA can be separated into two approaches (see Table 1). The first is dominated by an energy system perspective; and the second has its origin in LCA and still focuses on an LCT perspective.

The development of these approaches has experienced two stages: (1) either with energy system thinking or with LCT, and (2) with both life cycle and energy system thinking.

The approach of energy system thinking stands for the integration of life cycle environmental indicators into ESM. It is largely used to research the possible cost-effective pathways in energy systems to reduce GHG emissions and other pollutants. The strength of this approach is to apply standard process-based LCA allowing for adjustment in degree of detail and specificity of the ESM; furthermore, to provide the techno-economic and life-cycle results in one overall model. However, even though coupling both models, only the existing LCA databases are used as an input for ESM. There is no consideration of data harmonization, and no consideration of technical progress in LCA, leading to an overestimation of environmental impact and an underestimation of possible resource demands.

The approach of LCT to couple LCA and ESM is based on the idea of coupling different single technologies into a combined system in LCA which is then scaled up to the sector level (Berrill et al., 2016; Hertwich et al., 2015; Pehl et al., 2017). This approach is more widely applied to assess the trade-offs in terms of environment, resources, and various other aspects of the shaped energy system pathways. Contrary to the approach of energy system thinking, the approach of LCT tries to develop a prospective LCA for technology mix to achieve better assessment results. Technological improvements are reflected in the improved conversion efficiencies, load factors, and next-generation technology adoption, as well as materials parts (Berrill et al., 2016; Hertwich et al., 2015; Pehl et al., 2017). However, there is no consideration of the pathways of future emerging promising technologies. Hybrid-LCA is widely used for the LCA methodology, causing uncertainties due to the highly aggregated input-output data used. Additionally, data harmonization is incomplete and limited to the technological parameters related to energy sectors.

The development of the coupling approaches sees a combination of both life cycle and energy system thinking in subsequent studies (cf. Junne et al., 2021; Junne et al., 2020a). Life cycle and energy system thinking considers the development of prospective LCA, using process-based LCA (other than the IO based hybrid LCA) to avoid additional uncertainties due to the highly aggregated input-output data used. The LCI data are based on the existing databases. The prospective LCA model is done by adjusting the technological parameters according to the data from ESM, or from other sources. As a result, foreground data harmonization is considered to some extent. However, data harmonization of ESM and LCA is not the main focus of the studies, but the way to obtain data for the prospective LCA model, leading to incomplete consideration of data harmonization. For example, Junne et al. (2021) consider the future development of the background energy mix, however, from other sources. Additionally, in their prospective LCA model, only existing technologies are considered, without considering the pathways of future emerging promising technologies. The other unresolved challenges in coupling both models (i.e., data harmonization of energy mix in non-energy sectors, and prospective LCA for future emerging promising technologies) are considered by this thesis.

Table 1: Comparison of EAFESA and recent literature for LCA and ESM model coupling, adapted from Table S1 in the Supplementary Materials of Paper B (Xu et al., 2020a)

Responses to challenges	**Coupling approaches**		**Data harmonization**		**LCA approach**		**A breakdown of technologies (Specification)**	
	energy system thinking	life cycle thinking	Foreground technological parameters (Energy sectors)	Background energy mix (Non-energy sectors)	Process-based LCA	IO based Hybrid-LCA	Prospective LCI for representative existing technologies	Prospective LCI for future emerging technologies
This study	×	×	×	×	×		×	×
Junne et al. (2021)	×	×	×		×		×	
Junne et al. (2020a)	×	×	×		×		×	
Luderer et al. (2019)		×	×			×	×	
Fernández Astudillo et al. (2019)	×	×	×		×		×	
Volkart et al. (2018)	×	×	×		×		×	
Pehl et al. (2017)		×	×			×	×	
Rauner and Budzinski (2017)	×				×			
Berrill et al. (2016)		×	×			×	×	
García-Gusano et al. (2016a)	×				×			
García-Gusano et al. (2016b)	×				×			
Hertwich et al. (2015)		×	×			×	×	
Santoyo-Castelazo and Azapagic (2014)		×			×			
Loulou and Regemorter (2008)	×				×			

Learning from recent studies, the EAFESA framework explicitly overcomes unresolved challenges in coupling ESM and LCA with both life cycle and energy system thinking. Firstly, EAFESA proposes to map the scale of technologies considered in both approaches and disaggregate technologies if necessary. If aggregated technology groups in ESM models are formed (e.g., due to similar costs), and a disaggregation is not possible due to lack of data, then for each technology group sub-modules consisting of different technologies are defined, using primarily LCA data. As long as market-proven technologies are considered, modeling of technical progress typically follows learning curve approaches (Louwen et al., 2016). In addition, prospective but not yet market-proven technologies have to be added to the sub-modules, generating sub-module specific technology scenarios. The derived technology mix in each sub-module is then implemented into an ESM. Secondly, EAFESA suggests identifying the necessary set of harmonized data for both approaches and then making the harmonization of the data. Since both approaches differ in their system boundaries, only the harmonization of those data where both approaches address the same parts of the entire systems is necessary: data referring to energy carriers which overlap in the ESM and LCA. In addition, those environmental coefficients (both directly combustion-based and life-cycle based) which are implemented in ESM need to be harmonized. The data which should be harmonized comprises mainly those related to technical progress, e.g., energy conversion efficiencies, lifetime of energy technologies, operating time in both approaches. Next to the technology data, the used energy mix in the LCA should correspond to the ESM energy mix, since the energy mix has a significant effect on the environmental impacts of upstream and downstream energy and non-energy sectors. The remaining data, i.e. those which are only modeled in an LCA, are of no relevance for this step (see Table 2).

Table 2: Data harmonization of LCA and ESM (Paper B, Xu et al., 2020a)

	Energy sector	**Non-energy sector**
Energy carriers and material flows	×	-
Environmental coefficients	(×)	-
Energy mix	×	×
Technological progress	×	-

Notes: × fully harmonization, (×) partly harmonization, - excluded harmonization

The core of the EAFESA is an intensive exchange of information to improve the findings, which makes use of the general setting of the LCA methodology (ISO, 2006), consisting of the following four steps: goal and scope definition, inventory analysis, impact assessment, and discussion and implications, as shown in Fig. 9. The challenges mentioned above are recognized and considered in the four steps of EAFESA. In the first step, goal and scope definition, it is crucial that a common goal is established, with background information exchange based on defined scenarios. Additionally, the research scope (e.g., system and geographical boundaries) should be clarified. In the second step, inventory analysis, LCA focuses on technological data collection through the whole lifespan, while ESM revolves around both economic and technological data collection through the energy sector. Meanwhile, this step offers an interface for technology mix definition, collected data exchange and harmonization. In the third step, impact assessment, the calculated results (e.g., environmental impacts and energy mix) are exchanged and discussed between LCA and ESM. The interrelation between LCA and ESM might lead to an iterative feedback loop. The energy mix derived by the ESM should be used as an input for the LCA. The resulting life cycle environmental impacts of each technology could affect the environmental performance of the identified transformation pathways, leading to a possible necessary adjustment of the pathways, if e.g., policy targets are violated. In the final step, discussion and implications, the implications for decision-making processes and policy impact assessment studies are discussed.

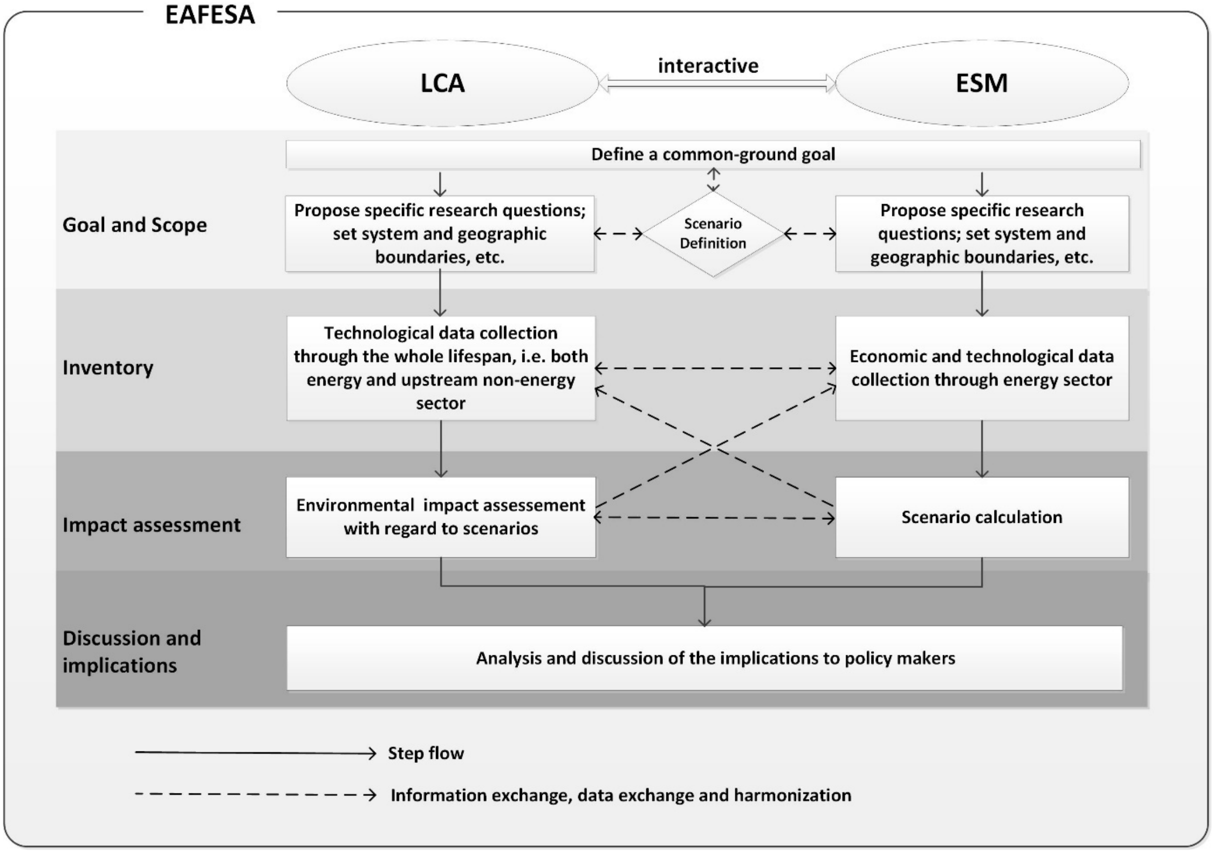

Fig. 9: Overview of Environmental Framework for Energy System Assessment (EAFESA) (Paper B, Xu et al., 2020a)

The applications of the EAFESA framework can be separated into two directions according to their different study aims: (1) to integrate the ESM output to LCA, and vice versa, i.e., (2) to integrate the LCA indicators to ESM. Different study aims require extension of the existing LCA and/or ESM models when coupling both models, in addition to applying the EAFESA framework.

3.2.2 Integrating the ESM output to LCA (an extended LCA model)

In order to adequately assess the trade-offs in terms of environment, resources, and various other aspects of the shaped energy system pathways, model extensions for LCA have to be carried out, in order to integrate the ESM output to LCA, based on the basic LCA model shown in Eq. (1) in Section 3.1. As shown in Eq. (2), the parameters of technology classification and temporal scale are added in the formulations.

$$h_{u,y,l} = \sum_{k \in K} \sum_{i \in I} \sum_{i' \in I} Q_{u,y,l,k} \, B_{u,y,k,i'} A_{u,y,i',i} f_{u,y,i} \quad (2)$$

$$\forall \, u \in U, \forall \, y \in Y, \forall \, l \in L$$

Where $h_{u,y,l}$ represents the potential environmental impact in category l over the life cycle of technology u in the year y in a functional unit. $Q_{u,y,l,k}$ is the characterization factor which reflects the relative contribution of emission k to the environmental impact in category l for the technology u in year y. $B_{u,y,k,i'}$ represents the environmental output in emission k from process i' for technology u in year y. $A_{u,y,i',i}$ represents the linkage between the processes i' and i that shows how many products from the process i' are required in process i for technology u in year y. $f_{u,y,i}$ denotes the final demand in process i which specifies the functional unit for technology u in year y. K represents the set of all emissions, while I is the set of all processes.

Subsequently, Eq. (3) is used to assess an energy system containing multiple technologies.

$$Z_{y,l} = \sum_{u \in U} h_{u,y,i} E_{u,y} \quad (3)$$

$$\forall \, \mathrm{y} \in Y, \forall \, l \in L$$

Where $Z_{y,l}$ is the total environmental impact in category l over the life cycle of all considered technologies in the year y. $E_{u,y}$ equals the energy generation or energy demand by technology u in the year y, derived from the ESM model.

The studies aiming to assess the trade-offs of the already-shaped energy systems do not integrate the LCA indicators to ESM. As shown in Fig. 10, applying the EAFESA framework to guide the model coupling between ESM and an extended LCA model requires no consideration of the iterative feedback loops.

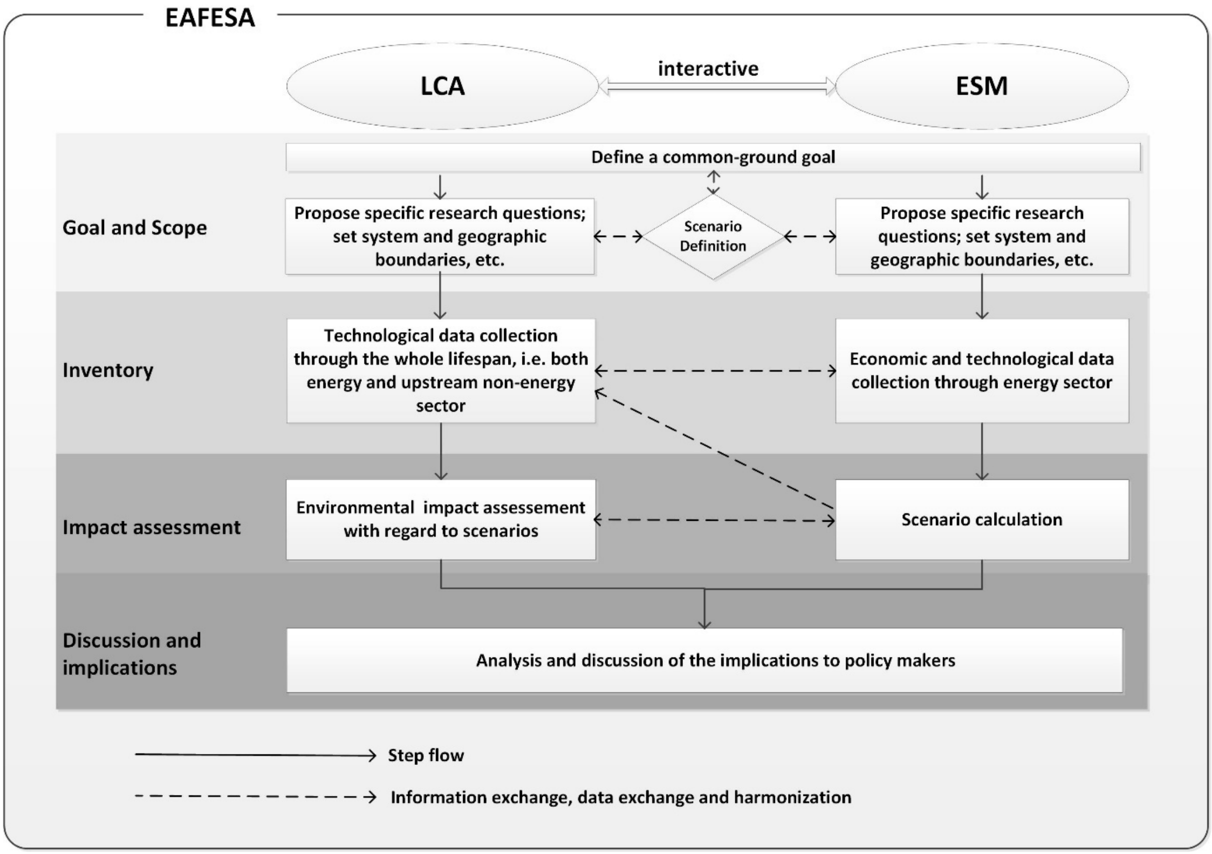

Fig. 10: Applying the EAFESA framework to guide the model coupling between ESM and an extended LCA model

3.2.3 Integrating the LCA indicators to ESM (extended LCA and ESM models)

To provide knowledge-based information on potentially feasible and effective solutions to balance trade-offs in future energy systems, model extensions for ESM have to be conducted in order to integrate the LCA indicators into ESM. The LCA indicators achieved are from an extended LCA model introduced in Section 3.2.1.

Energy system optimization models, which are widely used for climate change mitigation targets, are good tools for integrating other environmental life cycle non-climate impacts in the design of future energy systems. Based on this, the thesis focuses on the extension of the optimization models in order to integrate LCA indicators.

To integrate additional criteria, ESM is often extended with a multi-objective formulation (e.g., Haas et al., 2019; Parkinson et al., 2018). In the following, the augmented ε-constraint method is introduced. Generally, the ε-constraint method uses all but one objective function as secondary conditions in addition to the technological, political and environmental constraints, optimizing the selected objective function (Ahmadi et al., 2014; Najjarbashi and Lim, 2015; Zgür et al., 2019). The conventional ε-constraint approach fails to guarantee efficient solutions (i.e., Pareto-optimal solution), and an augmented version of the method avoids this flaw. Pareto-Optimality refers to a solution in which an improvement of one criterion is not possible without worsening the performance of at least one other criterion.

The augmented version of the method sees the implementation of slack variables related to those objective functions, which are used as constraints (Censor, 1977). For example (cf. Paper C), the selected objective function minimizes the total system expenditure (EX). The objective functions used as additional constraints are GHG emissions addressing climate change (CC), and metal demand addressing metal depletion (MD). Thus, the optimization problem looks as follows:

$$\text{Minimize } (f_{EX}(x) - \delta \times \left(\frac{s_{CC}}{r_{CC}} + \frac{s_{MD}}{r_{MD}}\right)) \tag{4}$$

Subject to:

$$f_{CC}(x) + s_{CC} = e_{CC} \tag{5}$$

$$f_{MD}(x) + s_{MD} = e_{MD} \tag{6}$$

$f_{EX}(x)$ represents all decision-relevant expenditure. δ is an auxiliary parameter, which is generally small, e.g., 10^{-3}. r_{CC} and r_{MD} gives the range of the objective functions regarding CC and MD, respectively. s_{CC} and s_{MD} are the slack variables to force the model to produce only efficient solutions, which drives the model to look for the optimal solution of Eq. (4). They are non-negative variables related to CC and MD, respectively. Eq. (5) and Eq. (6) are the constrained objective functions for CC and MD, respectively. e_{CC} and e_{MD} define the upper limits for GHG emissions and metal demand, respectively. $f_{CC}(x)$ and $f_{MD}(x)$ are positive variables representing the amounts of GHG emissions and metal depletion within the entire system, respectively.

The augmented version of the ε-constraint method allows for optimal solutions with GHG emissions and metal depletion below the given upper limit, i.e., below e_{CC} and e_{MD}, respectively. To explore possibly effective solutions to balance the trade-offs, some exploratory scenarios should be defined. The combination of the upper limits, e_{MD} and e_{cc}, characterizes each scenario.

To identify the upper limits, first, a payoff table is calculated by minimizing separately the EX, CC, and MD, to determine the best and worst solutions regarding the three objectives. For each objective optimization, the other two objectives are relaxed. The combined best solution of the three calculations regarding CC and MD defines the utopia point and is set to 0%. The combined worst solution is the nadir point and is set to 100%. The ranges between the utopia and nadir points of CC and MD obtained describe the upper limits regarding CC and MD, i.e., e_{MD} and e_{cc}, respectively.

Integrating the ESM output to LCA is suggested to be carried out before integrating the LCA indicators to ESM, as discussed above. The energy mix derived by the ESM is used as an input for the LCA. The resulting life cycle environmental impacts of each technology affect the shape of future energy systems and, in return, affect the environmental performance of the identified transformation pathway. The interrelation between LCA and ESM leads to an iterative feedback loop, which should be noted and achieved by both LCA practitioners and ESM modelers.

4 The appended papers with case studies

Firstly, a case study is introduced that applies the standard LCA model to assess an individual technology. Wind power, as one of the most promising emerging energy technologies, is chosen as the research object for the case study (Paper A).

Secondly, a case study to assess the environmental impacts in the European energy system is conducted, as a demonstration to explicitly show how to apply the EAFESA framework to overcome the challenges in the model coupling between ESM and LCA, (Paper B, which also develops the EAFESA framework). Additionally, two case studies are conducted which each consider one of the two model coupling directions, i.e., to integrate LCA indicators to ESM, or/and to integrate ESM output to LCA, respectively. These two case studies have specific study aims: to include the impact of metal depletion on the European decarbonized electricity system (Paper C), and; to assess the GHG emissions of EV considering different charging strategies (Paper D).

In the following, the case studies are summarized by briefly describing the respective background, methodologies applied, and major results. The corresponding papers are included in Part II of the thesis.

4.1 Applying LCA: assessing environmental impacts of wind technology

Switching from a fossil-based to an environment-friendly energy supply system requires the deployment of renewable technologies. Wind power is considered as one of the most promising renewable energy sources and has been rapidly developing worldwide, e.g., in China (Liu et al., 2017), in recent years. A detailed analysis of the life cycle environmental performance of wind power is able to provide scientific information to the relevant stakeholders, including the potential negative environmental impacts of wind technologies.

Against this background, Paper A provides a complete profile of the life cycle environmental impacts of wind power, based on the situation of a typical wind power plant in Inner Mongolia, China. The investigated wind power plant is equipped with 18 sets of 1500-kW wind turbines and 30 sets of 750-kW wind turbines. Each 1500-kW wind turbine tower is connected to a 1600-kVA box-type transformer, while each 750-kW wind turbine tower is connected to an 800-kVA box-type transformer. According to the statistics, average electricity generation is around 130 GWh with a 20-GWh power curtailment. The power plant is operational and the designed operational life is 20 years. It is assumed that in the end-use process, recovered materials would be included in the production of new components for wind technologies. The LCA analysis is credited for the recovered materials represented by negative values.

For this purpose, the standard LCA methodology is applied, according to the ISO guidelines (ISO, 2006). The goal is to evaluate the environmental impacts by applying an attributional process-based LCA model to a typical wind power plant in China. The functional unit is defined as 1 kWh electricity generation from the power plant. The system boundary is set from cradle to grave. It consists of both upstream and downstream processes in addition to the process of operation and maintenance of the power plant, including processing and production of raw materials as well as their transportation and installation, disassembly and disposal.

The data of the foreground system, i.e., data related to the wind power plant, is mainly collected from suppliers' technical and maintenance manuals. The data of the background system, i.e., upstream and auxiliary processes, are obtained from the Ecoinvent database.

The LCIA is conducted by applying the mid-point CML 2001 method. The results show low GHG emissions and low abiotic fossil depletion, accounting for 0.8% and 0.6% respectively, of those yielded by coal power plants in China, and 1.2% and 0.8% respectively, of those yielded by gas power plants in China. Further, the results show a significant reduction in the values of the environmental impacts of acidification, eutrophication, human toxicity and eco-toxicity, compared to those of coal and natural gas power plants. However, these encouraging results are accompanied by higher abiotic depletion (elements) and ozone layer depletion, which should be taken into consideration.

A contribution analysis of the environmental impacts with regard to the life cycle processes is shown in Fig. 11. The overall environmental impacts of environmental impact indicators are assumed to be 100%. A negative value, i.e., credits, is assigned to the disassembly and disposal, due to the utilization and substitution of the recovered materials for the primary materials. The results show that the production process is the largest contributor to all the environmental impacts. Among the components of a wind power plant, the production of towers contributes the most to the GWP, and the production of towers and rotors are the most important contributors to ADP fossil. The process of transportation has the lowest impacts in most cases. The environmental impacts in the processes of installation and operation are of minor importance compared to the production process, because there is no fuel consumption in the operation process, while in the production process there is a large raw materials input.

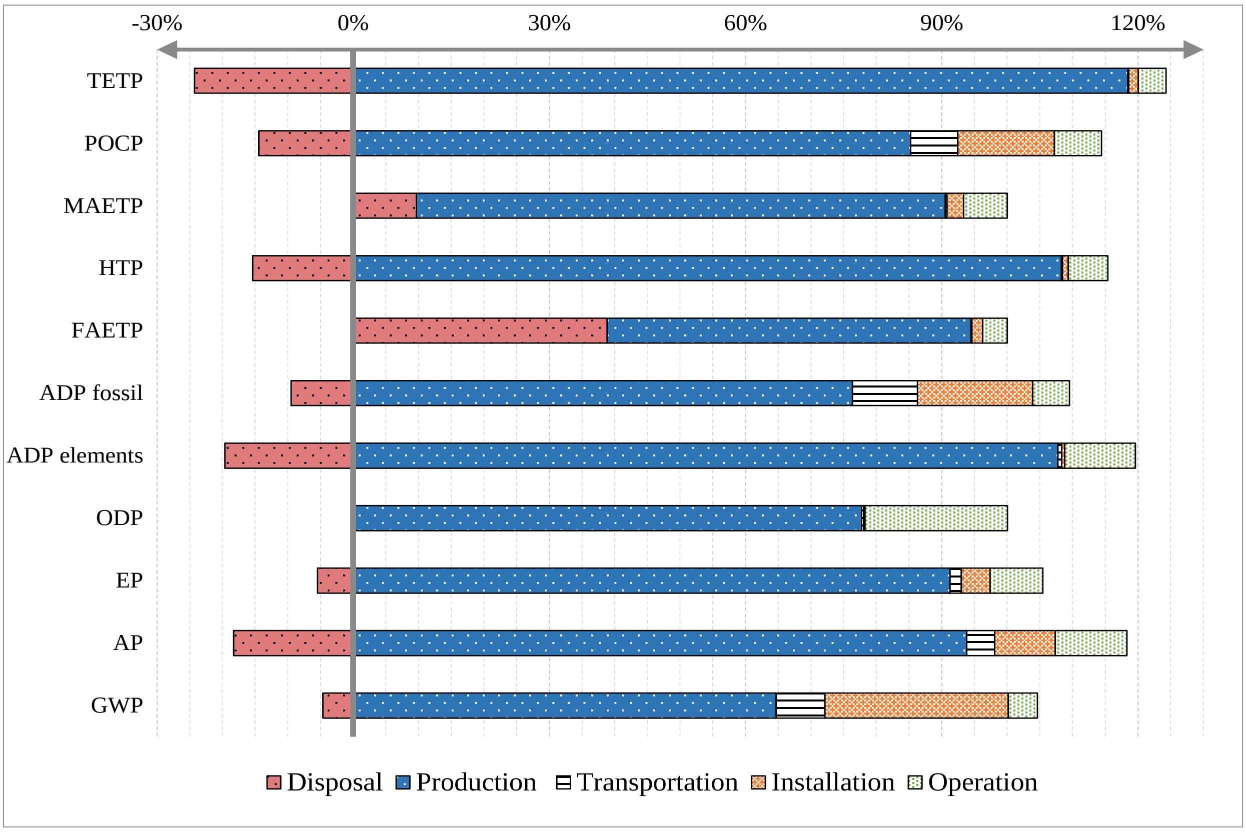

Fig. 11: Environmental impacts associated with different life cycle processes. Global Warming Potential (GWP), Abiotic Depletion (ADP elements and ADP fossil), Acidification Potential (AP), Eutrophication Potential (EP), Human Toxicity Potential (HTP), Ozone Layer Depletion Potential (ODP), Terrestrial Eco-toxicity Potential (TETP), Freshwater Aquatic Eco-toxicity Potential (FAETP), Marine Aquatic Eco-toxicity Potential (MAETP), Photochemical Ozone Creation Potential (POCP). (Paper A, Xu et al., 2018)

Additionally, sensitivity- and scenario-based uncertainty analyses are applied in order to explore technical and policy suggestions for the development of wind power technologies. Sensitivity analysis shows that steel, copper and resin are the most critical influences on several multiple environmental impacts, while fiber glass, cast iron, concrete, and reinforcing steel are not imperative for yielding environmental impacts. Uncertainty analysis explores the impacts of wind curtailment and the impacts of wind turbine sizes on the environmental impacts of the wind power plants. The power curtailment is mainly due to the poor power distribution capacity in the locality, i.e., the extension of the utility grid is not advancing at the same rate as the development of wind power. The avoidance of wind curtailment would decrease 14% of the entire environmental impacts of unit electricity generation, indicating a long-term requirement of the power grid development to support large-scale power transmission for wind power systems. The other uncertainty analysis is regarding the environmental impacts of different average turbine sizes. The current wind power plant with an average turbine size of about 1 MW (18 turbines of 1500 kW and 30 turbines of 750 kW) is compared with an average size of 1.5 MW (33 turbines of 1500 kW) originally designed for the plant. The results see both positive and negative impacts of scaling up the turbines on the environmental performances of the wind power plant. It indicates there is no direct relationship between the size of the turbines and the life cycle environmental impacts. In contrast, choices of materials or their substitution had a high influence from the perspective of climate change and environmental protection.

The case study indicates high environmental performance and renewability of wind power technologies. From the life cycle perspective, the upstream processes have the largest contribution to all of the environmental impact indicators. Additionally, it is the choice of materials, rather than wind turbine sizes, that determines the environmental performance of wind technologies.

4.2 Applying the EAFESA framework

4.2.1 Assessing the trade-offs in the low-carbon electricity system

The significance of the need to transition to a low-carbon energy system has been acknowledged worldwide considering sustainability and energy supply security. The European Union (EU) has established the Strategic-Energy-Technology-Plan (SET-Plan) to accelerate the development and deployment of low-carbon technologies, in particular, wind and solar technologies (European Commission, 2015c). The integration of intermittent wind and solar technologies leads to flexibility requirements such as energy storage systems, etc. The complex links and interdependencies between the technologies will play a crucial role for future energy systems. The analysis of the environmental impacts of the different technology mixes according to different interventions or policies from both life cycle and energy system perspectives will provide insights for policymakers beyond climate change.

Against this background, the case study in Paper B analyzes and assesses possible future European electricity systems based on three different energy scenarios. The focus is on flexibility options with different levels of renewable penetration and carbon mitigation targets for EU27 + 3 (i.e., Switzerland, Norway and the United Kingdom[1]) countries as they performed in the Horizon 2020 project REFLEX (Herbst et al., 2016a; Herbst et al., 2016b; Poganietz et al., 2017). The other intention to include the case study in Paper B, in which the EAFESA framework is developed, is to demonstrate the applicability of the EAFESA framework.

The first scenario, termed Mod-RES, serves as a reference scenario assuming that current climate and energy policy targets and actions are realized with no new policy measures introduced. Both of the other two scenarios suppose additional policy actions which achieve a GHG reduction target of 80% of GHG emissions until 2050 compared to 1990, and a specific GHG reduction target for the electricity sector of over 80% for the same period (Zöphel et al.,

[1] Paper B was published prior to the UK exit from the EU, hence data refers to EU+28.

2019). Although the climate target is becoming more stringent, as announced in the European Green Deal, to achieve carbon neutrality by 2050, the case study uses a looser target, as Paper B was published before the announcement of the new policy (Fetting, 2020). The scenarios differ by assuming a more centralized setting (High-RES Central), comparable to the Mod-RES Scenario, and a more decentralized setting (High-RES Decentral) of the energy system (Herbst et al., 2016a; Herbst et al., 2016b; Poganietz et al., 2017).

For this purpose, the framework of EAFESA is applied by coupling LCA and the ESM model ELTRAMOD. ELTRAMOD is used to analyze the penetration of different flexibility options and their contribution to renewable energy integration, as well as the interdependencies among various flexibility options in the European electricity system. The coupling direction is to integrate the ELTRAMOD output to the LCA model (see Fig. 12), and thus the extended LCA model (Eq. 2-2) is applied and no feedback loops are observed in this case study.

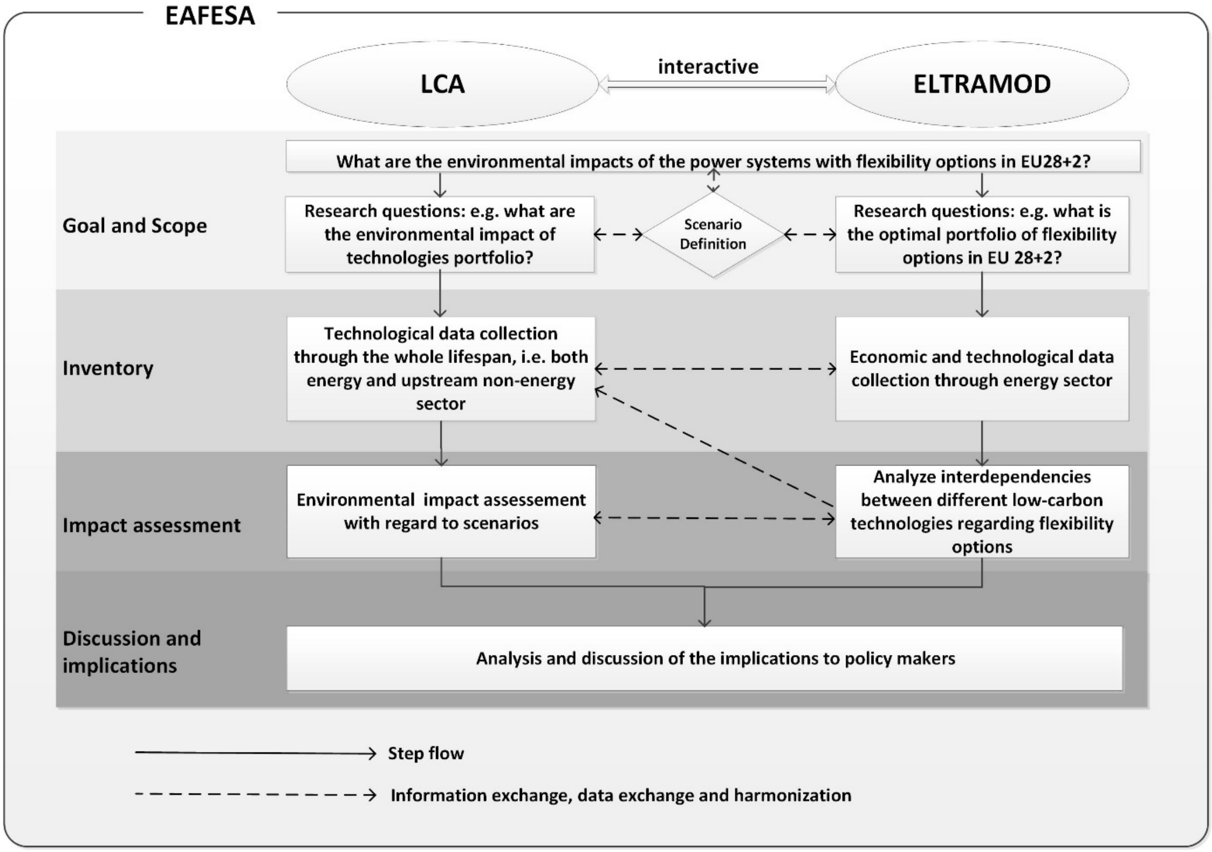

Fig. 12: Applying EAFESA: combining LCA and ELTRAMOD to a European electricity system (Paper B, Xu et al., 2020a)

The challenges in the model coupling between LCA and ELTRAMOD are overcome during the four steps of the EAFESA framework and are reflected in the two aspects.

Firstly, a prospective LCA considering both market-proved and emerging technologies is developed. The average technologies assumed in ELTRAMOD are disaggregated using LCA data. In this case, wind and solar energy are especially relevant. For example, four types of wind turbines are considered for the average wind technology used in the ELTRAMOD, i.e., the conventional asynchronous generators (AG), and three synchronous generators (SG), including Electrically Excited Direct Drive (SG-E-DD), Permanent Magnet (SG-PM) and High-Temperature Superconductors (HTS). Technological progress is implemented by varying resource inputs and key performance indicators (e.g., efficiency and lifetime). Additionally, material usage and substitution for future technologies is considered. For example, wind technologies are assumed to increase the tower height and use carbon fiber instead of glass fiber for the production of rotors.

Secondly, the data harmonization is conducted, including energy conversion efficiencies, life time of technologies, installed capacities by technologies, emission factor by technologies, and electricity mix. According to the figures, about 33% of parameters of ELTRAMOD and electricity generations by technologies were required to be harmonized with the LCA modelling.

For the environmental assessment, five non-climate environmental impact categories are selected in addition to climate change. These are: particulate matter formation, ozone depletion, freshwater eutrophication, urban land occupation and metal depletion. These five categories are chosen with the highest change (70%) or with no significant change compared to the base year 2014. Particulate matter formation and ozone depletion are chosen to highlight possible impacts on human health. Freshwater eutrophication and urban land occupation reflect the damage to ecosystems, while metal depletion stands for impacts with regards to metal resource availability.

Both life cycle and direct GHG emissions in 2050 in all scenarios show decreasing trends compared to 2014. However, a difference between the direct and life cycle emissions is also revealed. The share of the direct emissions at the life cycle emissions decreases from 61% (2014) to 25% (2050 High-RES Decentral). The results indicate the effectiveness of policy actions for carbon mitigation, yet reveal the increasing degree of importance of upstream and auxiliary emissions in an electricity system with a large share of RES.

The non-climate environmental impacts by technologies in the three scenarios for 2050 are compared to 2014, as shown in Fig. 13. Generally, freshwater eutrophication shows a similar pattern to that for climate change, i.e., a noteworthy decline of the indicator value over all scenarios compared to 2014. In the case of Mod-RES, ozone depletion and particulate matter formation are at similar levels to 2014, while the more ambitious GHG reduction target, i.e., both High-RES scenarios, induces increases for both impact indicators. Regarding metal depletion and urban land occupation, any transformation of the European electricity sector leads to even higher impacts, indicating that attention should be paid to any conditions for these two impacts. Freshwater eutrophication is mainly due to the upstream process of spoil treatment from lignite mining for the lignite power plant. The decline of freshwater eutrophication is mainly due to the phase out of the lignite power plant. A large contributor for particulate matter formation and ozone depletion is the gas power plant with the carbon capture and storage (CCS) technologies. This is mainly due to natural gas leakage from pipelines increasing the amount of gas in the atmosphere. Wind and solar technologies are the main contributors to metal depletion, while the growth of land use is mainly driven by ground-mounted solar PV for the installation of PV ground-mounting systems.

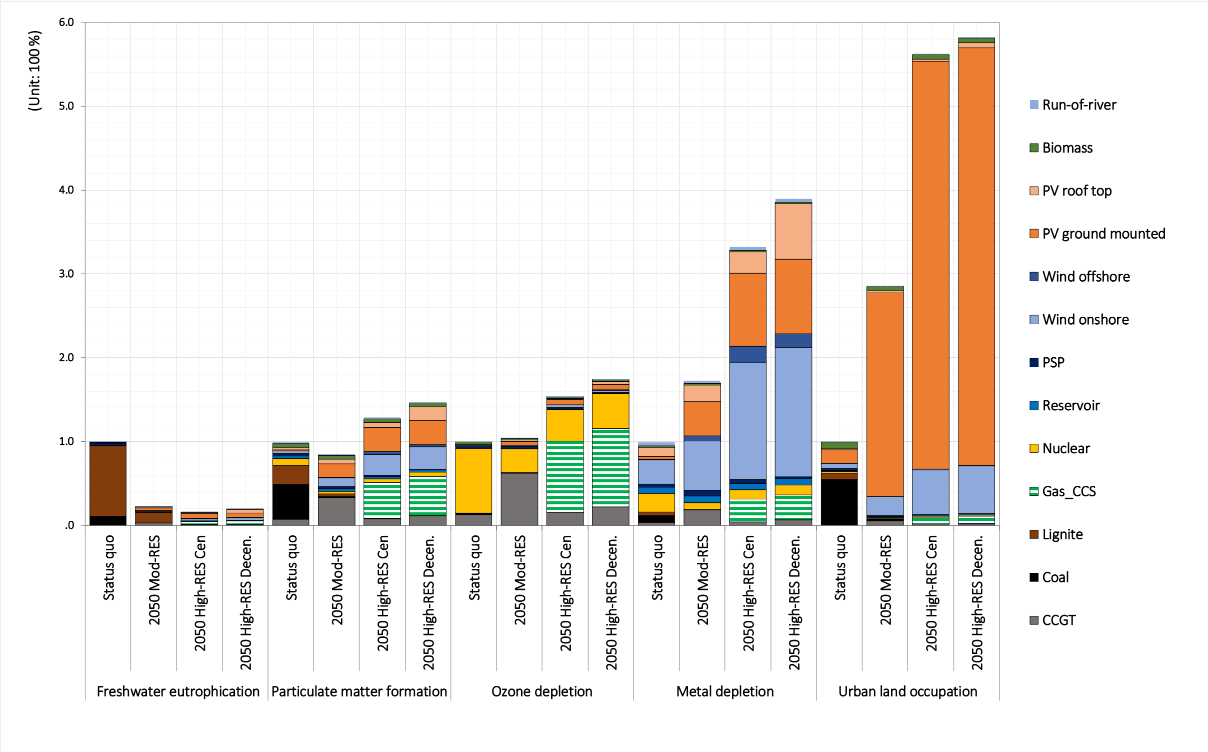

Fig. 13: Normalized results of non-climate environmental impacts by technologies in Mod-Res, High-RES Central and Decentral scenarios for 2050 compared to 2014. Technologies with less than 1% of total electricity generation are cut off, hereafter. (PSP, pumped storage; CCS, carbon capture and storage; CCOT, combined cycle oil turbine; CCGT, combined cycle gas turbine.) (Paper B, Xu et al., 2020a)

Additionally, the possible measures for policymakers to mitigate metal depletion and urban land occupation are discussed, for example, the measures of metal recovery and substitutions of materials for reducing metal depletion, and the measure of space multifunctionality for reducing urban land occupation.

4.2.2 Considering the impact of metal depletion on the European electricity system

As discussed in Paper B, unintended trade-offs related to environmental impacts are generated in the process of the energy transformation towards a renewable energies-based decarbonized system, such as an increased requirement for metal resources. To maintain metal availability and accessibility, the EU discusses and implements several strategies through, amongst others, trade agreements with exporting countries and recycling (European

Commission, 2015a, b). The long-term aim of the corresponding strategies is to secure the trade connections while reducing import dependency. However, environmental considerations in energy system transformation could also play a role in the formulation processes of these strategies. Bearing in mind these additional impacts, from a policy perspective, the question emerges of how to shape a future electricity system which is climate neutral, environmentally friendly, and economically sound.

Against this background, Paper C analyzes the impacts of different outlines of policy packages, which address both climate and resource policy targets, on the shape of the European electricity system in the year 2050. Apart from the focus on the interrelationship between climate policy and resource policy, the analysis in Paper C also includes system expenditure, as an additional factor addressed in political and societal discussions.

For this purpose, the EAFESA framework is applied for model coupling between LCA and the ESM model PERSEUS-EU, as a guide to handling the challenges due to the differences between the approaches with regard to system boundaries, databases, and assumptions. PERSEUS-EU is used to minimize all decision-relevant expenditure, by restrictions addressing technological, political and environmental constraints. The model coupling direction is to integrate LCA indicators to the PERSEUS-EU model, and the feedback loops are thus observed (see Fig. 14). Apart from the expanded LCA model (Eq. 2 and Eq. 3) that is applied in order to provide LCA indicators to the PERSEUS-EU model, the augmented ε-constraint method (Eq. 4 to 6) is applied to extend the original PERSEUS-EU model with LCA considerations.

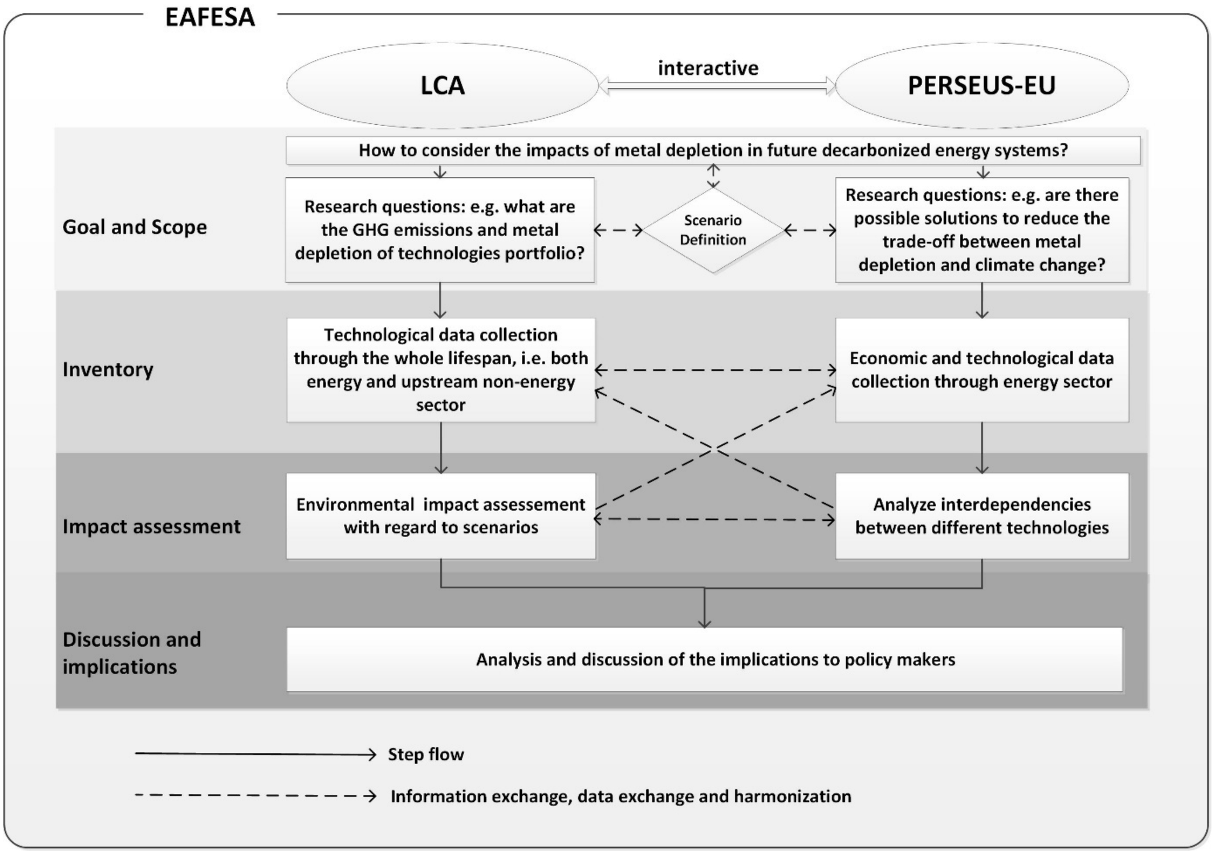

Fig. 14: Applying EAFESA: combining LCA and PERSEUS_EU

For the analysis, three different policy-ambitious levels are defined, each reflecting hypothetical decision-making preferences within the ranges between the utopia (0%) and nadir (100%) point, i.e., ambitious (25%), moderate (50%), relaxed (75%). Considering the main driver to transform the European energy system is to slow down climate change, in all scenarios the CO_2 price is set to 160 €/t CO_2 in 2050, according to the 450 ppm scenario of World Energy Outlook (International Energy Agency, 2016). To reflect different decision-making preferences, the precise GHG emission targets vary between the scenarios, allowing for less ambitious climate policies. However, to emphasize the current societal environment, which strives to slow down climate change, the upper limit of climate change is limited to 50%. Policy packages allowing for a relaxed preference for slowing down climate change are not scrutinized in Paper C. As a result, six scenarios are defined: (1) CC ambitious and MD ambitious (CAMA), (2) CC ambitious and MD moderate (CAMM), (3) CC ambitious and MD relaxed (CAMR), (4) CC moderate and MD ambitious (CMMA), (5) CC moderate and MD moderate (CMMM), and (6) CC moderate and MD relaxed (CMMR). The results obtained from single objective optimizations are called selfish scenarios, i.e., EX selfish, CC selfish, and MD selfish.

Similar to the case study in Paper B, the challenges in the model coupling between LCA and PERSEUS-EU are overcome during the four steps of the EAFESA framework. In addition to the mentioned data harmonization and the developed prospective LCA model with the breakdown of average technologies used in PERSEUS-EU, as well as the adjustments of material usage and substitution for future technologies, the feedback loops need to be accomplished. In this case, the feedback loops are accomplished with the exchange of data (electricity mix as well as environmental impact indicators, i.e., climate change and metal depletion of the production of 1 MWh electricity production from technology mix). The European electricity mix is used for the upstream non-energy sector (e.g., production of materials for the construction of wind power plants) to obtain or to update the life cycle indicators, while with the updated life cycle indictors, the already shaped electricity pathways are adjusted to obtain or to further update electricity mix. In this case, the scenarios with different decision-making preferences are conducted with feedback loops. As a global market is set for the upstream processes of the LCA model, in which the European electricity mix accounts for only around 10-20% of global electricity generation, the feedback loop terminated after the second iteration, when the threshold (0.1% error tolerance) is reached.

Of the six identified policy package scenarios, the two most ambitious scenarios (CAMA and CAMM) result in no mathematically feasible solutions. Fig. 15 plots the relationship between the system expenditure, GHG emissions, and metal depletion for the scenarios with mathematically feasible solutions. Comparing the scenario CC selfish with the scenario MD selfish confirms, from a different angle, the strong trade-off relation between climate policy and resource policy. The high costs of achieving the CC selfish scenario level emerge mainly when pursuing from the ambitious level (25%) to the utopia level (0%). Reducing the ambitious level of the climate policy will reduce the system expenditure notably, compared to the CC selfish scenario. A relaxed preference for slowing down climate change could achieve significant expenditure savings while still being ambitious from either a climate- or a resource-related perspective (see CAMR and CMMA). Taking into account the GHG emissions and the metal depletion of the scenario EX selfish as the bottom line, the CAMR scenario is the only one of all mathematically feasible policy package scenarios which sees improvements of both GHG emissions and metal depletion. The GHG emissions would drop by 13% and metal depletion by 8%; but CAMR is 2% more expensive. Other scenarios show a trade-off between GHG emissions and metal depletion, i.e., the reduction of metal depletion leads to an increase of GHG emissions.

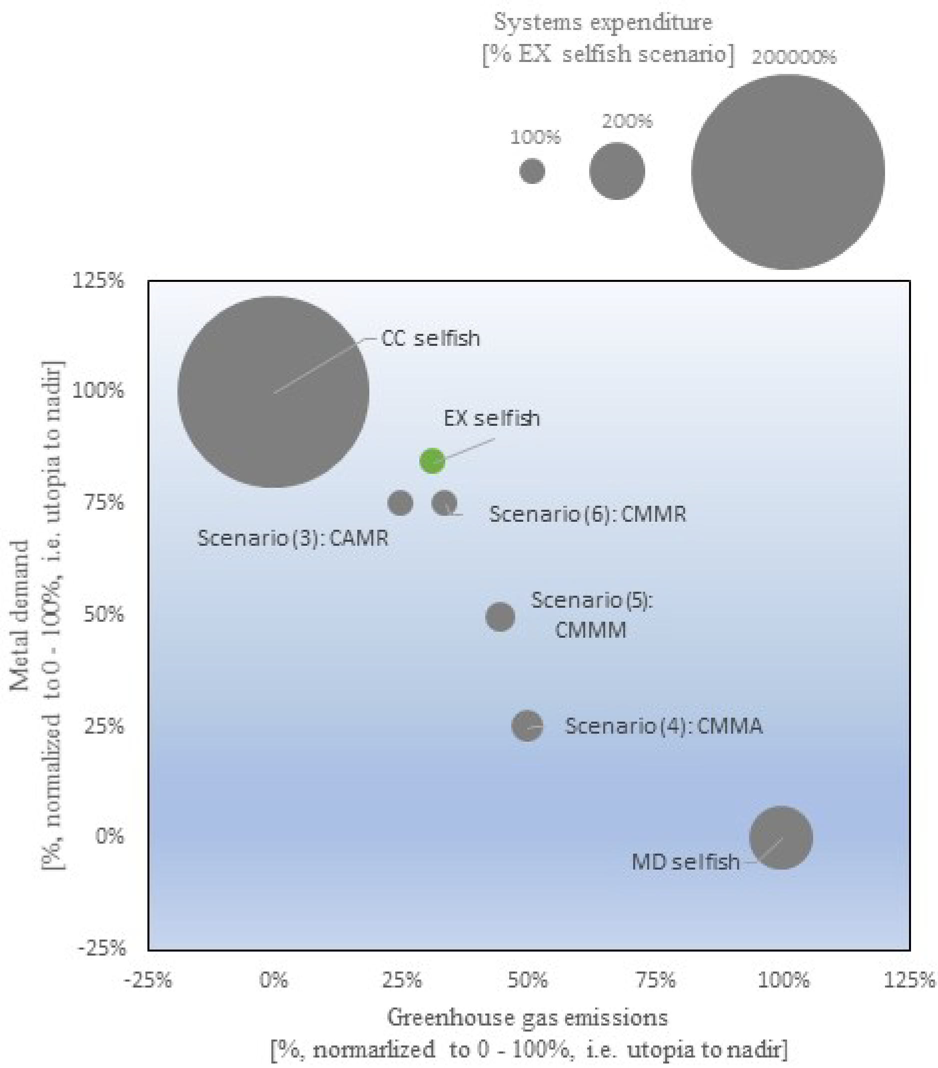

Fig. 15: Relations between system expenditure, GHG emissions and metal depletion. The marker area is proportional to system expenditure. The GHG emissions and metal depletion are normalized to the range between the utopia and nadir points, 0 – 100 %. (adapted from Paper C, Xu et al., 2021)

Electricity mixes of the scenarios with mathematically feasible solutions in 2050 are compared, in order to better understand the effects of resource policy in shaping an optimal energy system. Summing up, the results show that RES power plants exhibit lower GHG emissions but a higher metal depletion than fossil fuels-based or uranium-using power plants. Thus, climate policy will promote wind power, due to its low life-cycle GHG emissions; whereas resource policy supports the use of gas-fired power plants with their comparable low life-cycle metal depletion. PV show higher life-cycle GHG emissions and higher metal depletion than wind power; thus, a more relaxed resource policy is needed to achieve a noteworthy share in the electricity mix. Changing metal depletion targets will not affect the share of nuclear power and hydropower, as they show rather low metal depletion and low GHG emissions.

The analysis shows that a reduction of the trade-off is possible, but the space for possible solutions is limited. Paper C thus also discusses the possible solutions for policymakers to overcome, or least to smooth the trade-offs between the policy targets. An obvious possible option is to replace primary resources with secondary ones through increased recycling of metals. Any substitution of primary resources by secondary resources would reduce the amount of metal depletion, potentially causing a diminishing effect on the trade-off between both policy targets; a sufficiently large substitution could even overcome the trade-off. More ambitious climate policy targets would demand a higher substitution rate.

4.2.3 Assessing the GHG emissions of EV considering different charging strategies

The necessity of reducing GHG emissions has already been widely recognized for the transport sector. For example, the EU has announced that the transport sector has to reduce its GHG emissions by 54% to 67% in 2050 (European Commission, 2016). Currently, transport produces around a quarter of Europe's GHG emissions, with road transport having a share of over 70% (European Commission, 2016). This indicates the important role of innovative and green road transport measures in low-carbon mobility. EV are considered to be one of such measures.

Many studies (e.g., (Bauer et al., 2015; Lewis et al., 2014; Qiao et al., 2019)) focusing on environmental assessment of EV have already shown the large advantages of EV in climate change mitigation compared to conventional internal combustion engine vehicles (ICEV). They have confirmed the positive effects of renewable-dominated electricity systems compared to fossil-based ones for EV, even from a life cycle perspective. However, those studies mainly used the national or regional average annual electricity mix to calculate upstream GHG emissions of EV. Most studies consider neither the feedback effect which occurs due to the additional electricity demand from EV, nor a timing effect which considers different charging strategies. Controlled charging of EV affects the electricity mix and emissions considerably. From an energy system point of view, controlled charging is an acceptable demand-side flexibility option to cope with the challenges of increasingly intermittent electricity generation from RES, such as wind and PV, and fluctuating demand (Richardson, 2013). The controlled charging strategies can be divided into unidirectional controlled charging, and bidirectional controlled charging (the so-called Vehicle-to-Grid (V2G) approach). Depending on the EV charging strategy chosen, the electricity mix generated for EV may vary, and so will the resulting impact on the electricity system and climate change in the future. This calls for an evaluation of GHG emissions of EV with different charging strategies, based on the dedicated electricity mix generated for EV.

Against this background, Paper D assesses systematically the GHG emissions of EV in Europe in 2050 considering the different charging strategies. The investigated GHG emissions of EV are those associated with the generation of electricity mix during vehicle usage and EV battery production, including the use for V2G. Three scenarios with different charging strategies, i.e., UNCONTROLLED, ONEWAY, V2G, and a reference scenario WITHOUT_EV is calculated.

For this purpose, LCA is coupled with PERSEUS-EU, which is extended with EV charging considerations, applying the EAFESA framework. The model coupling direction is to integrate the PERSEUS-EU output into the LCA model (Fig. 16). The extended LCA model (Eq. 2 and Eq. 3) is applied for the assessment of GHG emissions.

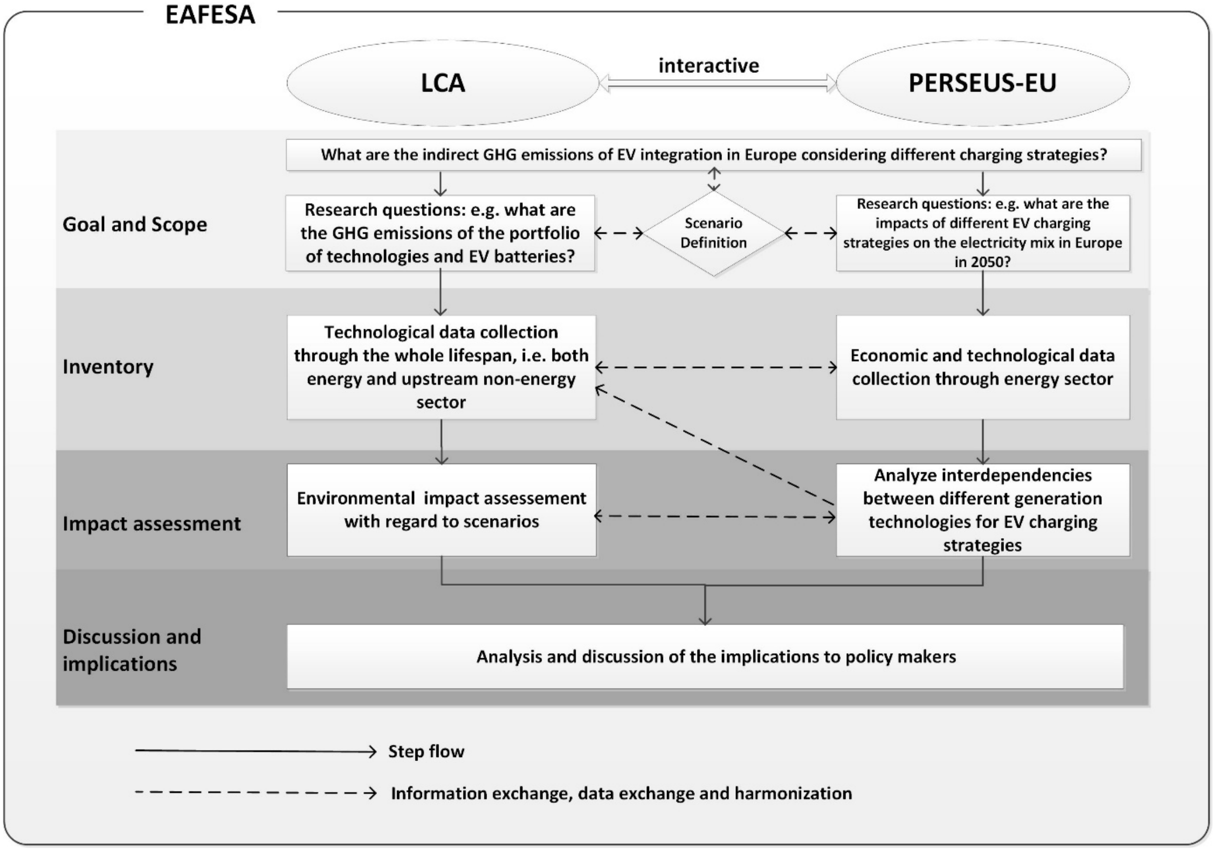

Fig. 16: Applying EAFESA: combining LCA and PERSEUS_EU with EV integration

Similar to the case study in Paper B, the challenges in the model coupling between LCA and PERSEUS-EU are overcome during the four steps of the EAFESA framework, i.e., data harmonization and the developed prospective LCA model with the breakdown of average technologies used in the PERSEUS-EU, as well as the adjustments of material usage and substitution for future technologies.

It should be noted that the EV battery lifetime is assumed with a fixed energy throughput (i.e., 30,000 kWh, which equals 150,000 km without V2G). The battery survives for the whole lifetime (i.e., 30,000 kWh) and dies at 30,001 kWh. Consequently, V2G leads to higher battery demand according to the assumptions.

The results show uncontrolled charging increases electricity production from natural gas slightly. The two controlled charging strategies, however, reduce dependence on gas-fired electricity production and increase the amount of electricity produced by renewable energy sources (mainly PV). Flexibilities from V2G exceed that of ONEWAY, as charging cannot only be postponed, but EV can be used as mobile storage in the electricity system. Due to the efficiency losses in EV charging and discharging, total electricity production in the V2G scenario is slightly higher than in the ONEWAY scenario.

Fig. 17 shows the GHG emissions associated with the production of electricity in the UNCONTROLLED, ONEWAY, and V2G scenarios compared to WITHOUT_EV in 2050. Emissions from UNCONTROLLED are higher than those of both controlled charging strategies. The emissions are lower in the ONEWAY scenario, and even further decreased by V2G, due to the increasing use of electricity from RES. It indicates that both controlled charging strategies have a positive impact on global climate change from an energy system perspective.

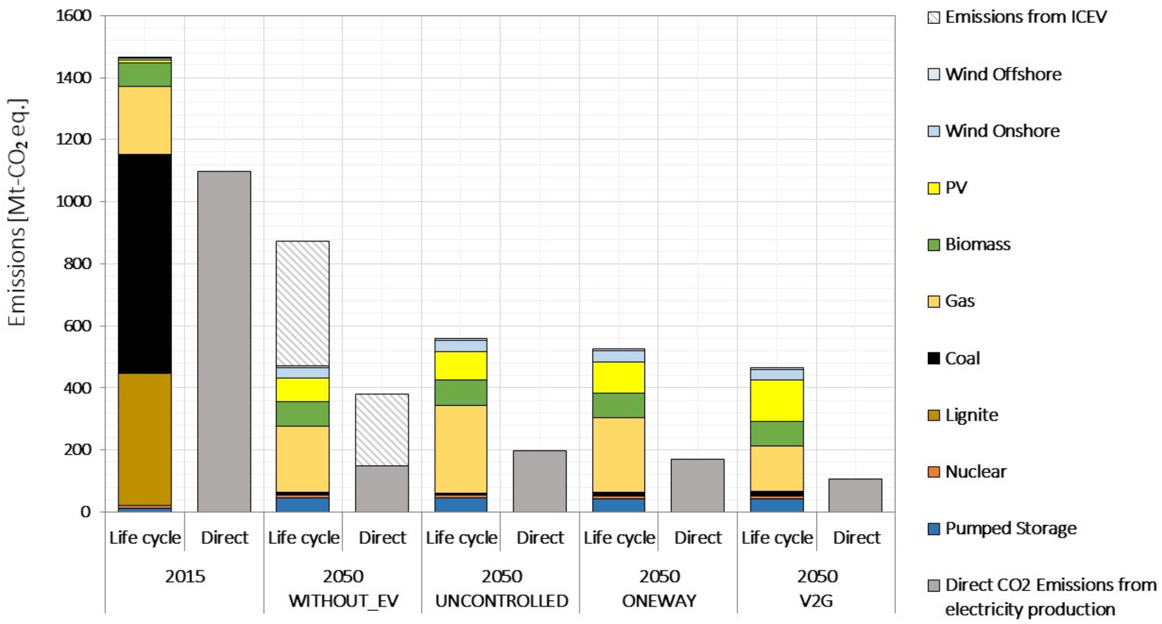

Fig. 17: The GHG emissions associated with the production of electricity in the UNCONTROLLED, ONEWAY and V2G scenarios compared to WITHOUT_EV in 2050 and the base year 2015. (Paper D, Xu et al., 2020b)

Using the WITHOUT_EV scenario as a reference, the life cycle GHG emissions of the UNCONTROLLED and ONEWAY scenarios are higher by 90 Mt CO_2-eq. and 57 Mt CO_2-eq., respectively, whereas emissions in the scenario V2G are 4 Mt CO_2-eq. lower. Considering the potential risk of accelerated battery degradation due to additional charging and discharging in V2G, V2G may cause more emissions only due to enhanced battery degradation. Nevertheless, in this scenario V2G still outperforms unidirectional charging in terms of GHG emissions. The reduced GHG emissions associated with electricity generation more than compensate for the increased emissions associated with the EV battery.

Paper D performs uncertainty analyses to examine the potential impacts of variations of some important inputs on the systematic performance. The first is related to further technical progress in EV batteries. The results confirm the effectiveness of technical progress in reducing life cycle GHG emissions. The second uncertainty is associated with EV availability in the V2G scenario. When the availability of EV increases from the initially assumed 50% to 100%, the total GHG emissions from EV increase, taking into account both electricity and battery production. One reason is the higher emissions due to the higher usage of the batteries. The other reason is due to the shift of electricity production from wind technologies towards PV technologies, as PV technologies produce more life cycle GHG emissions than wind technologies when generating the same amount of electricity. The results also show that a complete elimination of emission-intensive generation, such as electricity generation from gas, is not possible due to the days and longer periods without sufficient electricity generation from RES.

The discussion in the case study shows policymakers that the use of EV could reduce GHG emissions by 36% by simply replacing ICEV. Controlled unidirectional charging and V2G add another 4 or 11 percentage points on the European level. However, for these gains an efficient implementation of V2G is required.

5 Conclusions

The main driver of energy system transformation is anthropogenic-induced climate change and possible contributions to mitigate it. Without questioning this focus, the environmental impacts of a transformation of the energy system show the necessity of expanding the scope of the analyses and societal discussion, and thus, the importance of “integrated thinking”. Against this background, this thesis focuses on coupling LCA to energy systems analysis, aiming to shed light on the implications for policymakers with regard to environmental trade-offs due to climate change mitigation.

Overall, the thesis shows the important role of coupling the LCA approach to energy system analysis in the transition to a decarbonized energy system. The developed EAFESA framework provides a guideline to overcome the challenges in model coupling between LCA and ESM. The case studies bring awareness of issues which often receive little attention in the political discussion, and provide possible solutions for policymakers:

- Wind power technologies show low environmental burdens on most environmental indicators, except for high material use and ozone depletion.
- The effectiveness of renewable technologies on reducing GHG emissions has been verified, even from a life cycle perspective.
- The future decarbonized electricity systems are however accompanied by a series of environmental and resource-related trade-offs, especially increased metal depletion and urban land occupation.
- The trade-offs between climate change and metal depletion is possible to be reduced with only slightly increased system expenditure. However, recovery of metals could to some extent potentially reduce and even diminish the trade-offs between climate change and metal depletion.
- The effectiveness of EV in reducing GHG emissions is verified. Controlled charging strategies (unidirectional and V2G) have an enhanced influence on the reduction of GHG emissions over simply replacing conventional cars. However, V2G needs to be implemented efficiently.

Even though the development of EAFESA provides a guideline to overcome the challenges in the model coupling between ESM and LCA, the appended papers are subject to several limitations, which are addressed in the following.

As mentioned in Section 2, one of challenges in LCA studies is a lack of appropriate data for the product system under study. Although comprehensive research has been carried out to collect specific data for the foreground system, in Paper A, data assumption according to similar studies has to be made, as it is difficult to obtain detailed data on all components. The lack of specific datasets for the background system as well as the lack of impact assessment models related to China also weaken the accuracy of the results. Further efforts should be undertaken to regionalize the background data and strengthen the energy-related environmental impact assessment.

The case study performed in Paper B is limited by the abstraction of the breakdown of technologies. The future shares of technologies are built on projections by experts, considering learning curves for market-proven technologies and expectations regarding the techno-economic setting of innovative, but not market-ready technologies. However, the breakdown of technologies is limited to promising renewable technologies, i.e., wind and solar technologies, as well as the different types of biomass resources, without considering the conventional technologies, e.g., coal- or gas-fired electricity generation technologies. The consideration of material usage and substitution of technologies is also limited to wind and solar technologies. The upstream non-energy sectors in ESM are linked with the energy sectors via prices, which would influence the choice of upstream sectors via price fluctuations. This uncertainty in terms of choices in the upstream sectors is not recognized in LCA. A prospective LCA model with a comprehensive consideration of future technologies developments including both promising renewable and conventional technologies could be conducted in future research.

The LCA data used for Paper C and Paper D is derived from Paper B, with necessarily specific adjustments, i.e., harmonization, according to the PERSEUS-EU model. In addition to the aforementioned limitations in the development of the prospective LCA model for the European electricity system, Paper C and Paper D are also subject to methodological limitations due to the extension of the respective ESM models.

Paper C is subject to a methodological limitation due to the model complexity: the nadir point of each objective is selected from the single optimization solutions in the payoff table, which indicates that an exact Pareto set is not generated for the payoff table. The payoff table obtained from the lexicographic optimization of the objective functions could be conducted in future work to avoid the model producing non-Pareto optimal solutions. In general, the lexicographic optimization of a series of objective functions is to optimize the first objective function and then, among the possible alternative optima, optimize for the second objective function and so on (Mavrotas, 2007).

In Paper D, not every single EV or EV fleet is modeled in detail. EV are represented by aggregated loads or flexibilities for each country. The costs of EV batteries are not taken into account. Network restrictions are also not considered. For charging of EV, mechanisms in distribution and transmission grid level should be in place to avoid network congestion or even collapse. A detailed analysis with a network model should be performed in future work. In terms of data, the degradation level of a battery is assumed to depend linearly on the accumulated amount of charge. This assumption is applied to all batteries. However, battery life is significantly affected by a variety of complex factors, e.g., the temperature at which a battery is charged, the state of charge, the charging rate, etc. (Edge et al., 2021; Han et al., 2019; Hoke et al., 2011; Pelletier et al., 2017). Differences in battery life result in different life cycle emissions. These factors are usually not considered in macro-scope ESM, and might be a topic for future studies.

In addition to the specific limitations discussed above, the following research topics may also be of interest for research with a broader scope.

The coupling of LCA with ESM allows identification of the life cycle based environmental impacts of transforming the energy system. Sustainability of technologies or energy systems is normally seen as encompassing impacts in three dimensions i.e. the social, the environmental, and the economic. Thus, coupling LCA to life cycle costs and life cycle social impacts provides the possibility to show the potential trade-offs between economic, environmental and social impacts.

The trade-off between climate change and metal requirements of "bulk" metals are one of the focuses of this thesis. However, next to bulk metals, critical metals, like rare earths, are increasingly becoming the focus of the energy transformation, as they are indispensable to most innovative renewable technologies (Junne et al., 2020b; Moss et al., 2011; Schlichenmaier and Naegler, 2022). Although there is no common understanding regarding critical or strategic metals, mostly those are assigned to that group of metals which are essential for a technology with a high supply risk (Graedel et al., 2014). A growing share of renewable technologies will intensify the trade-off between climate policy and resource policy: critical material requirements increase with the degree of ambition of the decarbonization (cf. (Junne et al., 2020b)). The increased material dependency will also lead to import dependencies, which is becoming more important after the beginning of the Russia-Ukraine War (in 2022). Therefore, an in-depth analysis of this trade-off, comparable to the one presented in this thesis, needs additional research, in particular to consider the influence of possible critical material bottlenecks on future energy system transformation pathways.

In addition to metal depletion, a more systematic assessment of potential trade-offs to minimize possible side effects would broaden the scope, in particular, to consider land-use change.

Apart from the case studies conducted in this thesis, the EAFESA framework has the ability to be applied regardless of the types of model, in a broader scope including individual specific sectors (e.g., heat sector), and sector coupling (e.g., power to heat and power to hydrogen). For example, the integration of hydrogen in the electricity system model in combination with fuel cell EV, which might even lead to stronger decarbonization effects, could be of interest to consider in the future studies.

Lastly, LCA as a generic approach with the focus on different types of technologies has the potential to be coupled with other models in different fields, similar to being coupled with ESM. To couple LCA with other non-energy related models could be a topic for discussion in future studies.

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Part II: Papers A to D

Paper A

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Paper B

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Paper C

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Paper D

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Resources, Conservation & Recycling 132 (2018) 361–368

Contents lists available at ScienceDirect

Resources, Conservation & Recycling

journal homepage: www.elsevier.com/locate/resconrec

Full length article

Life cycle assessment of onshore wind power systems in China

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ARTICLE INFO

Keywords:
Wind power
Environmental impacts
Life cycle assessment (LCA)
China

ABSTRACT

The rapid recent economic growth in China was accompanied by a comparable demand for electricity, which is mainly provided by fossil-based power plants. Due to the impacts on climate change a switch to a more climate-friendly power system is required and part of the official policy of the Chinese Government. Wind power systems have been identified as one of the most promising technology to fulfill that goal. However, focusing only on the global warming potential of a technology could cover up other, possibly negative, environmental impacts.

The aim of the article is to learn more about the entire environmental performance of utility-scale wind power systems in China, based on a life cycle assessment for Saihan plant, a typical MW-level wind power plant in Inner Mongolia, China. The assessment results were compared to those of equivalent coal and natural gas power plants in China. Moreover, the global warming potential and ten other environmental impact indicators, differentiated by the five processes specified within the "cradle to grave" boundaries, i.e. production, transportation, installation, operation, and disposal, were calculated and analyzed by using CML 2001 method. The results show that, for producing 1 kWh of electricity, the studied wind power plant yields an 8.65E−03 kg CO2-e global warming potential and a 9.34E−02 MJ abiotic depletion fossil, which represent 0.8% and 0.6%, respectively, of those yielded by coal power plants, and 1.2% and 0.8%, respectively, of those yielded by gas power plants in China. Further, the results show a significant reduction in the values of most of the other studied impact indicators, e.g. acidification, eutrophication, human toxicity and eco-toxicity, compared to those of coal and natural gas power plants. However, these encouraging results were accompanied by higher abiotic depletion (elements) and ozone layer depletion, which should be taken into consideration. Finally, some recommendations for technical developments and policy that would further enhance the wind power systems in China were proposed based on sensitivity and uncertainty analysis.

1. Introduction

The rapid recent economic growth in China was accompanied by a comparable demand for electricity. It is expected that during the next few decades the economic growth will continue, which will need to be supported with comparable supply of electricity, in order to meet societal demands for an improving living standard (EIA, 2012). However, switching from a coal-based energy system, which currently dominates the power generation, to an environment-friendly energy supply system to avoid the severe impacts of fossil-based energy on the climate is a huge challenge for China (Pang et al., 2013). Wind power is considered as one of the most promising renewable energy sources in China and has been rapidly developing in the recent years (Liu et al., 2017; Shen et al., 2017; Zhou et al., 2010). The total installed capacity of wind power, which has turned to be the largest installed renewable source worldwide, experienced a steady increase from 381.2 MW in 2001 to 91,413 MW by the end of 2013 (Li et al., 2014; Li et al., 2010). However, taking into account the entire life cycle of a wind power system, which would include amongst others, fossil fuels, the production and provision of construction materials and electric generation equipment, some negative impacts of wind energy on the environment can be revealed (Cambero et al., 2015; Chen et al., 2011; Coelho and Lange, 2016; Han et al., 2013; Pang et al., 2015; Shao and Chen, 2013; Wu et al., 2015, 2014, 2016). Therefore, a detailed analysis of the environmental performance of wind power should be conducted to provide scientific information to the relevant stakeholders, because it is rapidly increasing to form a significant part of the future energy system in China.

In this study, life cycle assessment (LCA), which is a quantitative method used to assess the environmental impacts during the life cycle of a product or a service starting from the extraction and processing of raw materials and through the processes of production, utilization,

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http://dx.doi.org/10.1016/j.resconrec.2017.06.014
Received 19 December 2016; Received in revised form 14 June 2017; Accepted 15 June 2017
Available online 08 July 2017

recycling, and disposal, was used in the analysis (Finnveden et al., 2009; ISO, 2006). LCA is considered a 'cradle-to-grave' analysis method, which addresses the environmental aspects of products in a comprehensive manner, and it is useful to avoid partial-optimization when only few processes are evaluated (Finnveden et al., 2009). Over the past two decades, LCA has been widely applied to assess the life cycle impacts of wind power plants, wind turbines or certain power system components on the environment. Jungbluth et al. (2005) established a life cycle model to assess the environmental burdens including greenhouse gas (GHG) emissions, energy consumptions, ecotoxicity, etc., of wind turbines according to the European conditions. Similarly, LCAs on the country level (e.g. Germany, Italy, France, Australia, Brazil, and Denmark) have also been conducted to evaluate the environmental performances of worldwide wind power in the recent years focusing mainly on GHG emissions and energy consumption (Ardente et al., 2008; Crawford, 2009; Garrett and Rønde, 2013; Oebels and Pacca, 2013; Pehnt et al., 2008; Tremeac and Meunier, 2009).

Moreover, Chen et al. (2011) investigated the profile of wind power in China by assessing the energy consumption and GHG emissions for a case study of a wind power plant located in the Guangxi Province. Furthermore, Xue et al. (2015) conducted an LCA of the same wind power plant in Guangxi to evaluate the emissions of air pollutants other than GHGs. However, few studies have been carried out to evaluate the other environmental impacts of wind power in China e.g. toxicity and ozone layer depletion, which are also important and should be taken into account. Likewise, few studies have investigated this subject in the north of China, where the largest number of wind turbines has been installed with the greatest wind power potential. Thus, a study based on the north of China would be more representative of the wind power in the country. This study will fill the gap and give a complete profile of life cycle environmental impacts of the wind power in Inner Mongolia, which is a typical region for studying wind power in the north of China.

The following sections in the paper are organized as follows: Section 2 focuses on materials and methods, where first some insights regarding the case study were discussed, followed by the goal and scope definition as well as a description of the inventory of the site. Section 2 also aims to investigate the consumption of the resources and the environmental performance per kWh of electricity produced during the life cycle of the wind power plant. Section 3 presents and discusses the results of the assessment of the environmental impacts of the studied wind power plant and their comparison to those of other wind power plants as well as coal and gas power plants in China, because they represent the most important current power generation technologies. In addition, the results of the sensitivity and uncertainty of the calculations were also discussed in this section. The paper concludes with Section 4, which provides policy suggestions for sustainable development of wind power in China, aiming for environmental protection and reduction of non-renewable energy consumption.

2. Materials and methods

2.1. The case study

The investigated wind power plant is called Saihan and is located in the southern part of Suniteyou County, Saihantala Town (112°54′E, 42°24′N) in the Inner Mongolia Autonomous Region, China. It occupies an area of 24 km^2, and it has an average altitude of about 1140 m above the sea level. This is mainly a desert and grassland area with no groundwater underground and covered with stable sandstone, which can be used as a foundation-bearing layer. The physical geological condition is favorable, because no collapses or landslides have recently occurred in the area.

The site is equipped with 18 Goldwind GW77/1500 kW wind turbines (each with a blade diameter of 77 m and a hub height of 65 m) and 30 Goldwind S50/750 kW wind turbines (each with a blade diameter of 50 m and a hub height of 50 m). Each Goldwind GW77/1500 kW wind turbine tower is connected to a 1600 KVA box-type transformer, while each Goldwind S50/750 kW wind turbine tower is connected to an 800 KVA box-type transformer. The towers and the transformers are installed on steel-reinforced concrete and concrete foundations, respectively. A 220 kV step-up transformer is installed to connect the power plant to the existing Ondor substation, which is located 18.4 km away from it. The cables are buried underground rather than above the ground for an aesthetic reason. After a one-year period of construction, the plant started to operate in May 2009 and has a designed operational life of 20 years. Technical parameters of the plant are summarized in Table 1.

Table 1
Technical parameters of the studied power plant.

	Goldwind GW77/1500 kW wind turbine	Goldwind S50/750 kW wind turbine
Life time (year)	20	20
Quantity of Turbines	18	30
Turbine size (MW)	1.5	0.75
Installed capacity	27	22.5
Quantity of box-type transformers	18 (1600 KVA)	30 (800 KVA)

The installed capacity of the studied wind power plant is 49.5 MW. The annual average wind speed is 8.3 m/s at a 70 m height, and the corresponding average annual wind power density at this height is 569.4 W/m2. Electricity generation of the studied wind power plant was 130.1 GWh with a 26.1 GWh power curtailment in 2010. Due to the exceptional decrease of wind power density in 2011, the electricity generation shrinked to 105.4 GWh and the power curtailment became 19.0 GWh. An average electricity generation of 130 GWh with a 20 GWh power curtailment is assumed in this study and the capacity factor is set as 30% based on the practice in the past few years.

2.2. Goal and scope definition

The goal of this study was to evaluate the environmental impacts by applying a process-based LCA model to a typical wind power plant in Inner Mongolia, China, according to the ISO guidelines. The sole function of the studied power plant is to generate electricity, and the functional unit is thus defined as 1 kWh electricity generation provided by the 220 kV step-up transformer. Because there is no data regarding the specific generation from the 1.5 MW or the 0.75 MW wind turbines, electricity generation shares were assumed to be 54.5% and 44.5%, respectively, in accordance with the installed capacity shares.

The investigated system consists of five processes including operation and maintenance, disassembly and disposal of the entire wind power plant, and up-stream and auxiliary processes, e.g., processing and production of raw materials as well as transportation and installation. Fig. 1 shows all the processes considered in this study. It is worth noting that the manufacture of equipment was neglected due to the lack of information. The data for foreground processes was site specific, whereas for the background processes average data was used (Fig. 1) (Chen et al., 2011).

2.3. Life cycle inventory

The life cycle inventory (LCI) analysis was based on a comprehensive collecting, investigating, and managing of data. The data of the foreground system, i.e. data related to the wind power plant, were mainly collected from suppliers' technical and maintenance manual (BJNEC, 2012); data of the background system, i.e. upstream and auxiliary processes, were obtained from the Eco invent 2.2 database. It is worth noting that the most important background data, e.g. electricity mix, were Chinese specific, while the data for other background processes were based on the records of global areas, such as Europe or

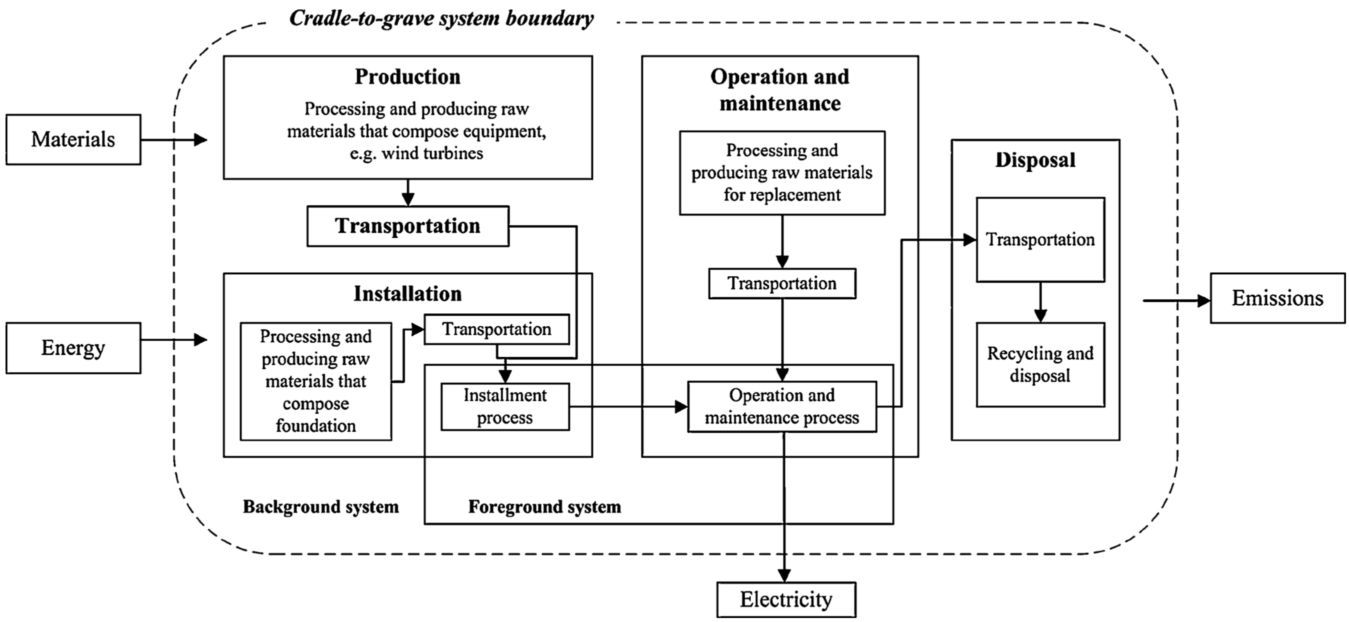


Fig. 1. The system boundary of the LCA analysis of the studied wind power plant.

globalized information, because of the lack of localized database for this information in China. In general this would lead to some uncertainties on the results, irrespective that some components are international traded. The life cycle inventory data for the production of 1 kWh of electricity were used in the analysis is listed in Table 2.

2.3.1. Production

The components mainly includes: 30 Goldwind S50/750 kW wind turbines, 30 box-type transformers (800 KVA), 18 Goldwind GW77/1500 kW wind turbines, 18 box-type transformers (1600 KVA), one 220 kV step-up transformer, and cables. Some materials and sub-components, such as lubricating oils used in wind turbines as well as lifts, lighting systems, and brakes used in wind nacelles are present in small quantities, which represent less than 1% of the total materials; and therefore were neglected.

2.3.2. Transportation

Transportation involves the transport of raw materials from factories to be processed into specific components in production plants, and the transport of components (wind turbines, towers, transformers, etc.) from the production plants of the components to the Saihan wind power plant. It is assumed that all materials and components were transported by trucks. The factories for processing of raw materials were selected either based on the cooperating raw materials production companies with the production plants of the specific components, or based on the principle of proximity, i.e. the nearest distance between the possible factories for raw materials and the components production plants, when no specific data were available. The location of the specific factories for the production of the components were obtained from the open tender information included in the post-evaluation report of the studied power plant (BJNEC, 2012).

2.3.3. Installation

The foundation of wind turbines is made of steel-reinforced concrete, where the total volume of reinforced concrete is 8526 m^3 and 7,662.42 m^3 for the 30 Goldwind GW77/1500 kW wind turbines and the 18 Goldwind GW77/1500 kW wind turbines, respectively. On the other hand, the foundation of the transformers is pure concrete. Additionally, power and water are used for the process of installation.

2.3.4. Operation and maintenance

During the 20-year life time of the wind turbine, it was assumed that one blade for each wind turbine and 15% of the components of the generator would be replaced (Ardente et al., 2008; Chen et al., 2011). The transportation considered in this process is limited to the raw materials and the replaced components but not the transportation of operating staff, which was assumed to have insignificant impact on the environment. Additionally, the daily water consumption of the 15 permanent personnel employed in the plant is 2.2 m^3.

2.3.5. Disassembly and disposal

In this study, a scenario was created for component disposal based on other types of wind power and renewable energy projects due to the data unavailability for disposal of similar plants. In the scenario, it was assumed that foundations would be left in place (Martínez et al., 2009). Rotors from wind turbines were managed separately, the composite materials were assumed to 100% incinerated, while the rest glass contents were landfilled in the nearby disposal plant. For the treatment of the other equipment materials, it is assumed that 20% would be recycled and the rest would be sent to the nearby landfill (Ardente et al., 2008; Chen et al., 2011; Pang et al., 2015; Wang et al., 2012). Assuming that the recovered metals were included in the production of new components, the LCA was therefore credited for the recovered materials and negative values were used to represent the credit. It is also worth noting that the transport of components from the studied power plant to the final disposal plant is included in this study.

3. Results and discussion

3.1. Life cycle impact assessment

Life cycle impact assessment (LCIA) was conducted by applying the problem-oriented (mid-point) CML 2001 method (baseline) to calculate the environmental impacts. CML 2001, as an established approach, offers a consistent but also rather wide range environmental assessment with eleven indicators. CML 2001 like most other widely spread assessment model base on European conditions, which differ from the one in China. The choice of the assessment model could be crucial for the finding of the calculation. However, comparable assessment models for China are until now not available (Pang et al., 2015; Xu et al., 2013).

The calculation was performed using the software GaBi 6. The

Table 2
Overall LCI data for the production of 1 kWh of electricity.

Items	Materials	Unit	Input
Production			
750 kW wind turbine			
Rotor	Fiberglass	kg	4.71E-05
	Resin	kg	7.06E-05
	Cast iron	kg	5.19E-05
	Steel	kg	2.08E-05
Nacelle	Steel	kg	1.85E-04
	Cast iron	kg	3.69E-05
	Silica	kg	1.38E-06
	Copper	kg	1.56E-05
	Fiberglass	kg	8.08E-06
	Resin	kg	1.27E-05
Tower	Steel, low alloyed	kg	6.39E-04
1500 kW wind turbine			
Rotor	Fiberglass	kg	4.59E-05
	Resin	kg	6.89E-05
	Cast iron	kg	4.25E-05
	Steel	kg	1.33E-05
Nacelle	Cast iron	kg	3.79E-05
	Fiberglass	kg	8.31E-06
	Resin	kg	1.25E-05
	Steel	kg	1.57E-05
Generator	Magnetic steel	kg	7.71E-05
	Copper	kg	1.38E-04
	Cast iron	kg	6.33E-05
Tower	Steel, low alloyed	kg	7.03E-04
Transformers	Copper	kg	3.38E-05
	Steel	kg	1.13E-04
	Silica	kg	4.61E-06
Cables	Copper	kg	5.03E-05
Transportation	Truck transport	tkm	3.48E-03
Installation	Concrete	m3	5.99E-06
	Reinforcing steel	kg	4.70E-04
	Electricity	kWh	1.38E-04
	Reservoir water	kg	2.08E-02
Operation and maintenance	Tap water	kg	6.14E-03
	Fiberglass	kg	3.10E-05
	Resin	kg	4.65E-05
	Silica	kg	1.92E-07
	Copper	kg	2.30E-05
	Steel	kg	4.88E-06
	Magnetic steel	kg	1.16E-05
	Cast iron	kg	9.50E-06
	Truck transport	tkm	1.52E-04
Disassembly and disposal			
Resin incineration	Resin	kg	2.11E-04
Fiberglass landfill	Fiberglass	kg	1.40E-04
Cast iron landfill	Cast iron	kg	1.94E-04
Silica landfill	Silica	kg	4.95E-06
Copper landfill	Copper	kg	2.09E-04
Magnetic steel landfill	Magnetic steel	kg	7.10E-05
Steel (low alloyed) landfill	Steel, low alloyed	kg	1.07E-03
Steel landfill	Steel	kg	2.82E-04
Cast iron recycling	Cast iron	kg	-4.84E-05
Silica recycling	Silica	kg	-1.24E-06
Copper recycling	Copper	kg	-5.21E-05
Magnetic steel recycling	Magnetic steel	kg	-1.77E-05
Steel (low alloyed) recycling	Steel, low alloyed	kg	-2.68E-04
Steel recycling	Steel	kg	-7.06E-05
Transportation	Truck transport	tkm	4.55E-04

environmental impacts are based on the characterization models (ISO, 2006). The potential environmental impacts considered in this study were:

- Global Warming Potential (GWP)
- Abiotic Depletion (ADP elements and ADP fossil)
- Acidification Potential (AP)
- Eutrophication Potential (EP)
- Human Toxicity Potential (HTP)
- Ozone Layer Depletion Potential (ODP)

Table 3
Characterized environmental impacts per kWh of electricity generated by the studied power plant.

Environmental impact indicators	Unit	Quantity
Global Warming Potential (GWP)	kg CO_2-e	8.65E-03
Abiotic Depletion (ADP elements)	kg Sb-e	2.49E-07
Abiotic Depletion (ADP fossil)	MJ	9.34E-02
Acidification Potential (AP)	kg SO_2-e	7.25E-05
Eutrophication Potential (EP)	kg PO_4-e	5.45E-05
Human Toxicity Potential (HTP)	kg DCB-e	5.46E-02
Ozone Layer Depletion Potential (ODP)	kg R11-e	3.68E-08
Terrestrial Eco-toxicity Potential (TETP)	kg DCB-e	1.30E-03
Freshwater Aquatic Eco-toxicity Potential (FAETP)	kg DCB-e	3.33E-02
Marine Aquatic Eco-toxicity Potential (MAETP)	kg DCB-e	4.78E+01
Photochemical Ozone Creation Potential (POCP)	kg C_2H_4-e	6.36E-06

- Terrestrial Eco-toxicity Potential (TETP)
- Freshwater Aquatic Eco-toxicity Potential (FAETP)
- Marine Aquatic Eco-toxicity Potential (MAETP)
- Photochemical Ozone Creation Potential (POCP)

The results of the characterized environmental impacts calculated per kWh of electricity generated by the studied wind power plant are listed in Table 3. The total non-renewable energy consumption for the 20-year operating period was found to be approximate 67 GWh. As mentioned in Section 2.1, the average annual power generation of the studied wind power plant is 130 GWh in the presence of power curtailment, i.e. the energy payback time is 0.52 years, indicating a high renewability.

A contribution analysis of the environmental impacts with regard to the life cycle processes is shown in Fig. 2. The overall environmental impacts of all eleven indicators were assumed to be 100%. A negative value, i.e. credits, was assigned to the process of disassembly and disposal, because 20% of the recycled materials were assumed to be utilized and thus included as an added value to the plant. Therefore, the share of other processes could be more than 100%. The production process is the largest contributor to all the environmental impacts, with the shares ranging between 56% (for FAETP) and 118% (for TETP). Although both transport of raw materials and components were considered, transportation had the lowest impacts in most cases (with less than 5% of the total share) except for the indicators GWP, ADP fossil, and POCP, with shares of 7%, 10%, 7% for GWP, ADP fossil, and POCP, respectively.

The environmental impacts in the processes of installation and operation were of minor importance compared to the production process, because there was no fuel consumption in the operation process while in the production process there was a large raw materials input. Whereas recycling generally results in credits, in case of FAETP and MAETP, the entire impacts of disassembly, transport and treatment of materials within the disposal process outmatches the positive impacts of recycling.

Because the production process shows the highest share of the environmental impacts, a detailed analysis of this process is important to determine the share of the different sub-processes. Fig. 3 shows a more detailed investigation of ADP fossil and GWP in the production process. In case of ADP fossil, towers (41.8%), nacelles (28.3%) and rotors (20.6%) are the largest contributors and responsible for more than 90% of the total ADP fossil potential, while transformers represent 8.9% of the total potential and cables have the lowest proportion (only 0.4%). Similar analysis was applied to the GWP, which is mainly influenced by towers (41.0%), nacelles (30.0%), and rotors (19.0%). These three components represent about 90.0% of the total GWP in the production process, while transformers and cables represent only 9.6% and 0.4%, respectively.

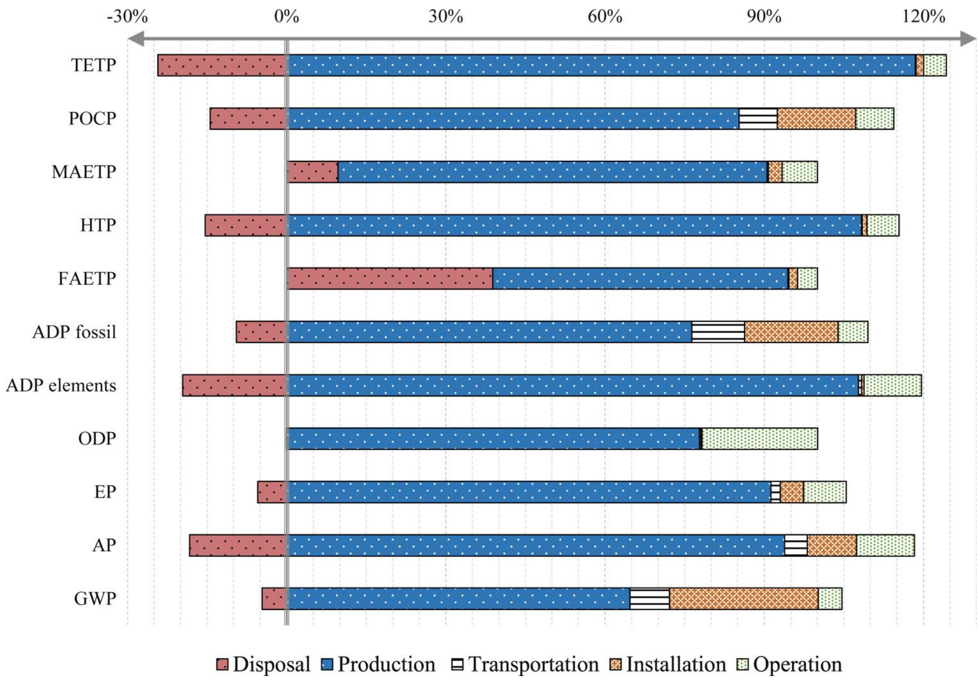


Fig. 2. Environmental impacts associated with different life cycle processes. (a) The ADP fossil in the production process (b) The GWP in the production process.

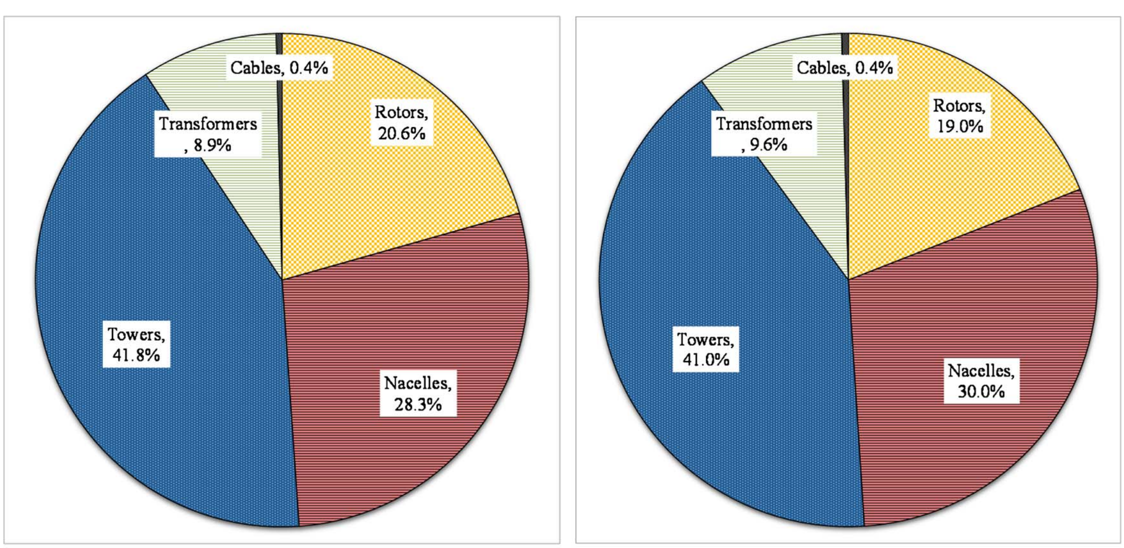
3.2. Comparison between wind power and other electricity production alternatives

3.2.1. Comparison between wind power and coal and natural gas power plant in China

The assessment results of the case study were compared to those of coal and natural gas power plants in order to establish a complete profile of the environmental impacts of wind power systems in China. For this comparison, we have calculated the environmental impacts of the average coal and natural gas power plants using the CML 2001 method, because it was difficult to obtain all the environmental impacts investigated in this study from the literature. In addition, the inventory data were derived from the Eco invent database. In order to compare the three energy technologies accordingly, the eleven environmental impact indicators were normalized by assuming that each technology produced the same amount of electricity, i.e. the share of each technology at the hypothetical electricity system was a third.

The results of this study showed that the GWP of coal power plants was more than 160 times higher than that of wind power plants, which confirmed the advantages of switching from a coal-based to a wind-based electricity system in China (Fig. 4). Additionally, wind power showed the lowest emissions per kWh regarding AP, EP, ADP fossil, and POCP, because they were 5% to 41% lower than those of coal and natural gas power plants. However, these encouraging results were accompanied by higher abiotic resource depletion (ADP elements) and higher ODP, which should be taken into account in the future development of wind power. The specific source analysis for environmental impact indicators, especially the ADP elements and the ODP, which were higher in case of wind power, can be found in the sensitivity analysis in Section 3.3.1.

The calculations regarding environmental impacts of fossil-based power plants are to some extent supported by other studies. For instance, the ADP fossil of a coal-fired power plant in China has been calculated by Wu et al. (2016) to be 2.9 kWh/kWh, while the one



(a) The ADP fossil in the production process (b) The GWP in the production process

Fig. 3. Environmental impacts of (a) the ADP fossil indicator and (b) the GWP indicator on the production process.

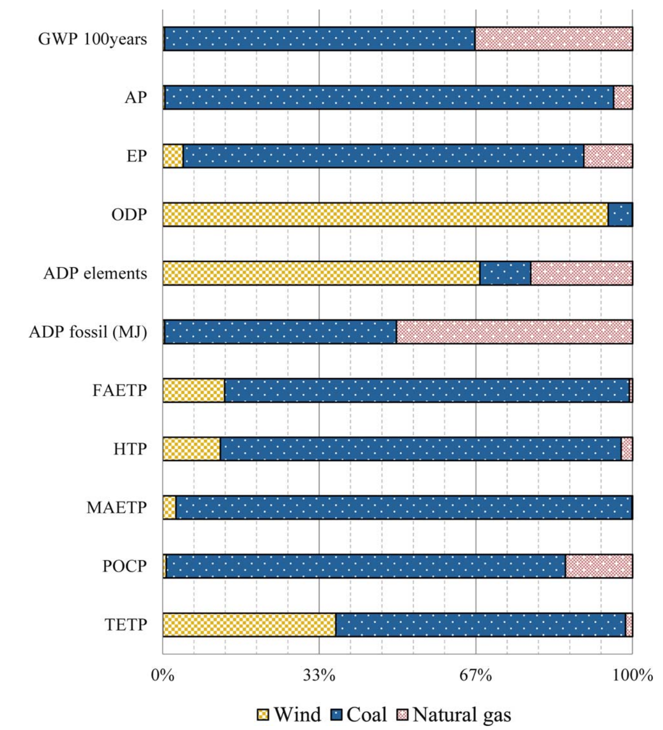


Fig. 4. Results of life cycle assessment of 1 kWh electricity production in different power plants.

calculated in this study was 3.2 kWh/kWh. Both of the results are much larger than that of the wind power plant, confirming the great reliability of the analysis conducted in this study.

3.2.2. Comparison with other wind power plants in other countries

Because ADP fossil and GWP are the most important indicators that are usually focused on in similar studies, they were used for comparison with the other wind power plants in other regions of the world.

Table 4 lists the results obtained in this study and those of several typical wind power plants that were investigated in previous studies. As shown in the table, ADP fossil ranged from 0.014 to 0.150 kWh/kWh, and GWP ranged from 7 to 440 g/kWh. Therefore, compared to the other wind power plants, the ADP fossil in this study (0.026 kWh/kWh) was within the advanced range, while the GWP (8.6 g/kWh) was within the moderate range.

When the specific sizes of wind turbines were considered in the comparison, the ADP fossil and the GWP of the Chinese 1.5 MW and

Table 4
Comparison between the studied plant and other wind power plants in other region.

Reference	Location	Turbine type	ADP fossil (kWh/kWh)	GWP (g/kWh)
This study, 2016	China	1.5 MW and 0.75MW	0.026	8.6
Garrett and Rønde (2013)	Denmark	2MW	0.028 – 0.036	7–10
Oebels and Pacca (2013)	Brazil	1.5MW	–	7.1
Crawford (2009)	Australia	0.85MW	0.048	10.3
		3.0MW	0.043	9.3
Tremeac and Meunier (2009)	France	250W	0.33	46.8
		4.5MW	0.08	16
Pehnt et al. (2008)	Germany	5.0MW	–	22
Kubiszewski (2010)	Worldwide	–	0.04	7.2–440
Lenzen (2002)	Worldwide	–	0.014–0.150	28.8–440

0.75 MW wind turbines were found to be close to those of the Danish 2 MW wind turbines and the Australian 3 MW wind turbines, but less than that of the 4.5 MW wind turbines in France and 5.0 MW wind turbines in Germany. However, the smaller-size wind turbines (250W turbines in France) has a much higher ADP fossil and GWP. Therefore, no direct relationship was found between the size of the turbines and the life cycle environmental impacts.

3.3. Sensitivity analysis and uncertainty

3.3.1. Sensitivity analysis

The sensitivity analysis is a method to quantify the effect of changing any component on the whole system, and it shall reveal the robustness of the results (Huang et al., 2012; Xu et al., 2013). Therefore, the effects of a 10% increase of every raw material used in the equipment fabrication on all the discussed impact indicators were investigated (Table 5).

The table lists the numerical values of sensitivity, which ranges from 0 to 100%. Standard deviations (σ) were calculated for all the environmental impact indicators to represent their variation in order to support the sensitivity analysis, and they were found significant when the material had over 50% numerical sensitivity.

The results show that ODP was significantly influenced by the resin material (> 98%), which corresponds to the highest standard deviation. Other impact indicators, such as AP, EP, ADP elements, FAETP, and TETP, were highly sensitive to one single material. For example, AP was sensitive to magnetic steel, while EP and ADP elements were easily influenced by copper; on the other hand, FAETP and TETP were significantly affected by steel. In contrast, GWP and ADP fossil were rather not sensitive to a single material, i.e., only a combination of several materials in large amounts can reduce them.

In addition, it was found that steel, copper, and resin were the most critical influencers on several multiple environmental impacts. However, fiber glass, cast iron, silica, concrete, and reinforcing steel were not imperative for yielding environmental emissions.

3.3.2. Uncertainty of wind curtailment

As mentioned in Section 2.1, the average annual electricity generation of the studied wind power plant was assumed to be 130 GWh with a curtailment of 20 GWh. The power curtailment was due to the poor power distribution capacity in North China, i.e. the extension of utility grid is not advancing at the same rate as the development of wind power. At full capacity operation, i.e., if the current wind curtailment was avoided, the entire environmental impacts of unit electricity generation would decrease by 14%. The results were obtained assuming that the use of fuels and materials in upstream sectors as well as efficiency were not related to the amount of wind curtailment. It is therefore suggested that local power grid should be developing along with building new wind power plants, which should be slowed down at the present stage to decrease the impacts on the environment. In addition, the power grid development to support large-scale power transmission from west to east is a long-term requirement for wind power systems, because the wind resources in China are mainly concentrated in the north, northeast, and northwest, while the power demand is mainly concentrated on the eastern coastal areas (Li et al., 2013; Wang et al., 2011).

3.3.3. Scenario-based uncertainty analysis due to changing the turbine size

The size of the wind turbine should have an effect on the environmental burdens of a wind power plant. In the following the environmental impacts of different average turbine sizes are analyzed, i.e. the current wind power plant with an average turbine size of about 1 MW (18 turbines of 1.5-MW and 30 turbines of 0.75-MW) is compared to a wind power plant with an average size of 1.5 MW (33 turbines of 1.5-MW), as it was originally designed.

Fig. 5 illustrates comparative results of the utilization of wind

Table 5
Sensitivity analysis on the relationship between raw materials and environmental impacts (unit: %).

	GWP	AP	EP	ODP	ADP elements	ADP fossil	FAETP	HTP	MAETP	POCP	TETP
Fiberglass	4.28	3.09	1.15	0.09	18.72	5.04	0.28	2.41	0.96	2.61	0.49
Resin	12.35	2.71	1.85	98.78	1.11	12.87	0.42	0.42	0.63	4.77	0.35
Cast iron	4.04	1.72	9.71	0.04	0.06	4.62	0.93	0.32	1.04	3.68	1.09
Steel	15.74	9.69	5.51	0.20	16.79	16.47	51.11	44.47	29.46	11.05	57.97
Silica	0.17	0.08	0.05	0.03	0.02	0.25	0.01	0.01	0.03	0.11	0.00
Magnetic steel	3.80	54.62	6.26	0.07	4.53	3.84	5.02	14.58	6.02	27.35	17.52
Steel (Low alloyed)	21.33	10.26	12.28	0.23	8.88	25.85	16.75	15.68	12.68	22.15	19.65
Copper	1.51	3.53	56.75	0.02	48.75	1.76	23.62	21.02	46.29	5.02	1.32
Concrete	18.35	3.66	1.29	0.14	0.25	6.55	0.21	0.30	0.38	4.89	0.29
Reinforcing steel	7.82	3.36	2.84	0.08	0.20	9.61	1.39	0.51	1.79	8.65	1.13
Standard deviation σ	0.07	0.16	0.17	0.31	0.15	0.08	0.17	0.14	0.16	0.09	0.18

turbines with different sizes to produce 1 kWh of electricity, which was calculated as the normalized difference between the assumed scenario and the real case. Whether the higher average size turbine (assumed scenario) produces higher or lower emissions compared to the smaller size turbine (reality) can be determined by positive or negative results, respectively, of the analysis.

The results indicate that the higher average size of the turbines improved most environmental impact indicators, which ranged between 7.5% (HTP) and 21% (TETP) below those in the case of the smaller turbine size. In contrast, AP, EP, ADP element, MAETP, and POCP showed higher environmental impacts. It should be noted that ODP was the only impact indicator with a unanimously improvement of the environmental performance over all processes.

As mentioned, a scaling up of the turbine leads to a large increase in AP and EP due to the high amount of magnetic steel and copper used in the equipment, which results in high emission-intensity and consequently higher AP and EP, respectively. The results also confirm that there is no direct relationship between the size of the turbines and the life cycle environmental impacts, which is consistent with the findings discussed in Section 3.2.2.

4. Conclusions and policy implication

As one of the most promising renewable alternatives to fossil fuels-based energy systems in China, wind power has been intensively developed in the recent years. This study applied LCA to evaluate the environmental impacts of a typical wind power plant in Inner Mongolia, China, and the following results were obtained:

(1) The results indicate high environmental performance and renewability of the studied wind power plant. In addition, the results of investigating the contributions of different processes in the life cycle revealed that the production process was the largest contributor to all of the environmental impact indicators, which can be attributed to the large input of raw materials in this process. Among the components of a wind power plant, the production of towers contributes the most to the GWP, and the production of towers and rotors were the most important contributors to ADP fossil.
(2) Compared to coal and natural gas power plants in China, wind power exhibits a significant reduction regarding most of the impact indicators, i.e. GWP, ADP fossil, AP, EP, HTP, TEP, and POCP. In contrast, these results are accompanied by higher ADP elements and higher ODP, which should be taken into further consideration.
(3) Sensitivity and scenario-based uncertainty analysis was applied in order to explore some technical and policy suggestions for the development of wind power in China. The results of this analysis were as follows: the optimization of the structural design and the application of raw materials is an effective measure to improve the

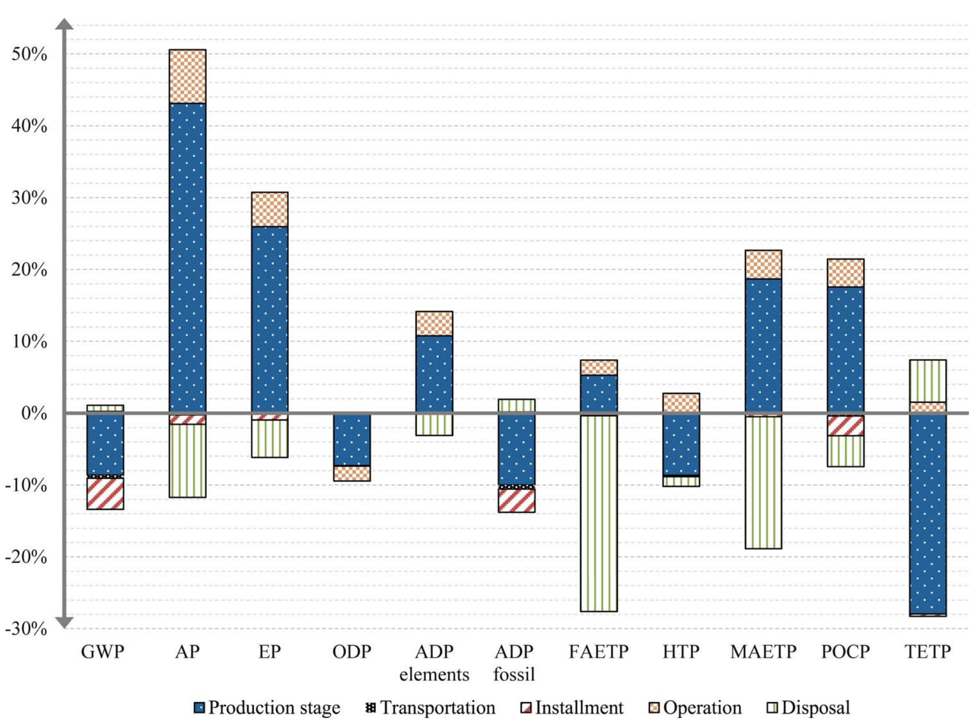


Fig. 5. The comparative results of utilizing different wind turbines for 1 kWh electricity production.

environmental performance of wind power in China. Moreover, the environmental performance of wind power in China is affected by the slow development of the electric grid compared to that of the wind power expansion, which resulted from the over-investment in large-scale wind power and consequently its overcapacity in the north, northeast, and northwest, which are the main areas of China's wind resources, while the high power demand is concentrated in the east. Therefore, the regional and national development of wind power should be carefully planned.
Finally, the size of the turbine did not show any clear relationship with the environmental impact indicators. In contrast, choices of materials or their substitution had a high influence from the perspective of climate change and environmental protection.

Nevertheless, it should be noted that this study was conducted under certain limitations, such as the lack of specific datasets or impact assessment models related to China. Therefore, further efforts should be undertaken to strengthen the energy-related environmental impact assessment in China.

Acknowledgements

This work was supported by the Funds for International Cooperation and Exchanges of the National Natural Science Foundation of China (Grant No. 51661125010), Fund for Innovative Research Group of the National Natural Science Foundation of China (Grant No. 51421065), and National Science and Technology Major Project of the Ministry of Science and Technology of China (2017YFC0505703). The authors thank the reviewers for their thoughtful comments and suggestions.

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Journal of Cleaner Production 243 (2020) 118614

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

An Environmental Assessment Framework for Energy System Analysis (EAFESA): The method and its application to the European energy system transformation

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A R T I C L E I N F O

Article history:
Received 12 June 2019
Received in revised form
4 September 2019
Accepted 26 September 2019
Available online 26 September 2019

Handling Editor: Bin Chen

Keywords:
Life cycle assessment
Energy system modeling
Energy scenarios
Prospective analysis

A B S T R A C T

Coupling life cycle assessment (LCA) and energy systems models (ESM) is a suitable approach to assess energy systems from both life cycle and energy systems perspectives. However, methodological challenges need to be taken into account due to differences between both modeling approaches considering system boundaries, databases, and different levels of detail of their input data. This paper brings these challenges into discussion and introduces the Environmental Assessment Framework for Energy System Analysis (EAFESA), which enables to identify life cycle based non-climate environmental impacts of energy scenarios consistently. EAFESA is applied to analyze potential future decarbonized European electricity systems with a focus on flexibility options using ELTRAMOD as an example of an ESM to test the conceptual approach of combining ESM and LCA. The application confirms the importance and benefits of "integrated thinking" proposed by EAFESA, which allows minimizing the pitfalls of combining both models comprehensively. At the same time, EAFESA has the potential to bring awareness of issues not discussed among policy-makers. One example is the insight that the decarbonized electricity system will be accompanied by increased metal demand and urban land occupation.

1. Introduction

Climate change is such a severe issue that the current transformation of the energy system is driven mainly by climate considerations. A good example is the EU's energy and climate policy aiming at reducing greenhouse gas (GHG) emissions by 80–95% by 2050 compared to 1990 (European Commission, 2011). However, the transformation towards a low-carbon climate-friendly energy system will also affect non-climate environmental aspects, e.g., freshwater eutrophication. As can be observed, these impacts are increasingly important in the discussion of how the transformation should be carried out (Berrill et al., 2016).

Typical Energy Systems Model (ESM) does not consider these non-climate environmental impacts. Generally, ESM aims to identify a cost minimization system distribution of energy technologies and energy carriers satisfying the energy demand from end-use sectors (i.e., residential and tertiary, industry, and mobility sectors). A straightforward method is to extend the number of environmental emission coefficients in the ESM, thus providing a broader picture. In most cases, however, this approach fails to capture the environmental impacts as they occur either in upstream or downstream processes required for energy supply. These impacts are mostly not recognized by ESM, as they have no impact on the optimal solution of the entire system, as long as cost minimization is the predominant objective.

A way to overcome the challenges mentioned above is to link ESM with Life Cycle Assessment (LCA), as a transformation of the

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https://doi.org/10.1016/j.jclepro.2019.118614
0959-6526/

ideas of Life Cycle Thinking (LCT) in a precise model-based setting. The idea of LCT is to consider the environmental impacts due to the entire process chain ("cradle to grave") of a technology, to reveal environmental hot spots along the process chain of a technology (Heiskanen, 2002). Methodological challenges of coupling ESM and LCA arise due to their different explanation aims. In detail, both approaches (LCA and ESM) differ with respect to

- the system's boundaries;
- the scale of technology description: ESM tends to describe conventional technologies in some depth, whereas innovative technologies or technologies with non-standardized feedstocks are recognized rather briefly, e.g., bioenergy or photovoltaics (PV). LCA aims to model technologies as detailed as possible, without considering the relevance to the energy system as a whole;
- differing temporal and geographical scales: the two approaches thus differ in their data requirements. Due to this data from ESM databases and LCA databases are seldom directly compatible.

Whereas ESM is based on the logic of linked technologies (typically, but not only, via prices), LCA considers the relationship between competing technologies in a different way, generally at aiming to compare their environmental impacts. That means focusing on single process chains, typical LCA does not consider possible interlinked impacts e.g., due to changes in the composition of materials or due to changing efficiencies. Prima facie the interaction between ESM and LCA seems to be quite un-challenging. However, the environmental impacts of single technologies or a set of technologies depend crucially on the chosen energy mix in the upstream sectors. For example, the life cycle environmental burdens of wind power technologies depend partly on the upstream electricity mix that was used to produce wind turbines, while the installed capacity of wind technologies in ESM will in return influence the electricity mix. This implies that a simple connection of ESM and LCA does not consider the possible feedback loops (i.e., non-energy sectors work as upstream sectors for energy systems and vice versa) which potentially leads to an over- or underestimation of the environmental impacts. The first challenge to overcome is therefore to identify elements (variables, parameters, etc.) in both approaches which should be interlinked in coupling these two methods in a systematic way.

An important driver for the energy transition is technical progress, i.e., innovation to improve energy efficiency while reducing, in particular, the resource requirements (Capros et al., 2016). Typically, ESM implements technical progress by changing energy conversion efficiencies or by implementing new technologies. However, LCA in general does not take into account technical progress by considering learning curves when analyzing a particular technology. Technical progress is considered only by analyzing "new" (non-mature) technologies. Thus, the second challenge to overcome requires a prospective (dynamic) LCA model (Arvidsson et al., 2018). Such a model needs to consider technological progress in market-proven technologies and emerging technologies. Additionally, the assumptions with regard to technical progress should match those used in the coupled ESM.

There is a growing body of research aiming to overcome the challenges of coupling LCA and ESM mentioned above. For example, technologies which are aggregated in ESM are broken down in LCA based on the market-proven technologies, for which a prospective LCA considering future potential higher efficiencies is also considered and conducted (Berrill et al., 2016; Hertwich et al., 2015; Pehl et al., 2017). However, further development is still required, for example in data harmonization between the two approaches and in consideration of promising and emerging technologies.

Aiming at filling these gaps, this study presents the Environmental Assessment Framework for Energy System Analysis (EAFESA), in which some insights about model coupling between LCA and ESM are identified and highlighted. An exemplary application of EAFESA with ELTRAMOD, a fundamental ELectricity TRAnsshipment MOdel for the European electricity market (Ladwig, 2018; Schubert, 2016), is further performed to demonstrate the conceptual framework in practice.

The structure of this article is as follows: Section 2 describes the state of the art of applying LCA to energy systems. Section 3 proposes and discusses the means to overcome the challenges when coupling LCA and ESA and presents EAFESA. Section 4 presents an application of the framework. Section 5 concludes our main findings.

2. State of the art

The current research on coupling ESM with LCA can be separated into two approaches. The first one is dominated by energy systems perspective; and the second one has its origin in LCA and still focuses on an LCT perspective.

The approach of energy systems thinking stands for the integration of life cycle environmental indicators into ESM. Such an application has been done in the NEEDS project (Loulou and Regemorter, 2008), and recently followed by García-Gusano and colleagues (García-Gusano et al., 2016a, 2016b) as well as other research studies e.g. by Rauner and Budzinski (2017). In the NEEDS project, different scenarios for electricity generation technologies were assessed. Emissions, i.e. only CO_2 and particulate matter, were derived from an average of existing technologies for the reference scenario and then implemented in the TIMES energy system model (Loulou et al., 2005). This approach is largely used to research the possible cost-effective pathways in energy systems to reduce GHG emissions and other pollutants. The strength of this approach is to apply standard process-based LCA (Majeau-Bettez et al., 2011) allowing for adjustment in degree of detail and specificity of the ESM; furthermore, to provide the techno-economic and life-cycle results in one overall model. However, technical progress is typically not considered leading to an overestimation of environmental impacts and an underestimation of possible resource demands.

The approach of LCT to couple LCA and ESM is based on the idea of coupling different single technologies to a combined system in LCA which is then scaled up to the sector level, using an Input-Output Model (IOM) (Hendrickson et al., 1998) as a macroeconomic reference, generating a so-called Hybrid-LCA (Lenzen and Crawford, 2009). The Hybrid-LCA and ESM are then linked, i.e. findings of the ESM are used as an input for a Hybrid-LCA. Typically, a Hybrid-LCA takes into account technical progress, using a prospective dynamic LCA (Hertwich et al., 2015). A current study implemented outputs of REMix (an electricity system optimization model) (Scholz, 2012) into the Hybrid-LCA model THEMIS (Gibon et al., 2015) to present a life cycle environmental assessment of multiple European electricity scenarios for 2050 (Berrill et al., 2016). Technological improvements are reflected in the improved conversion efficiencies, load factors, and next-generation technology adoption as well as materials parts. A comparable study was carried out by Pehl et al. (2017) through linking THEMIS with REMIND (an integrated assessment model) (Luderer et al., 2015). However, the approach shows no direct interconnection between LCA and ESM, i.e., data harmonization between the parameters of both models is incomplete. There is no consideration of the pathways of future emerging promising technologies and further, the uncertainties are caused due to the highly aggregated input-output data used in the Hybrid-LCA (Yang et al., 2017). This approach is more widely applied to assess the trade-offs in terms of environment, resources, and various other aspects of the shaped energy system pathways.

3. EAFESA as a framework for LCA and ESM model coupling

Energy systems studies have often used the reductionist approach of LCA methodology to remedy the lack of environmental considerations for scenario analysis. EAFESA is developed to enable energy systems analysts to extend the scope of energy systems analyses while minimizing the potential pitfalls of combining ESM with LCA in a transparent and comprehensive manner. The idea is hereby to use the most promising methodological advantages from both the coupling approach based in LCT and the coupling approach based in energy systems thinking (cf. Section 2), and merge them into one holistic methodology, making use of the lessons learned from recent studies (cf. Supplementary Material (SM) Table S1). Thus, EAFESA explicitly overcomes otherwise unresolved challenges in coupling ESM and LCA.

Firstly, EAFESA proposes to map the scale of technologies considered in both approaches and disaggregate technologies if necessary. If aggregated technology groups in ESM models are formed (e.g. due to similar costs), and a disaggregation is not possible due to lack of data, for each technology group sub-modules consisting of different technologies are defined, using primarily LCA data. As long as market-proven technologies are considered, modelling of technical progress follows typically learning curve approaches (Louwen et al., 2016). In addition, prospective but yet not market-proven technologies have to be added to the sub-modules, generating sub-module specific technology scenarios. The derived technology mix in each sub-module is then implemented into an ESM. Secondly, EAFESA suggests identifying the necessary set of harmonized data for both approaches and, as a follow-up, making the harmonization of the data. Since both approaches differ in their system boundaries, only the harmonization of those data where both approaches address the same parts of the entire systems is necessary: Data referring to energy carriers which overlap in the ESM and LCA; in addition, those environmental coefficients (both directly combustion-based and life-cycle based) which are implemented in ESM need to be harmonized. The data, which should be harmonized comprehends mainly those related to technical progress, e.g. energy conversion efficiencies, lifetime of energy technologies, operating time in both approaches. Next to the technology data, the used energy mix in the LCA should correspond to the ESM energy mix, since the energy mix has a significant effect on the environmental impacts of upstream and downstream energy and non-energy sectors (Rangaraju et al., 2015). The remaining data, i.e. those which are only modelled in an LCA, are of no relevance for this step (cf. Table 1).

The framework of EAFESA, the core of which is an intensive exchange of information to improve the findings, makes use of the general setting of the LCA methodology (ISO, 2006), consisting of the following four steps: goal and scope definition, inventory analysis, impact assessment, as well as discussion and implications, which is shown in Fig. 1. The challenges mentioned before are recognized and considered in the four steps of EAFESA. In the first step, goal and scope definition, it is crucial that a common goal with background information exchange based on defined scenarios is established. Additionally, the research scope (e.g. system and geographical boundaries) should be clarified. In the second step, inventory analysis, LCA focuses on technological data collection through the whole lifespan, and ESM revolves around both economic and technological data collection through the energy sector. Meanwhile, this step offers an interface for technology mix definition, collected data exchange and harmonization. In the third step, impact assessment, the calculated results (e.g., environmental impacts and energy mix) are exchanged and discussed between LCA and ESM. The interrelation between LCA and ESM might lead to an iterative feedback loop. The energy mix derived by the ESM should be used as an input of the LCA. The resulting life cycle environmental impacts of each technology could affect the environmental performance of the identified transformation pathways, leading to a possible necessary adjustment of the pathways, if e.g., policy targets are violated. The last step, discussion and implications, the implications to decision-making processes and policy impact assessment studies are discussed.

Table 1
Data harmonization of LCA and ESM.

	Energy sector	Non-energy sector
Energy carriers and material flows	×	–
Environmental coefficients	(×)	–
Energy mix	×	×
Technological progress	×	–

Notes: × fully harmonization, (×) partly harmonization, - excluded harmonization.

4. Application of EAFESA on an exemplary case

4.1. Background information

The exemplary case within the EFESA framework serves two objectives: (1) it demonstrates the applicability of our approach and (2) content-wise it certifies which valuable results could be extracted for policy implications beyond climate change. Under this frame, three different energy scenarios focusing on flexibility options with different levels of renewable penetration and carbon mitigation targets are analyzed for EU28 + 2 (i.e. Switzerland and Norway) countries as they were performed in the Horizon 2020 project REFLEX (Herbst et al., 2016a, 2016b; Poganietz et al., 2017).

The first of the three scenarios, i.e. Mod-RES, serves as a business-as-usual scenario, assuming that currently existing climate and energy policy targets and actions are realized with no new policy measures introduced. The Mod-RES scenario assumes an economy-wide GHG reduction target of ca. 50% until 2050 compared to 1990 and a GHG reduction target for the electricity sector of ca. 68% for the same period (Poganietz et al., 2017; Zöphel et al., 2019). The scenario follows the European Commission's PRIMES Reference Scenario (Capros et al., 2016). The population growth is around 3% between 2014 and 2050. GDP is projected to increase at an average annual rate of 1.5% from 2015 to 2050. The prices of oil, natural gas, coal, lignite and uranium are set to 61.40 €'14/MWh, 33.36 €'14/MWh, 10.72 €'14/MWh, 8.73 €'14/MWh and 3.24 €'14/MWh, respectively, in 2050. Thus, the prices for crude oil would increase by 141%, natural gas by 79%, coal by 125% and lignite by 125%. The fuel price for uranium would stay constant. CO_2 prices rise to 90 €'14/tCO_2eq by 2050.

Both other two scenarios suppose additional policy actions which allow achieving a GHG reduction target of 80% of GHG emissions until 2050 compared to 1990 and a specific GHG reduction target for the electricity sector of over 80% for the same period (Zöphel et al., 2019). Both scenarios differ by assuming, on the one hand, a more centralized setting (High-RES Central), comparable to the Mod-RES Scenario, and on the other a more decentralized setting (High-RES Decentral) of the energy system (Herbst et al., 2016a, 2016b; Poganietz et al., 2017). In both High-RES scenarios GDP, population development and energy prices are the same as those assumed the Mod-RES scenario, while CO_2 prices are assumed to be higher, with a price of 153 €'14/tCO_2eq in 2050, compared to 90 €'14/tCO_2eq in the Mod-RES scenario.

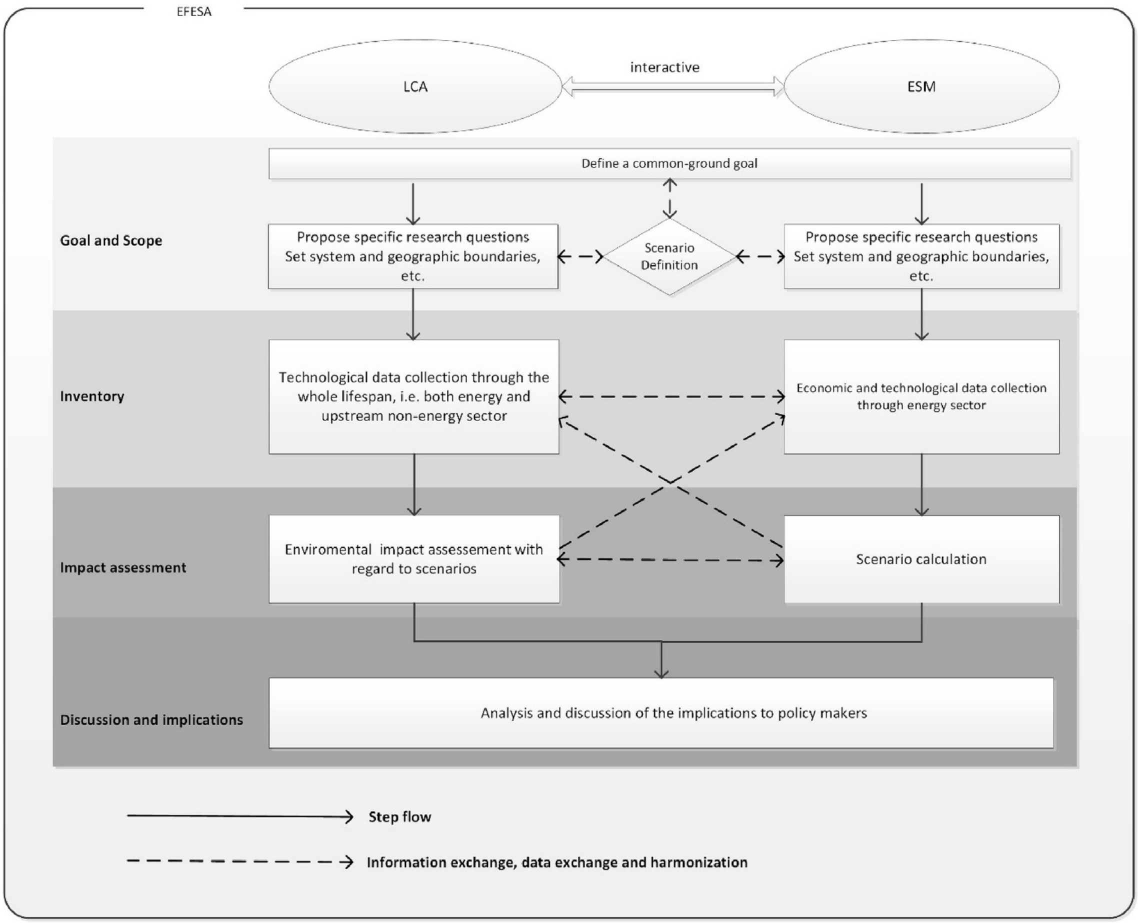

Fig. 1. Overview of environmental framework for energy system assessment (EAFESA).

The High-RES Central scenario is characterized by large-scale onshore and offshore wind power plants at prime locations and an intra-European electricity trade, i.e., excess demand or supply in one region can be mostly buffered by other regions or by other central options, like flexible power plants or the use of back-up capacity. In the case of long-lasting excess supply or excess demand, energy storage systems are available to balance the grid system. Other flexibility options include Demand Side Management (DSM) measures (appliances or energy services with a large energy requirements such as cold storage buildings, large night storage heater or heat pumps, large ventilation and air-conditioning systems), electric vehicles and power-to-x technologies (Herbst et al., 2016b; Poganietz et al., 2017; Zöphel et al., 2019).

In contrast to the centralized world depicted above, the High-RES Decentral scenario is characterized by electricity generation near load centers, thus minimizing transmission investments. PV plants, as well as onshore wind power plants at all possible locations, will dominate the electricity market, amended by further small-scale technologies, such as small-scale biomass power plants. The increased complexity of the electricity system and the number of market participants on the supply side will hamper the precision of electricity generation forecasting, leading to an increased demand for local and regional flexibility options (Herbst et al., 2016a; Poganietz et al., 2017; Zöphel et al., 2019).

Within these scenarios, the framework of EAFESA is applied by coupling LCA and the ESM model ELTRAMOD to analyze and assess the future European electricity system (cf. Fig. 2). ELTRAMOD is randomly chosen here only as a case to show the application of the EAFESA framework.

ELTRAMOD, a bottom-up Electricity Transshipment Model, is formulated as a linear optimization model with perfect foresight and perfect competition as central assumptions. From a central European electricity system perspective, the optimal investment and dispatch decisions of relevant technologies are based on electricity market fundamentals taking existing regulatory frameworks into account. Keeping the underlying assumptions in mind the interpretation of the results allows for the analysis of trade-offs between key technologies. While the scenario assumptions (e.g., RES share, CO_2 price) define the modelling framework, the strength of ELTRAMOD is the identification of interdependencies within the endogenously calculated electricity generation plant and flexibility option portfolios against the background of scenario-based flexibility requirements. With endogenously calculated power plant and storage investment and dispatch decisions, electricity price patterns can be explained by ELTRAMOD. The model can also calculate technology and country-specific CO_2 emissions and transnational electricity exchange (Ladwig, 2018; Schubert, 2016).

For the environmental assessment different impact indicators are selected. As the societally most important one, climate change is due to anthropogenic GHG emissions (Goedkoop et al., 2009). Of the residual analyzed non-climate relevant impact categories, those impact categories are chosen, with the highest change (>70%) or with no significant change compared to 2014. Particulate matter formation and ozone depletion are chosen to highlight possible impacts on human health. The former represents a complex mixture of organic and inorganic substances with a diameter of less

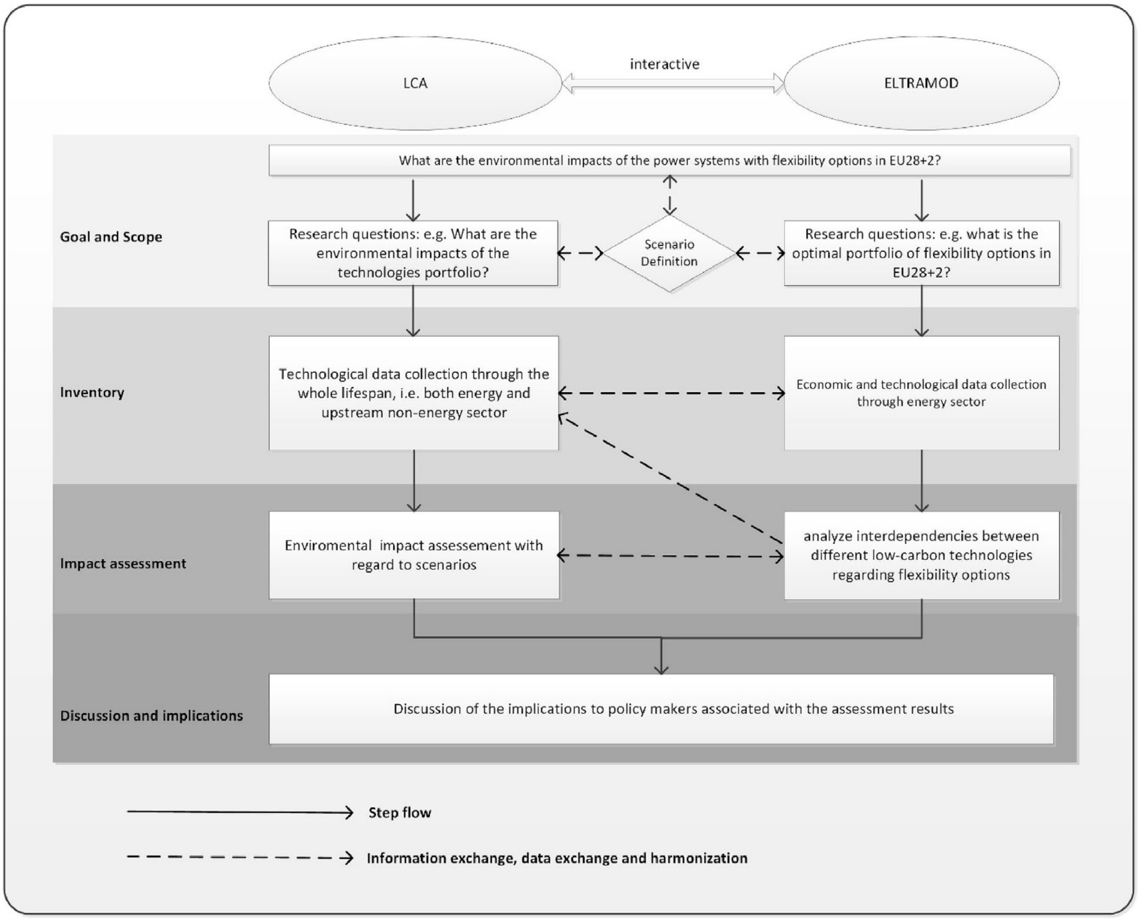

Fig. 2. An illustration of applying EAFESA: combining LCA and electricity market model ELTRAMOD.

than 10 μm that cause respiratory morbidity (Ebi and McGregor, 2008; Goedkoop et al., 2009; Huijbregts et al., 2016; Valavanidis et al., 2008). The latter is characterized by the destruction of the stratospheric ozone layer by anthropogenic emissions of ozone depleting substances, increasing in such substances causes a larger portion of harmful ultra violet B radiation to reach the earth (Huijbregts et al., 2016; Norval et al., 2011; van der Leun et al., 1998). Freshwater eutrophication and urban land occupation reflect the damages to ecosystems. Freshwater eutrophication arises due to the discharge of nutrients into freshwater bodies or into soil causing nutrient levels to rise (Huijbregts et al., 2016). Urban land occupation refers to the occupation of a certain developed area (e.g. industrial area, traffic area) for a certain period of time (Huijbregts et al., 2016). Metal depletion stands for impacts with regard to metal resource availability. The indicator is used as a measure of the scarcity of metals (Goedkoop et al., 2009). The calculation of environmental impacts uses the ReCiPe method for life cycle impact assessment (Goedkoop et al., 2009), as it is currently one of the most comprehensive methods for LCA analysis.

4.2. Goal and scope definition

Under EAFESA approach, ELTRAMOD and LCA establish a common goal i.e., analyzing and discussing the environmental implications of electricity generation in the EU28 + 2 countries given different sets of flexibility options and climate change mitigation scenarios (i.e., Mod-RES, High-RES Centralized and Decentralized scenarios) for 2050. ELTRAMOD is used to analyze the penetration of different flexibility options and their contribution to renewable energy integration as well as the interdependencies among various flexibility options in the European electricity system, taking existing regulatory frameworks into account. The system and geographical boundaries are set to be within the electricity sector and within EU28 + 2 countries, respectively. In this case, LCA follows the target approach to disaggregate the scenarios into different technological roadmaps linked to the impacts of future changes along the lifetime. Technological progress is implemented by varying resource inputs and key performance indicators (e.g., efficiency and lifetime). LCA includes the upstream and auxiliary processes, such as raw material production, fuel production and generation plant construction. Additionally, a global market for the upstream non-electricity sectors and a European market for the use and downstream disposal processes are assumed.

4.3. Inventory analysis

Data for both LCA and ELTRAMOD modelling are gathered in this step to develop a consistent scenario database, in line with the defined scenario storylines.

As mentioned above, ELTRAMOD assumes average technologies, using only limited economic data but no detailed technological description, impeding precise calculations of environmental impacts. To overcome this, where necessary, average technologies are disaggregated using LCA data, in our case wind and solar energy that are especially relevant. In other cases, the data characterizing the technologies modelled in ELTRAMOD are supplemented with

LCA data (cf. Table S2).

Broadly speaking, there are two groups of wind turbines: the conventional asynchronous generators (AG) and the more sophisticated synchronous generators (SG). Due to higher efficiency, it is expected that in the long run the latter gain greater market share. Currently, SGs are further subdivided between Electrically Excited Direct Drive (SG-E-DD), which is a relatively well-established technology, Permanent Magnet (SG-PM) and High-Temperature Superconductors (HTS), both are considered to be the most promising technologies for the future (Maples et al., 2010). Due to the lower share of RES for electricity production in Mod-RES, the market for wind power plants is not considered to change considerably in the scenario, with SG-E-DD and AG still dominating the market with a share of above 50% in 2050 (SG-E-DD for wind onshore, AG for wind offshore). A complete market change is however expected in the case of High-RES. In these scenarios, SG-PM will be the main technology, with shares of over 90% (High-RES Central) and over 80% (High-RES Decentral) for 2050. Because of high demand for large-scale onshore wind plant in High-RES Central (Herbst et al., 2016b; Poganietz et al., 2017; Zöphel et al., 2019), an ongoing increase in wind generator size is assumed, led by a market preference for SG-PM (Viebahn et al., 2015). It is expected that SG-PM will require less maintenance and produce less noise in operation compared with currently dominant technologies. In High-RES Decentral with a wide-spread deployment of wind power plants at all possible locations, HTS will also enter the market.

The solar technology follows the scenario storylines, which considers PV rooftop and ground mounted. Conventional PV technologies (with crystalline cells) and advanced technologies (with thin-film cells) are considered to constitute the solar technology market. The future of solar technology is considered not to be limited by space restrictions, and due to this and their lower material usage and increasing generation efficiencies, the development of thin-film solar modules is highly probable (Viebahn et al., 2015). For rooftop solar power plants, thin-film technology will gain a third of the market, whereas in case of ground-mounted plants, they could amount to half of the market. However, this happens only in case of High-RES scenarios, with the higher ambitions for RES technologies compared to Mod-RES (cf. Table S3).

In LCA, data for foreground processes (i.e., the technologies under review) and background (upstream and auxiliary systems) constitute the Life Cycle Inventory (LCI). Technical progress, which can lead to a complete replacement of the currently dominant technologies, can happen in both foreground and background processes. To capture possible technical progress in this study, the relevant parameters of the processes under investigation are adjusted using the learning curve approach or data from the literature (Junginger et al., 2010; Louwen et al., 2018a, 2018b; Treyer and Bauer, 2016). The input data for ELTRAMOD are mainly specific investment costs varying between technologies, energy carrier prices, CO_2 prices, etc. Their harmonization with LCA data is rather straightforward. About 33% of parameters of ELTRAMOD and electricity generations by technologies have been required to be harmonized with LCA modelling (cf. Table S4).

4.4. Impact assessment

The target shares for renewables and GHG emissions reduction are the main drivers for the development of European electricity systems in the future. Whereas in Mod-RES the electricity generation in 2050 is 10% higher than in 2014, the GHG emissions reduction target leads to an increase in electricity generation in the High-RES scenarios by 65% (High-RES Central) and 78% (High-RES Decentral) compared to 2014, due to enhanced electrification of the mobility, industry, and heat sectors.

The European electricity system that achieves the 2050 carbon dioxide emissions target is generally transformed from a fossil-based system using coal (22%), nuclear (28%), and lignite (10%) in 2014 to a system with increasing shares of wind and solar generation supplemented with gas with carbon capture and storage (CCS) and nuclear (cf. Fig. 3). The major investments in the Mod-RES scenario up to 2050 are on- and off-shore wind technologies and combined cycle gas turbines (CCGT), with shares of 27% for both technology groups respectively. Ground and rooftop mounted solar technologies reach a combined share of 12%.

In both High-RES scenarios the electricity mix sees the same general pattern, with wind power (29–34%), gas CCS (25%), solar (15–18%) and nuclear (8–9%) as the main generation technologies. The difference between a centralized system and a more decentralized one is ultimately reflected by higher shares of typical large size power plants and lower shares of typical small-scale power plants in the former. For example, offshore wind plays a larger role in the High-RES Central scenario with a contribution to 10% of total generation compared to 6% in the High-RES Decentral scenario by 2050. Rooftop mounted solar reaches only 3% in the High-RES Central scenario while 8% in the High-RES Decentral scenario by 2050.

The contributions of battery-based flexibility options (e.g., lithium ion and redox flow) are marginal with less than 1% share of the electricity mix in all three scenarios. This is mainly due to the scenario framework assuming an exogenously enforced application of DSM measures as well as an increasing role of sectoral coupling (power-to-x) technologies. These flexibility options are in competition with storage technologies and decrease the values of the latter.

The variations in the electricity mix between the scenarios lead to varying environmental impacts. Both High-RES scenarios fulfill the electricity sector's direct GHG emission reduction targets with 80% (Central) and 88% (Decentral) reduction in 2050 compared to 1990. In case of the Mod-RES scenario, the GHG emissions reduce by about 68% (cf. Section 4.1). The life cycle GHG emissions in 2050 in all scenarios show decreasing trends compared to 2014. The fossil-combustion based emission target setting of High-RES scenarios shows its benefit for limiting global temperature rise, even from a life-cycle perspective. This is mainly because the fossil fuel combustion process alone plays a major role in the GHG emissions of fossil-fired electricity generation technologies, e.g., coal-fired electricity plants (over 95% of life cycle GHG emissions are from coal combustion process).

Comparing the direct emissions (of the entire electricity sector) with the life cycle emissions, as expected the direct are generally lower, but the share of direct at life cycle emissions vary between 61% (2014) and 25% (High-RES Decentral), indicating the increasing relevance of upstream and auxiliary emissions in an electricity system with large share of RES (cf. Fig. 4).

Generally speaking, freshwater eutrophication impacts show a similar pattern to that for climate change, i.e. a noteworthy decline of the indicator value overall scenarios compared to 2014 (cf. Fig. 5). In the case of the Mod-RES scenario, ozone depletion and particulate matter impacts are at similar levels to 2014, while the more ambitious GHG reduction target, i.e. both High-RES scenarios, induces increases for both impact indicators. Regarding metal depletion and urban land occupation any transformation of the European electricity sector leads to even higher impacts.

Compared to 2014, freshwater eutrophication declines by 78% in the Mod-RES scenario; the GHG reduction target brings a reduction by 84% (High-RES Central) and 81% (High-RES Decentral). The decline of the freshwater eutrophication is mainly caused by the transformation of the electricity system away from fossil-based

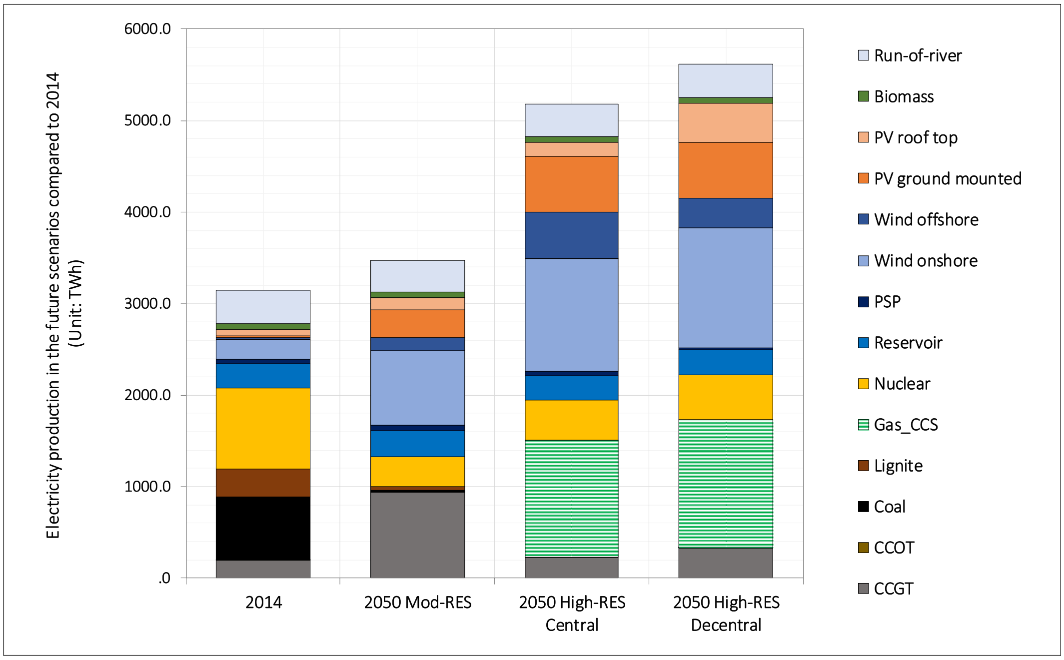

Fig. 3. Electricity mix in Mod-RES, High-RES Central and Decentral scenarios for 2050 compared to 2014. Technologies with less than 1% of total electricity generation are cut off, hereafter. (PSP, pumped storage; CCS, carbon capture and storage; CCOT, combined cycle oil turbine; CCGT, combined cycle gas turbine).

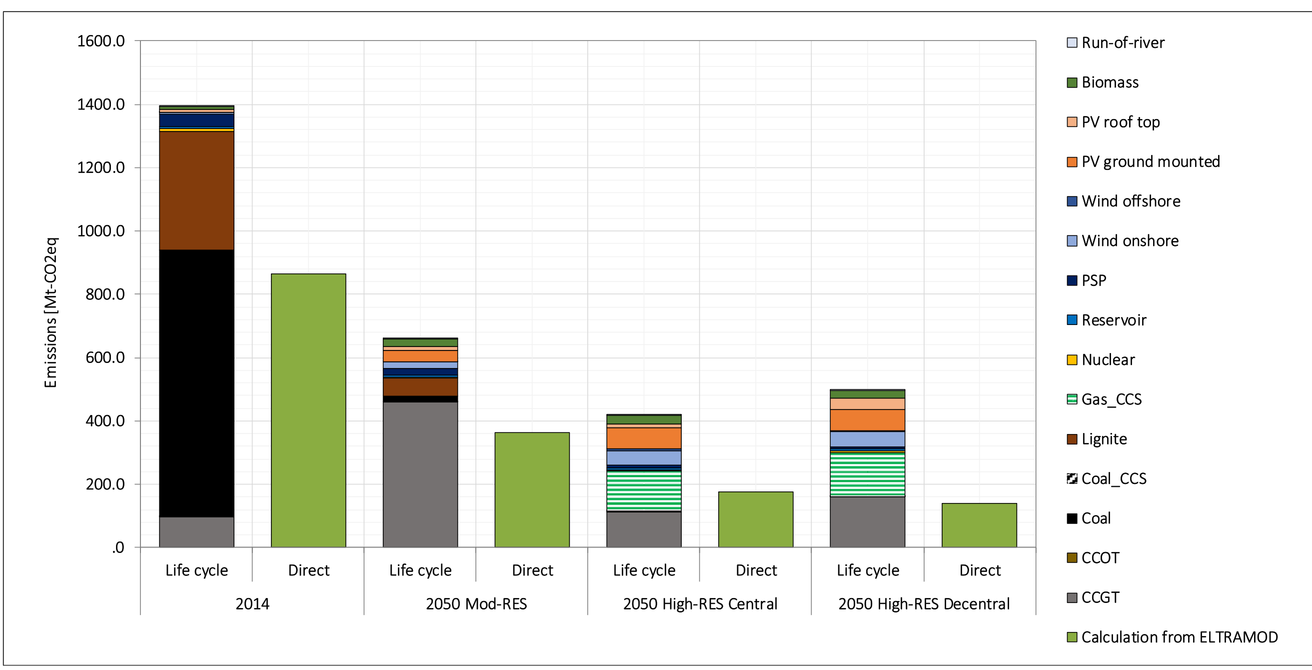

Fig. 4. Comparison of life cycle and direct GHG emissions for European power system in Mod-RES, High-RES Central and Decentral scenarios for 2050 compared to 2014. For comparison, total direct GHG emissions in Europe accounted to ca. 4290 MtCO2eq in 1990 (excluding land use, land use change and forestry) (EEA, 2018).

power plants to RES. Lignite's 10% share of generation in 2014 contributes to 84% of the freshwater eutrophication relevant emissions. The upstream process of spoil treatment from lignite mining plays a major role from a life cycle perspective. In the Mod-RES scenario lignite still causes about 56% of freshwater relevant emissions, in spite of amounting to only 1.3% of total generation. In the High-RES scenarios lignite is virtually eliminated in the mix, and the main contributor is the production of solar power plants.

Compared to 2014 particulate matter formation declines by only 10% in the Mod-RES scenario, but in the High-RES scenarios it increases by about 30% (High-RES Central) and 50% (High-RES Decentral). The negative impact from increased use of solar PV and gas CCS in the High-RES scenarios exceeds the positive impact from the reduction of coal and lignite in the same scenarios. Similar trends are seen for ozone depletion. In this category, the impact from increased use of gas CCS in the High-RES scenarios compared to the current case outweighs the decrease over the same period due to reduced demand for nuclear power.

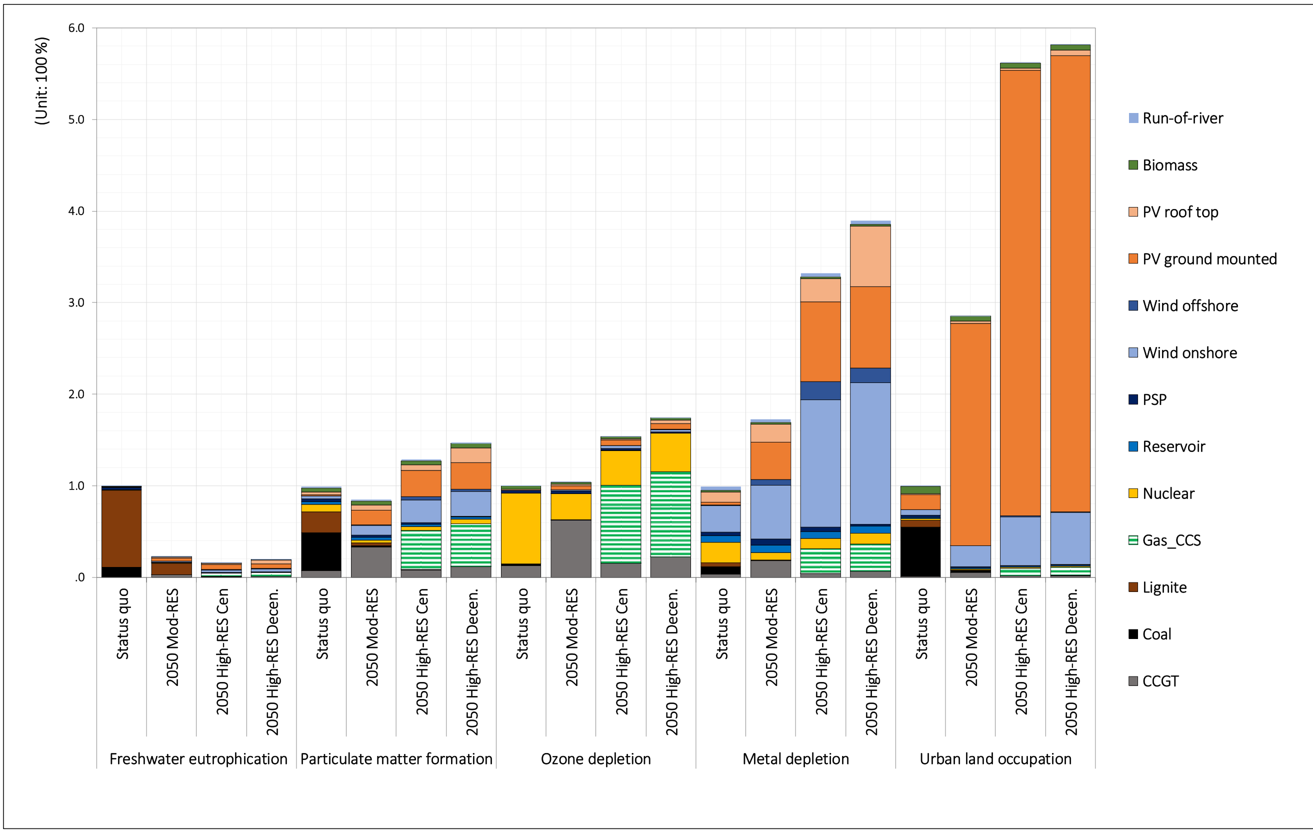

Fig. 5. Normalized results of non-climate environmental impacts by technologies in Mod-Res, High-RES Central and Decentral scenarios for 2050 compared to 2014.

Impacts in both categories are higher in the High-RES Decentral scenario because gas CCS and solar PV have higher shares in the generation mix than in the High-RES Central scenario. The assessment shows that the use of natural gas in future scenarios reduces the pace of minimizing ozone depletion. This is mainly due to the high risk of natural gas leakage from pipelines, increasing the amount of methane in the atmosphere. Similarly, natural gas that contains other hydrocarbons increasesthe impact by particulate matter, too.

Metal depletion increases in all scenarios compared to 2014. Even in the Mod-RES scenario, the impacts in this category increases by around 75%. With the GHG reduction targets metal depletion impacts increase by about 235% in the High-RES Central scenario and by 290% in the High-RES Decentral scenario. Wind and solar PV technologies are the main contributors to this. For example, in the High-RES Central scenario, wind onshore (24% of generation, 42% of metal depletion) and PV ground mounted (12% of generation, 26% of metal depletion) are the largest contributors to metal depletion for 2050. The high contributions from wind are mainly due to the demand for chromium steel, low-alloyed steel, reinforced steel and cast iron used for towers, rotors and nacelles; copper for connecting wires for all types of wind power plants as well as rare earth metal for super conductor production process for HTS. Metal depletion due to solar PV technologies arises due to demand for steel, silicon, copper, silver and other metals required in their production.

Like metal depletion, urban land occupation is dramatically affected by the transition to electricity production with low GHG emissions. Impacts in the category increase by 180% (Mod-RES), by 460% (High-RES Central) and even by 480% (High-RES Decentral) compared to the current case. The growth of land use is mainly driven by ground mounted solar PV. This single generation technology causes about 85% of total impacts in the category for all future scenarios. The high impacts for ground mounted solar PV arise as a result of the land needed to install these PV systems.

4.5. Discussion and implications

The combined analysis of ELTRAMOD with LCA using the EAFESA framework confirm the main findings of Hertwich et al. (2015) and others. Establishing climate and energy policy to address only climate change could neglect other environmental and resource-related impacts, impeding to some extent the success of these policies. This could be of particularly relevant if the impacts occur locally in Europe. The life cycle perspective also considers impacts arising in upstream processes performed outside of Europe, such as extraction of metals.

Comparing all scenarios, ambitious GHG emission reduction targets lead to more significant changes in the electricity mix and changes in environmental impacts compared to 2014, i.e. in High-RES scenarios the emission levels are either lower, e.g. freshwater eutrophication, or higher, e.g. ozone depletion, compared to the Mod-RES scenario. This is because the technologies with low climate impact promoted by ambitious climate targets are not necessarily so environmentally benign in all respects. It is important to note that with the exception of climate impacts, life cycle impacts in all other categories are higher in the decentralized scenario than in the centralized. Differences for climate change, freshwater eutrophication and urban land occupation are rather negligible, amounting to only 4% in case of urban land occupation for example. However, differences are larger for other categories: 16% for metal depletion and 20% for ozone depletion.

In light of the increased metal depletion, metal use strategies are indispensable for the EU to have a secure and sustainable supply chain for metals and their corresponding components, especially considering that Europe is to some extent dependent on imports of ores or processed ores (in particular critical metals) (Moss et al., 2013). First, to maintain a high level of metal availability and accessibility is important: it is a valuable strategy to closely cooperate with companies in supplier countries and their governments. In the EU, raw materials diplomacy aiming to establish dialogues with the EU's strategic partners in raw materials has been pursued. So far, the EU has developed relations with more than ten countries which have important mineral reserves that are strategic to the EU industry (European Commission, 2015a). Metal supply could certainly benefit from this strategy. Second, recycled sources are creditable in mitigating metal depletion, which implies that enhanced recycling and recovery in the EU could to some extend decrease the possible restriction of metal supply. Further, a potential option is to find substitutes with higher availability, which can also play a role on reducing the metal dependence, and should be promoted (European Commission, 2015b).

PV technologies, which are the main drivers for the future increased urban land occupation, are an essential component for future sustainable cities (Amado and Poggi, 2014). However, higher urban land occupation due to PV ground mounted technologies is a challenge to sustainability in an urban context, considering land use competition for different uses, e.g. industry, traffic, and green areas. Spain, France, and Italy amongst others are the main countries to invest in PV ground mounted technologies. The authority for ground mounted PV has been given by many countries (e.g. Spain, cf. (McKenzie, 2019)). Urban land use strategies still need to be developed for urban evolution and development considering the installation of PV ground mounted technologies. Space multifunctionality is a possible form for urban sustainability (Ghafouri, 2016). Functional overlaps in space (e.g. install PV in the industrial area, green area, in the baffle between green and traffic areas) could decrease pressure on future urban land use, especially for compact cities, and could serve as one of the effective measures for mitigating urban land use impacts. It should be noted that potential ecological impacts e.g. biodiversity damage may occur especially due to the installation of PV in the green area and therefore, attention should be paid (Taylor et al., 2019).

Considering the impacts of ozone depletion and particulate matter formation, leakage from natural gas pipelines has negative effects to human health. Gas leakage associated regulations have been put into place in many countries, e.g. Russia (one of the most important gas supplier countries for the EU). It specifies the concept of piplines and their interrelated parts, such as: the installation of electromechanical protection of the pipline against corrosion (Kurmaev and Malinin, 2018). Further, in industry and academia, many efforts have been devoted to the development of technologies, e.g. timely leak detection and localization techniques and shut-off systems, which are important to reduce leakage and limit the subsequent damage to environment and human health (Rui et al., 2017; Sun et al., 2016; Xiao et al., 2018).

5. Conclusions

The main driver of the current European energy policy is the anthropogenic induced climate change and the possible contribution of a transformed energy system to mitigate climate change. Without questioning this focus, the above-discussed findings with respect to the environmental impacts of a transformation of the European energy system show the necessity of expanding the scope of the analyses and societal discussion, and thus, the importance of “integrated thinking”. The assessment in the case identifies potential trade-offs of increased metal depletion and urban land occupation alongside reduced greenhouse gas emissions. The trade-offs are insufficiently considered in current decarbonization policies and should be taken into account to avoid potential restrictions or resistance in the transition to a decarbonized energy system.

The necessity of integrated thinking had been addressed by other researchers, by coupling LCA with ESM directly or indirectly via Input-Output approaches (e.g. García-Gusano et al., 2016a). Considering the identified gaps of the discussed approaches, a methodological framework, EAFESA, is thus developed to overcome the challenges of coupling LCA and ESM. It highlights the importance of “integrated thinking” and is designed as a general, holistic and carefully formulated approach that can be applied to a variety of energy systems. In general, EAFESA is proposed to be applicable in cases regardless of the various geographical and technological scopes, for one single energy sector or entire energy systems, and in conjunction with different energy systems models. Particular considerations need to be made according to the scope of the study in each case.

With EAFESA a systematic framework to couple ESM with LCA is presented. However, additional research is needed. A crucial step of the framework is the identification of technology scenarios for the sub-modules. Due to a lack of data and knowledge of how future markets will react to new technologies, the future shares of technologies are built on projections by experts, considering learning curves for market-proven technologies and expectations regarding the techno-economic setting of innovative, but not market-ready technologies. The upstream non-energy sectors in ESM are linked with the energy sectors via prices, which would influence the choice of upstream sectors via price fluctuations. This uncertainty in terms of choices in the upstream sectors is not recognized in LCA. The linking of LCA with ESM allows identifying the life cycle based environmental impacts of transforming the energy system. Linking the LCA to life cycle costs, the entire system costs could be quantified, thus showing the potential trade-offs between economic and environmental impacts.

Acknowledgements

This work is performed within the Reflex project funded by the European Union's Horizon 2020 research and innovation programme [GA-No. 691685]. The first author is supported by China Scholarship Council (CSC). The authors thank the reviewers for their thoughtful comments and suggestions. Declarations of interest: none.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.118614.

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Supplementary Materials (SM)

Table S1: Comparison of EAFESA and recent literature for LCA and ESM model coupling

Responses to challenges	A breakdown of technologies (Specification)		Data harmonization	LCA approach		Coupling approach	
	Dynamic LCI for representative existing technologies	Dynamic LCI for future emerging technological markets		Process-based LCA	IO based Hybrid-LCA	life cycle thinking	energy system thinking
Pehl et al. 2017	×		(×)		×	×	
Rauner et al. 2017				×			×
Berrill et al. 2016	×		(×)		×	×	
Hertwich et al. 2015	×		(×)		×	×	
Garcia-Gusano et al. 2016a				×			×
Garcia-Gusano et al. 2016b				×			×
Santoyo-Castelazo et al 2014				×		×	
Loulou et al. 2008				×			×
This study 2019	×	×	×	×		×	×

Note: × fully considered; (×) partly considered.

Table S2: Full list of technology mix considered in ELTRAMOD and LCA

ELTRAMOD	LCA
	Technologies
Wind onshore and offshore	Asynchronous generators (AG)
	Synchronous Generator - Electrically excited - Direct drive (SG-E-DD)
	Synchronous Generator - Permanent Magnets generators (SG-PM)
	High temperature superconductor (HTS)
Solar ground and rooftop mounted[1]	Thin film
	Crystalline
Biomass	Direct combustion
	Biogas conversion
Hydro power plant: Run-of-river Pumped storage (PSP) Reservoir	Hydro power plant: Run-of-river Pumped storage (PSP) Reservoir

Nuclear	Nuclear pressure water reactor
Lignite	lignite-fired in an average condition
Lignite_CCS	Lignite-fired with CCS in post-combustion process
Coal	Coal-fired in an average condition
Coal_CCS	Coal-fired with CCS in post-combustion process
Oil steam	Oil steam
Combined cycle oil turbine (CCOT)	CCOT
Open cycle oil turbine (OCOT)	OCOT
Gas steam	Gas steam
Open cycle gas turbine (OCGT)	OCGT
Combined cycle gas turbine (CCGT)	CCGT
Gas_CCS	CCGT_CCS in post-combustion process
Other renewables (RES)	Geothermal
Advanced Compressed Air Energy Storage (A-CAES)	A-CAES
Battery lithium-ion small	Battery lithium-ion small
Battery redox flow	Battery redox flow

[1]Solar only refers to Photovoltaics

Table S3: Market shares of wind and solar technologies according to scenarios for LCA modelling

ELTRAMOD	LCA Technology	2014	2050 Mod-RES	2050 High-RES Central	2050 High-RES Decentral
Wind onshore	AG	18%	12%	2%	2%
	SG-E-DD	57%	53%	4%	4%
	SG-PM	25%	35%	94%	82%
	HTS	0%	0%	0%	12%
Wind offshore	AG	85%	50%	2%	2%
	SG-E-DD	0%	0%	0%	0%
	SG-PM	15%	50%	98%	81%
	HTS	0%	0%	0%	17%
Solar rooftop	Thin film	3%	1%	32%	32%
	Crystalline	97%	99%	68%	68%
Solar ground	Thin film	3%	2%	50%	50%
	Crystalline	97%	98%	50%	50%

Source:(Viebahn et al., 2011)

Table S4: qualitative lists of harmonized parameters utilized in both ELTRAMOD and LCA

Indicators	Unit

Efficiency assumptions by technology (Coal IGCC)	%
Efficiency assumptions by technology (Coal IGCC CCS)	%
Efficiency assumptions by technology (Coal PC Supercritical)	%
Efficiency assumptions by technology (Coal PC CCS Supercritical)	%
Efficiency assumptions by technology (Lignite)	%
Efficiency assumptions by technology (Lignite CCS)	%
Efficiency assumptions by technology (Gas CC)	%
Efficiency assumptions by technology (Gas Combustion)	%
Efficiency assumptions by technology (Gas Steam)	%
Efficiency assumptions by technology (Gas CCS)	%
Efficiency assumptions by technology (Oil CC)	%
Efficiency assumptions by technology (Oil Combustion)	%
Efficiency assumptions by technology (Oil Steam)	%
Efficiency assumptions by technology (Nuclear)	%
Efficiency assumptions by technology (Reservoir)	%
Efficiency assumptions by technology (PSP)	%
Efficiency assumptions by technology (Battery Lithium-Ion)	%
Efficiency assumptions by technology (Battery Redox-Flow)	%
Efficiency assumptions by technology (A-CAES)	%
Lifetime of investment by technology (Coal)	years
Lifetime of investment by technology (Coal CCS)	years
Lifetime of investment by technology (Lignite)	years
Lifetime of investment by technology (Lignite CCS)	years
Lifetime of investment by technology (Gas CC)	years
Lifetime of investments by technology (Gas Combustion)	years
Lifetime of investments by technology (GasSteam)	years
Lifetime of investments by technology (Gas CCS)	years
Lifetime of investment by technology (Oil CC)	years
Lifetime of investment by technology (Oil Combustion)	years
Lifetime of investment by technology (Oil Steam)	years
Lifetime of investment by technology (Nuclear)	years
Lifetime of investment by technology (Reservoir)	years
Lifetime of investment by technology (PSP)	years
Lifetime of investment by technology (Battery Lithium-Ion)	years
Lifetime of investment by technology (Battery Redox-Flow)	years
Lifetime of investment by technology (A-CAES)	years
Lifetime of investment by technology (Power-to-Gas)	years
Lifetime of investment by technology (Power-to-Heat)	years
Lifetime of investment by technology (wind)	years
Lifetime of investment by technology (solar)	years
Emission factor by technology (Lignite)	kg/MWh
Emission factor by technology (Coal)	kg/MWh
Emission factor by technology (Gas)	kg/MWh
Installed capacity by technology (solar_ground_mounted)	MW
Installed capacity by technology (solar_rooftop)	MW
Installed capacity by technology (wind_onshore)	MW
Installed capacity by technology (wind_offshore)	MW

Installed capacity by technology (biomass)	MW
Installed capacity by technology (run-of-river)	MW
Installed capacity by technology (other_RES)	MW

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Considering the Impacts of Metal Depletion on the European Electricity System

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Abstract: The transformation of the European electricity system could generate unintended environment-related trade-offs, e.g., between greenhouse gas emissions and metal depletion. The question thus emerges, how to shape policy packages considering climate change, but without neglecting other environmental and resource-related impacts. In this context, this study analyzes the impacts of different settings of potential policy targets using a multi-criteria analysis in the frame of a coupled energy system and life cycle assessment model. The focus is on the interrelationship between climate change and metal depletion in the future European decarbonized electricity system in 2050, also taking into account total system expenditures of transforming the energy system. The study shows, firstly, that highly ambitious climate policy targets will not allow for any specific resource policy targets. Secondly, smoothing the trade-off is only possible to the extent of one of the policy targets, whereas, thirdly, the potential of recycling as a techno-economic option is limited.

Keywords: system expenditures; climate change; metal depletion; multi-criteria analysis; LCA; electricity system model

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Citation: Xu, L.; Wang, Z.; Yilmaz, H.Ü.; Poganietz, W.-R.; Ren, H.; Guo, Y. Considering the Impacts of Metal Depletion on the European Electricity System. *Energies* **2021**, *14*, 1560. https://doi.org/10.3390/en14061560

Academic Editor: Dalia Štreimikienė

Received: 23 November 2020
Accepted: 8 March 2021
Published: 11 March 2021

1. Introduction

Slowing down climate change is one of the main societal drivers of the transformation of the European energy system from a conventional fossil-based to a decarbonized sustainable energy supply [1]. Whereas energy policies as instruments to implement societal aims are of great significance to drive the transformation, energy policy generally uses energy system models (ESMs) for advice regarding the adequate shape of the future energy system. The mainstream approach of modeling energy systems is to minimize the total system expenditures while constraining CO_2 or greenhouse gas (GHG) emissions [2,3].

Nevertheless, an increasing amount of research highlights the importance of non-climate environmental and resource-related impacts of the transformation, which could generate unintended trade-offs [4–6]. With the transformation to a decarbonized energy system, co-benefits could be expected, such as a decreased dependency on fossil fuels or lower eutrophication, but potentially important trade-offs could emerge, like an increased requirement for metal resources [4]. According to Xu et al. [4], in scenario High-RES Cen, reduced life-cycle GHG emissions of the European electricity system of 84% in 2050, compared to 2014, would raise metal depletion by about 235%. Metal depletion accounts for the system's demand for primary metal [7]. The findings refer to "bulk" metals, like steel and iron, and do not consider strategic metals. The main reasons for the trade-off are the low full load hours, and the small size of renewable energy power plants per generated kWh electricity compared to power plants using fossil fuels or uranium, indicating a negative scale effect when comparing conventional and renewable energy technologies in respect to metal requirements [4].

Correspondingly, the EU discusses and implements strategies to maintaining metal availability and accessibility through, amongst others, trade agreements with exporting countries and recycling [8,9]. The long-term aim is to secure the trade connections while reducing import dependency; but environmental considerations also play a role in these considerations [10].

Bearing in mind these additional impacts of the transformation process towards a renewable energies-based electricity system, from a policy perspective, the question emerges of how to shape a future electricity system which is climate neutral, environmentally friendly, and economically sound. What policy packages could serve to attain which different policy targets, such as an ambitious climate policy in combination with an aspiring resource policy? A policy package combines different single policy measures, aimed at addressing one or more policy targets [11–14]. The rationale is "to improve the impacts of the individual policy measures, minimize possible negative side effects, and/or facilitate interventions' implementation and acceptability" [12].

ESMs, as the main instrument to support energy policies, seldom address non-energy resource demands. Additionally, due to their generally single-objective perspective, they cannot elaborate different policy aims, and thus potential trade-offs, accordingly [2,3]. To analyze the above-mentioned question, extending the scope of ESMs, as well as using a multi-objective perspective, seems to be necessary.

Combining ESMs with life cycle assessment (LCA) has been identified as a suitable approach to broaden the scope of the analyses through including additional environmental and resource-related impacts [4–6,15]. Furthermore, the combination of both approaches allows switching from a direct emission perspective to a life-cycle perspective. Not only the direct emissions and resource demands of the electricity system under review are taken into account, but also those emissions and resource requirements of the upstream sectors induced by the electricity system. Recent literature has discussed performing trade-off analysis by applying such an approach. However, most research conducts ex-post LCA analysis to assess the trade-offs in terms of environment, resources, and other aspects connected to energy system pathways, calculated by ESMs [4–6,15–17]. Those studies fail to provide knowledge-based information on potentially feasible and effective solutions to balance trade-offs between policy targets. Only a few studies have focused on integrating LCA indicators to ESMs [18–21]. However, these studies either follow the ex-post assessment approach [18,19], or aggregate all considered environmental impacts into only one or a few indicators [20,21], though a multi-objective optimization approach is applied. None of them has thoroughly analyzed the potential impacts on the shape of the electricity system if the trade-offs are implemented in respective policies.

The high-level objective of the presented study is to analyze the impacts of different outlines of policy packages, which address both climate and resource policy targets, on the shape of the European electricity system in the year 2050. The analysis will make use of a multi-criteria analysis in combination with a coupled ESM-LCA model. Although the focus of the study is on the interrelationship between climate policy and resource policy, the analysis also includes system expenditures, as an additional factor addressed in political and societal discussions.

The paper is organized as follows: Section 2 introduces the methodological framework, data, and the scenarios representing different policy packages. Section 3 presents the results and conducts a comparative analysis of the defined scenarios. The findings are discussed in Section 4; Section 5 offers some concluding remarks.

2. Methods

The methodological framework consists of an algebraic model, which couples the energy system model PERSEUS-EU with an LCA model into the LCA-PERSEUS-EU model, with a multi-objective formulation, and the scenarios used for the analyses. PERSEUS strands for "Programme-package for Emission Reduction Strategies in Energy Use and Supply-Certificate Trading". The chosen methodological frame allows for identification of the best solution for different sets of societal-relevant objectives, as discussed in the introduction (Section 1), considering important technological, political, and environmental constraints.

2.1. Energy System Model PERSEUS-EU

PERSEUS-EU [22–24] is a long-term energy system optimization model of the European electricity system. The model consists of the EU27 (without the islands of Cyprus and Malta), but includes Switzerland, Norway, and the United Kingdom, i.e., in total 28 states. The objective of the optimization is to minimize all decision-relevant expenditures. The expenditures are composed of the fuel costs, the costs for emitting CO_2, other operating costs, as well as investment costs of electricity generation units, to thereby simulate economic decision-making behavior. The objective function is complemented by restrictions addressing technological, political, and environmental constraints. The optimization is driven by the restriction to satisfy the exogenously given electricity demand. The most important decision variables are electricity production capacities, electricity production levels, and electricity exchanges between the modeled European countries. The time horizon of the model is 2050. PERSEUS-EU is implemented in GAMS, the programming language for writing mathematical optimization problems, and is solved with the CPLEX solver, a solution algorithm for large scale mixed integer linear programming problems. CO_2 and energy carrier costs are based on [25]. Techno-economic parameters of the investment options are from [26]. The investment expenditures of renewable energy sources are based on [27]. The existing power plant portfolio of the European countries are modeled using the WEPP database [28].

2.2. Life Cycle Assessment and the Coupled Model LCA-PERSEUS-EU

LCA is defined by the International Organization for Standardization as a method to evaluate the input, output, and the potential environmental impacts of a product system throughout the entire lifespan, i.e., from extraction of resources, manufacturing and processing, transportation, use of the product, to disposal management [29]. An LCA includes four phases: goal and scope, inventory analysis, impact assessment, and interpretation. The target product system of the LCA analysis is the European electricity system, consistent with the PERSEUS-EU model. The goal is to provide environmental and resource-related indicators to the PERSEUS-EU model. The life cycle inventory (LCI) makes use of the Ecoinvent 3.3 database [30], as well as of the findings of the ReFlex project [17]. The ReFlex project implemented the learning curve approach in process models, as well as expectations about photovoltaic cells (PV) and wind power technologies expectable in the future. The calculations of the LCI of the year 2050 make use of these assumptions. The functional unit of each electricity generation technology is one MWh. The identified emissions assigned to the technologies, as they are modeled in the LCI, are assessed using the assessment approach ReCiPe [31]. The GHG emissions and metal depletion by main technologies from 2015 to 2050 are presented in Table A1 [17]. The phase of interpretation allows for checking and evaluating the results to guarantee their reliability. The coupling of the LCA model with PERSEUS-EU applies the Environmental Assessment Framework for Energy System Analysis (EAFESA). EAFESA is a guide for coupling ESM and LCA models to handle the challenges due to the differences of both approaches with regard to the system boundaries, databases, and assumptions [4].

2.3. Augmented ε-Constraint

The multi-objective analysis applies the ε-constraint method [32]. The ε-constraint method uses all but one objective function as secondary conditions in addition to the above-mentioned technological, political, and environmental constraints, optimizing the selected objective function. However, since the conventional ε-constraint approach fails to guarantee efficient solutions (i.e., Pareto-optimal solution), an augmented version of the method is used in this study. Pareto-optimality refers to a solution in which an improvement of one criterion is not possible without worsening the performance of at least one other criterion [33].

The augmented version of the method sees the implementation of slack variables related to those objective functions, which are used as constraints. In our case, the selected objective function minimizes the total system expenditures (EX). The objective functions used as additional constraints are GHG emissions addressing climate change (CC), and metal demand addressing metal depletion (MD). Thus, the optimization problem looks as follows:

$$\text{Minimize } (f_{EX}(x) - \delta \times (s_{CC}/r_{CC} + s_{MD}/r_{MD})). \tag{1}$$

Subject to:

$$f_{CC}(x) + s_{CC} = e_{CC}, \tag{2}$$

$$f_{MD}(x) + s_{MD} = e_{MD}, \tag{3}$$

where $f_{EX}(x)$ represents all decision-relevant expenditures. δ is an auxiliary parameter, which is generally small, e.g., 10^{-3}. r_{CC} and r_{MD} give the range of the objective functions regarding CC and MD, respectively. s_{CC} and s_{MD} are the slack variables to force the model to produce only efficient solutions, which drives the model to look for the optimal solution of Equation (1). They are non-negative variables related to CC and MD, respectively. Equation (2) and Equation (3) are the constrained objective functions for CC and MD, respectively. e_{CC} and e_{MD} define the upper limits for GHG emissions and metal demand, respectively. $f_{CC}(x)$ and $f_{MD}(x)$ are positive variables representing the amounts of GHG emissions and metal depletion within the entire system, respectively.

The augmented version of the ε-constraint method allows for optimal solutions with GHG emissions and metal depletion below the given upper limit, i.e., below e_{CC} and e_{MD}, respectively.

2.4. Scenarios

To analyze the consequences of different shapes of policy packages, which represent altered decision-making preferences regarding climate change and metal depletion, a couple of scenarios are defined. Hereby, each scenario represents a potential policy package. The combination of the upper limits, e_{MD} and e_{cc}, characterizes one scenario.

To identify the upper limits, first, a payoff table is calculated by minimizing separately the system expenditures (EX), GHG emissions (CC), and metal depletion (MD), to determine the best and worst solutions regarding the three objectives. For each objective optimization, the other two objectives are relaxed. The combined best solution of the three calculations regarding GHG emissions and metal depletion defines the utopia point and is set to 0%. The combined worst solution is the nadir point and is set to 100% [34,35].

In the second step, the ranges between the utopia and nadir points of CC and MD obtained describe the upper limits regarding GHG emissions and metal depletion, i.e., e_{MD} and e_{cc}, respectively. For the analysis, three different policy ambitious levels are defined, each reflecting hypothetical decision-making preferences. For each ambitious level, an upper limit is set. Hereby, the three intermediate equidistant grid points between the utopia and nadir points specify the limits. The most ambitious policy strives to realize 25% of the difference between the utopia and the nadir points. To derive the aspired GHG emissions or metal depletion, the calculated value is added to the utopia value. The moderate policy aims at 50%, and a relaxed policy is content with 75% of the difference between the utopia and nadir points. The ranges of CC and MD are divided into four equal intervals by three intermediate equidistant grid points (i.e., 25%, 50%, and 75%) that are used to vary parametrically e_{CC} and e_{MD}. This means policy is able to control the electricity system in a way that guarantees the respective upper limits in each scenario.

The main driver to transform the European energy system is to slow down climate change. Thus, in all scenarios the CO_2 price is set to 160 €/t CO_2 in 2050, according to the 450 ppm scenario of World Energy Outlook [25]. To reflect different decision-making preferences, the precise GHG emission targets will vary between the scenarios, allowing for less ambitious climate policies. However, to emphasize the current societal environment, which strives for slowing down climate change, the upper limit of e_{cc}. is limited to 50%. Policy packages allowing for a relaxed preference for slowing down climate change will be not scrutinized in this study.

Consequently, six scenarios are defined in the following policy package. These are: (1) CC ambitious and MD ambitious (CAMA), (2) CC ambitious and MD moderate (CAMM), (3) CC ambitious and MD relaxed (CAMR), (4) CC moderate and MD ambitious (CMMA), (5) CC moderate and MD moderate (CMMM), and (6) CC moderate and MD relaxed (CAMR). For comparison, the results obtained from single objective optimizations are often called selfish scenarios [35]. These are EX selfish in case of minimizing the system expenditures, CC selfish for minimizing the GHG emissions, and MD selfish for minimizing metal depletion. Table 1 summarizes the definition of the three selfish scenarios and the six policy package scenarios with different decision-making preferences.

Table 1. Definition of the scenarios with different decision-making preferences.

Scenario	Ranges of Decision-Making Preferences				
	Utopia (0%)	**Ambitious (25%)**	**Moderate (50%)**	**Relaxed (75%)**	**Nadir (100%)**
EX selfish	EX				
CC selfish	CC				
MD selfish	MD				
CAMA		CC, MD			
CAMM		CC	MD		
CAMR		CC		MD	
CMMA		MD	CC		
CMMM			CC, MD		
CMMR			CC	MD	

3. Results

The payoff table obtained by the optimization of the single objectives defines a "skewed" triangle in which all mathematically feasible solutions can be located. The corner points of the triangle regarding system expenditures, metal depletion, and climate change are set by the scenarios CC selfish—the first two corner points—and MD selfish—the last one (see Table 2). The EX selfish scenario is within that triangle, with the lowest system expenditures, while GHG emissions and metal depletion are in between the other two selfish scenarios.

Table 2. Payoff table obtained by the optimizations of a single objective.

	EX (10^{12} €)	**CC (10^{13} kg CO_2 eq)**	**MD (10^{12} kg Fe eq)**
EX selfish	3.10	3.08	1.93
CC selfish	9196	0.74 (utopia)	2.20 (nadir)
MD selfish	8.42	8.54 (nadir)	0.47 (utopia)

Note: The figures are the outcome of several model runs using different objective functions as described in Section 2.4. The "utopia" figure gives the lowest possible value, and the "nadir" the highest possible value, regarding GHG emissions and metal depletion, achieved by minimizing GHG emissions or metal depletion, respectively.

Striving solely to slow down climate change (scenario CC selfish) leads, naturally, to the lowest GHG emissions of all selfish scenarios. Consequently, the scenario CC selfish shows the highest metal depletion level, setting the nadir point in respect to metal depletion.

However, the expenditures are around three thousand times higher than that in the EX selfish scenario, and a thousand times higher than that in the MD selfish scenario. The very high difference between the selfish scenarios regarding expenditures stems mainly from the necessity to invest excessively in low-carbon renewable energy sources (RES) technologies, e.g., wind power plants, to achieve the lowest possible GHG emission level while securing a reliable electricity supply. The high investments in RES technologies are at the expense of dispatchable technologies. The high expenditure in the CC selfish scenario accounts for low storage technology investments, since the model assumes only pumped storage (PSP) technologies.

A world with a high preference for low metal depletion, i.e., scenario MD selfish, would result in the highest GHG emissions of all selfish scenarios, defining the nadir point, but clearly the lowest metal depletion, the utopia point. Comparing the scenario CC selfish with the scenario MD selfish confirms, from a different angle, the strong trade-off relation between climate policy and resource policy.

Of the six identified policy package scenarios, the two most ambitious scenarios (CAMA and CAMM) result in no mathematically feasible solutions. The model assumes a reliable electricity supply, satisfying the electricity demand at each model time-slice. Since demand responses or power-to-gas technologies are not modeled in hours in which RES cannot match electricity demand, the supply gap has to be closed by gas-fired power plants and pumped storage power plants. Due to the restricted investment opportunities regarding pumped storage power plants, gas-fired power plants must be dispatched. However, setting the GHG emission target, which corresponds to an ambitious decision-making preference regarding climate, i.e., GHG emissions of about 2.69×10^{13} kg CO_2 eq, demands a specific mix of renewable energy technologies that corresponds to metal depletion, which goes beyond the level of 1.34×10^{12} kg Fe eq, which equals an ambitious level of 50%.

Figure 1 plots the relationship between the system expenditures, GHG emissions, and metal depletion for the scenarios with mathematically feasible solutions. The Appendix A lists the corresponding figures (Table A2).

In contrast to the significant differences in respect to the system expenditures between CC selfish and MD selfish scenarios on the one side, and the EX selfish scenario on the other, the discrepancies between the policy package scenarios is comparably small. CMMR shows 0.3%, CAMR 2%, CMMM 8%, and CMMA 23% higher expenditures, compared to the EX selfish scenario.

The high costs of achieving the CC selfish scenario level emerge mainly when pursuing from the ambitious level (25%) to the utopia level (0%). Reducing the ambitious level of the climate policy will reduce the system expenditures notably, compared to the CC selfish scenario. The system expenditures would drop to at least 0.0079% of the CC selfish system expenditures. The corresponding scenario CAMR is the policy package scenario with the highest system expenditures. Any relaxing of the climate policy targets would allow installing base load energy technologies with higher life-cycle greenhouse gas emissions per generated kWh, reducing the necessity of RES technologies.

The system expenditures of the MD selfish scenario are higher by a factor of 2.7 compared to the EX selfish scenario. Relaxing the ambition level of the resource policy would not have the same noteworthy impact on the relative expenditures as a reduced climate change policy ambition. The expenditures of the corresponding scenario CAMR reaches 12.8% of the expenditures of the MD selfish scenario.

A relaxed preference for slowing down climate change could achieve significant expenditure savings while still being ambitious from either a climate or a resource-related perspective (see CAMR and CMMA). As mentioned above, the model allows only PSP for storage systems. Implementing other, on average less costly storage systems, the "cost jump" should be less pronounced. The size of the drop depends on the average investment and operating costs of the storage systems, as well as the total size of unrequired RES plants. However, available data of grid-connected storage power plants are subject to large uncertainties, and thus were not included.

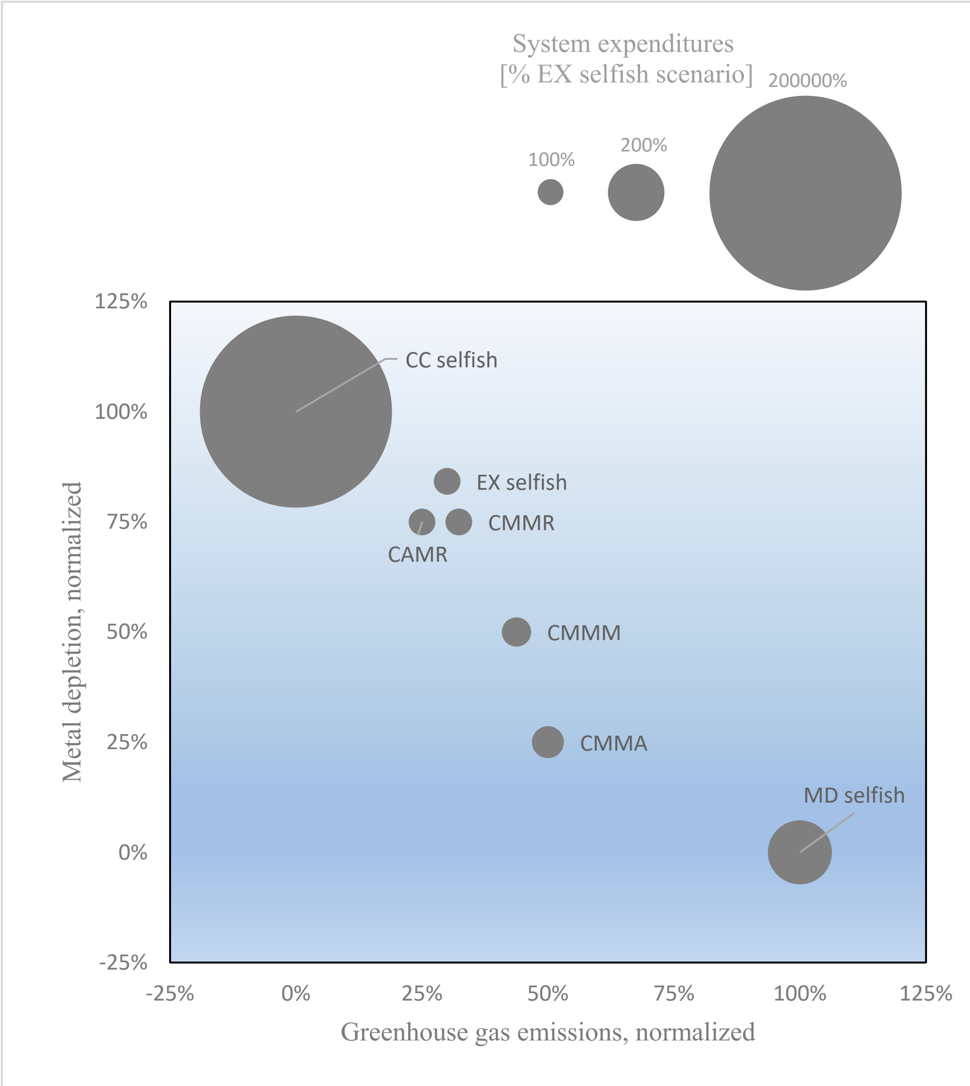

Figure 1. Relationship between system expenditures, GHG emissions, and metal depletion. The marker area is proportional to system expenditures. The GHG emissions and metal depletion are normalized to the range between the utopia and nadir points, 0–100%.

Comparing CAMR with CMMR, i.e., enhancing the preference for slowing down climate change from a moderate level (32%) to an ambitious level (25%) while realizing a relaxed resource policy preference (75%), would lead to increased expenditures of 2%. Raising the preference for a lower metal depletion from a moderate level (50%) to an ambitious level (25%) while maintaining the preference for slowing down climate change at the moderate level, i.e., comparing CMMA with CMMR, would cause higher expenditures of 14%. It seems that the system expenditures are more sensitive to metal depletion than to climate change, as long as only policy package scenarios are considered. This is mainly because a high CO_2 price has already been set for all considered scenarios.

Taking into account the GHG emissions and the metal depletion of the scenario EX selfish as the bottom line, only scenario CAMR would see improvements to the situation. The GHG emissions would decrease by 13% and metal depletion by 8%. Enhancing the preference for decreasing metal depletion further would sacrifice the performance of GHG emissions. However, climate change is an inactive constraint in the scenarios CMMM and

CMMR. The actual GHG emissions are lower than the possible maximum upper limit. Relaxing the climate policy from ambitious to moderate without changing the ambitious level of the resource policy would induce an increase of the GHG emission of 7%-points, compared to the ambitious climate policy, even though the maximum upper limit for a moderate ambition would allow an increase of the GHG emissions by 25%-points. This leads to a non-linear trade-off between the impacts of climate policy and resource policy (Figure 2). Increasing the ambition of the resource policy, i.e., reducing metal depletion, would not lead to a corresponding growth of the GHG emissions.

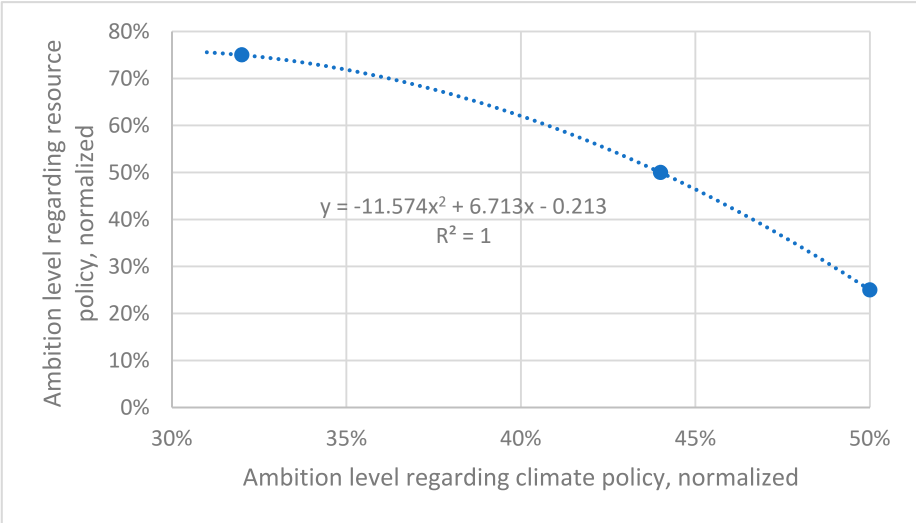

Figure 2. Trade-off between climate policy and resource policy in the policy package scenarios.

Summing up, using the EX selfish scenario as a reference, of all mathematically feasible policy package scenarios, the CAMR scenario is the only one which sees improvements of both GHG emissions and metal depletion. The GHG emissions would drop by 13% and metal depletion by 8%; but CAMR is 2% more expensive. The CMMM scenario combines both moderate policy ambitions. Compared to the EX selfish scenario, the CMMM reduces metal depletion by 31%, but raises GHG emissions and system expenditures by 36% and 8%, respectively. The CMMA scenario with a rather strong preference for resource policy, results in a drop of metal depletion of 53%, but emits 51% more GHG emissions and is 23% more expensive.

Understanding the effects of taking into account resource policy in shaping an optimal energy system requires a detailed comparison of the different scenarios. Figure 3 shows the resulting electricity mix in 2050 of the scenarios with mathematically feasible solutions.

In the EX selfish scenario, the shape of the electricity mix in 2050 is determined by the relative generation costs of each energy technology when considering electricity production capacities, electricity production levels, and electricity exchanges between the modelled European countries, as well as a CO_2 price of 160 €/t CO_2. In this scenario, coal and lignite power plants are completely crowded out. The main energy technologies are PVs with 26% share of the entire electricity generation, wind onshore (20%), and wind offshore (9%). To balance the fluctuating supply of electricity, gas-fired power plants with a share of 14% of the electricity mix are required, supported by PSP as the sole storage system. Hydropower (16%) and nuclear power plants (11%) provide base load.

In the case of the CC selfish scenario, the electricity mix is set by the life-cycle GHG emissions of each energy technology. Since wind power plant shows the lowest GHG emissions per produced kWh, the share of both technologies reaches 37% (wind onshore) and 34% (wind offshore), respectively. To balance the fluctuating supply of electricity, only hydropower (17%) and nuclear power (11%) plants are installed; energy carriers with quite low life-cycle GHG emissions. Under these conditions, PV, which has higher GHG emissions than wind power, is not required. Notwithstanding, all fossil-based power plants are also no longer required.

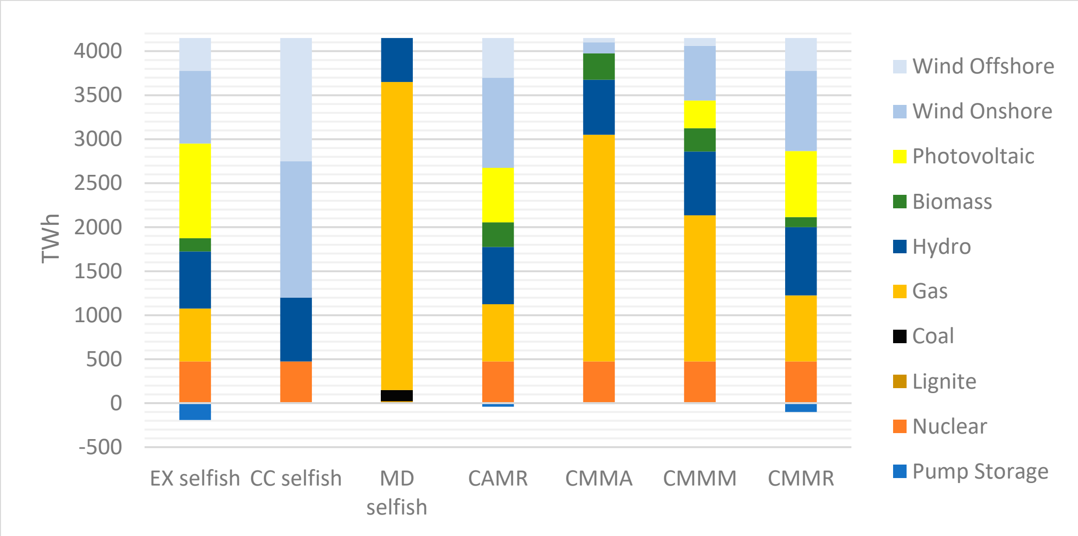

Figure 3. Electricity mix in 2050 of the scenarios with feasible solutions.

Minimizing life-cycle metal depletion leads to a complete reverse of the electricity mix compared to the scenarios EX selfish and CC selfish. In the MD selfish scenario gas-fired power plants will contribute 84% of the electricity generation, since gas-fired power plants show the lowest metal depletion per produced kWh. The other technologies with low metal depletion are hydropower (12% share), coal (3%) and lignite (1%).

Available capacities limit the share of nuclear power in the scenarios EX selfish and CC selfish. In addition, a large part of the hydropower is retained in all scenarios. These results hold in all scenarios, with the exception of the MD selfish scenario, where the metal depletion target leads to a negligible share of nuclear and the lowest share of hydropower in the electricity mix in all scenarios.

Introducing a metal depletion target affects the electricity mix quite significantly. Combining an ambitious climate change target with a relaxed metal depletion target, as assumed in the CAMR scenario, reduces the shares of wind power, compared to the scenario CC selfish, to 25% (wind onshore) and 11% (wind offshore), whereas the share of gas-fired power plants increases to 16%. PV contributes 15% to the electricity production. Compared to the EX selfish scenario, the shares in the CAMR scenario are higher in respect to wind power plants.

The relevance of metal depletion targets for the electricity mix is also obvious in the case of a moderate climate policy target. A combination of a moderate climate policy with an ambitious resource policy, i.e., scenario CMMA, leads to a share of gas-fired power plants of 62%, replacing completely PV and a huge part of wind power, compared to the EX selfish and CC selfish scenarios. While lowering the metal depletion target and thus increasing the relevance of the life-cycle GHG emissions, the relevance of gas-fired power plants decreases to 40% (scenario CMMM) and 18% (scenario CMMR), respectively. Wind power and PV, compared to scenario CMMA, increasingly substitute gas-fired power plants. In the CMMM scenario, wind onshore contributes 15%, PV 8%, and wind offshore 2% to the electricity generation. In the CMMR scenario, the shares are 18% for PV, 22% for wind onshore, and 9% for wind offshore.

Summing up, RES power plants exhibit a higher metal depletion than fossil fuels-based or uranium-using power plants. The main reasons are the generally lower full load hours and the small size of renewable energy power plants per generated kWh electricity [4]. Thus, climate policy will promote wind power, due to its low life-cycle GHG emissions;

whereas resource policy supports the use of gas-fired power plants with their comparable low life-cycle metal depletion. PV show higher life-cycle GHG emissions and higher metal depletion than wind power; thus a more relaxed resource policy is needed to achieve a noteworthy share of the electricity mix. Changing metal depletion targets will not affect the share of nuclear power and hydropower, as they show rather low metal depletion and low GHG emissions.

4. Discussion

The findings in Section 3 reveal the dynamics of different preferences regarding policy targets, and thus of the shape of policy packages, on the trade-offs between climate policy and resource policy. This evokes the question of how to overcome, or at least to smooth, the trade-offs between the policy targets.

An obvious possible option is to replace primary resources with secondary ones through increased recycling of metals.

The presented approach calculates life-cycle metal depletion induced by the transformation of the electricity system. Metal depletion measures the metal content-to-yield relation per extracted primary metal, measured in iron equivalents [7]. Any substitution of primary resources by secondary resources per generated kWh electricity would reduce the amount of metal depletion, potentially causing a diminishing effect on the trade-off between both policy targets; a sufficiently large substitution could even overcome the trade-off. For example, reducing the life cycle GHG emissions of the European electricity system between 2014 and 2050 by 84% would require substituting primary metals by about 58% [4] (Scenario High-RES Cen). More ambitious climate policy targets would demand a higher substitution rate. However, the required amount of secondary resources depends on the metal requirements of each technology used, and the mix of technologies of the electricity system and the upstream sectors.

Several factors limit the potential impact of an enforced recycling of metals on the trade-off. First, the possibility of downgrading during recycling of metals. Some recycled metal, like aluminum, shows worse properties in respect to stiffness, purity, deformability, and corrosion resistance than primary metals, limiting the possible applications [36,37]. Thus, primary metals will be necessary to install RES power plants. The substitution potential depends on the techno-economic conditions of using recycled metals, and the metal mix of both the electricity system and the upstream sectors.

Whereas the occurrence of downgrading limits the share of potentially replaceable metals, the electricity mix (which is the outcome of political and market decisions), and the induced structure of the upstream sectors as well as the electricity demand, determines the size of the sector-wide trade-off. These could overturn the recycling efforts described above.

The focus of this study is on the trade-off between climate change and metal requirements of "bulk" metals. However, next to bulk metals, critical metals, like rare earths, are increasingly becoming the focus of the energy transformation, as they are indispensable to most innovative RES technologies [38]. Although there is no common understanding regarding critical or strategic metals, mostly those are assigned to that group of metals which are essential for a technology with a high supply risk [39]. A growing share of RES technologies will intensify the trade-off between climate policy and resource policy. However, an in-depth analysis of the trade-off, comparable to the one presented, needs additional research, in particular a comprehensive database.

5. Conclusions

Considering the potential impacts of metal depletion on the future European decarbonized electricity system, these should affect the shape of policy packages regarding the energy transformation. Transforming the European electricity system to a RES-based one will affect the strategic position on the international metal markets, while the relevance of imported energy carriers to the EU electricity market would decrease notably [40]. The switch of strategic position could jeopardize the political aims of the EU Commission "to increase energy supply security, and to foster the sustainability and competitiveness of the European economy" ([38], p. 13) for challenging climate change [38].

This leads to the question of whether the trade-off could be smoothed, i.e., finding an electricity mix with less pronounced requirements for metals compared to 1990, while aiming at an ambitious GHG emission target to contribute to slowing down climate change. Considering in all scenarios a CO_2 price of 160 €/t CO_2, our analysis shows that a reduction of the trade-off is possible, but the space for possible solutions is limited. An ambitious climate policy is only feasible when the resource policy is relaxed. To realize GHG emissions corresponding to an ambitious climate policy requires a specific mix of renewable energy sources in the electricity market, which would not allow installation of a sufficient number of low metal-depleting energy technologies, like gas-fired power plants, to reach a moderate or even ambitious resource policy target. Smoothing the trade-off will generally happen to the extent of either climate policy targets or resource policy targets.

One aim of the presented research is to make a first attempt to identify the possible space for defining policy packages considering both policy targets in the discussed frame. Additional research is needed to generate a better knowledge of how different policy targets interact, and thus to identify in a better way the space for political solutions. For this, a more detailed analysis of the shape of potential policy packages by considering potential policy instruments is recommended. Nevertheless, whereas climate policy targets are clearly communicated, this is lacking regarding other environmental and resource-related targets [41,42]. Consequently, a more in-depth analysis of policy packages would profit from more elaborated policy targets.

The study focused on one trade-off; a more systematic assessment of potential trade-offs to minimize possible side effects would mean broadening the scope, in particular to consider, amongst others, land use change [4].

The findings of the study are based on a model focusing on electricity generation technologies. An enhanced inclusion of storage options and demand responses would have an impact on the results. Future studies will address this. Furthermore, from a methodological point of view, this study is subject to the following limitation. The nadir point should be selected out of the Pareto optimal solutions [34]. However, due to the model complexity, the nadir point in this paper is selected from the single optimization solutions in the payoff table. This should be improved in further studies.

Author Contributions: Conceptualization, L.X.; methodology, L.X., Z.W. and H.Ü.Y.; software, L.X., Z.W. and H.Ü.Y.; resources, data curation, L.X., Z.W. and H.Ü.Y.; writing—original draft preparation, L.X., Z.W. and H.Ü.Y.; writing—review and editing, W.-R.P., L.X., Z.W., H.Ü.Y., H.R., Y.G.; supervision, W.-R.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available in the article itself and the Appendix A of the article.

Acknowledgments: The authors would like to thank Patrick Jochem (DLR, Stuttgart Germany) for his inspiring suggestions; thank Lisa Schmieder (KIT ITAS, Karlsruhe Germany) for her valuable input with regard to policy packages; and thank the anonymous reviewers for their thoughtful comments and suggestions.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. GHG emissions and metals depletion by technologies, 2015 and 2050.

Technology	GHG Emissions		Metal Depletion	
	kg CO_2 eq/MWh		kg Fe eq/MWh	
	2015	2050	2015	2050
Nuclear	11.7	11.5	4.1	4.1
Coal	1227.3	1227.2	2.0	2.0
Lignite	1229.0	1221.2	2.3	2.4
Gas	488.4	488.4	3.2	3.2
Hydro	4.6	4.6	1.7	1.7
Pump Storage	56.8	56.8	4.7	4.7
Biomass	201.4	419.4	5.2	5.7
Photovoltaic cells	85.8	83.4	24.6	25.9
Wind	27.1	36.6	23.5	18.7

Table A2. Achieved levels regarding system expenditures, GHG emissions and metal depletion of each scenario in respect to the nadir point.

Scenario	EX	CC	MD
EX selfish	0%	31%	84%
CC selfish	100%	0%	100%
MD selfish	0.0615%	100%	0%
CAMR	0.0006%	25%	75%
CMMA	0.0079%	50%	25%
CMMM	0.0027%	44%	50%
CMMR	0.0001%	32%	75%

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Transportation Research Part D 87 (2020) 102534

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Greenhouse gas emissions of electric vehicles in Europe considering different charging strategies

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ARTICLE INFO

Keywords:
Electric vehicles
Greenhouse gas emissions
Life cycle assessment
Electricity system model
Electricity mix
Batteries

ABSTRACT

The growing market share of electric vehicles (EV) has increased the interest in charging strategies and their effects on the electricity system as well as their climatic soundness. However, the benefits of different charging strategies including Vehicle-to-Grid (V2G) on a large regional scale, e.g. in Europe, have not been analyzed sufficiently. This study examines the impact of different charging strategies on greenhouse gas (GHG) emissions from electricity generation and EV batteries in Europe in 2050. To consider indirect emissions and potentially additional battery degradation due to V2G, a model coupling concept is applied to link Life Cycle Assessment (LCA) with the electricity system model, PERSEUS-EU. Overall, EV could reduce the GHG emissions by 36% by simply replacing conventional cars. Controlled unidirectional charging and V2G add another 4 or 11 percentage points on the European level. However, for these gains an efficient implementation of V2G is required.

1. Introduction

The necessity of reducing greenhouse gas (GHG) emissions has already been widely recognized. Consequently, the European Commission has announced a series of long-term low-carbon policy plans and has explored pathways for key sectors, such as electricity and transport, to achieve GHG emission reductions by 80% to 95% by 2050 compared to the level of 1990 (European Commission, 2015). As one of the essential components, the transport sector has to reduce its GHG emissions by 54% to 67% in 2050 (European Commission, 2011). Currently, transport produces around a quarter of Europe's GHG emissions, with road transport having a share of over 70% (European Commission, 2016). This indicates the important role of innovative and green road transport measures in low-carbon mobility. Electric vehicles (EV) including battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) are considered to be one of such measures. BEV, in particular, are still regarded as zero-emission vehicles by the European legislation even though their indirect emissions might be significant (Jochem et al., 2015).

Emissions from upstream, downstream, and auxiliary processes are not included in these considerations (e.g. Teixeira and Sodré,

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https://doi.org/10.1016/j.trd.2020.102534

Nomenclature

Indices and Sets

$ec \in EC$	Energy carriers
$ec \in EC^{re} \in EC$	Renewable energy carriers
$ec \in EC^{time} \in EC$	Balanced energy carriers for each time slice
$ec \in EC^{year} \in EC$	Yearly balanced energy carriers
$el \in EC$	Electricity
$no \in NO$	System nodes
$pc \in PC$	Processes
$pc \in PC^{re} \in PC$	Renewable processes
$pump \in PC^{ps} \in PC$	Pump process
$si \in SI \in NO$	Sinks of the graph structure
$so \in SO \in NO$	Sources of the graph structure
$t \in T$	Time slices
$turbine \in U^{ps} \in PC$	Turbine process
$u \in U$	Units
$u \in U^{PS} \subset U$	Pumped storage units
$y \in Y$	Years

Parameters

$\eta_{n,n',ec,y}$	Efficiency of flow between n and n′ for energy carrier ec in year y
$\eta_{n,n',ec}$	Efficiency of flow between n and n′ for energy carrier ec
$\eta_{pc,y}$	Efficiency of process pc in year y
$av_{u,y,t}$	Availability of unit u in time slice t in year y
$c^{fix}_{u,y}$	Fixed annual operation costs of unit u in year y
$c^{inv}_{u,y}$	Investment expenditures for commissioning unit u in year y
c^{lv}_{ec}	Load variation costs for units using energy carrier ec
$c^{var}_{pc,y}$	Variable operating costs of process p in year y
$ct_{ec,no,y}$	Capacity target of a node for the energy carrier for a year
$flh^{max}_{u,y}$	Maximum full-load hours of unit in year y
$flh^{min}_{u,y}$	Minimum full-load hours of unit u in year y
h_t	Number of hours of time slice t
$k^{exist}_{u,y}$	Initial capacity of unit u in year y considering shutdowns and life times
$np_{ec,no,y}$	Potential of a node for each energy carrier for a year
ph^{life}_{u}	Physical lifetime
$po_{ec,no,y}$	Maximum potential of energy carrier ec in node no in year y
pt_y	Production target in percentage for a year
r	Discount rate of future cash flows
$RT_{ec,no,y}$	Maximum potential
$rt_{ec,y}$	Production targets for renewable energy carrier ec in year t
$rt_{n,ec,y}$	Capacity expansion targets at node n for energy carrier ec in year y
sc_u	Secured capacity of unit u
sf	Factor for security of supply
$tr_{t-1,t}$	Number of transitions between time slice t-1 and t
$v_{u,y}$	Planned volume of a storage system in planning phase
$c^{fuel}_{ec,y}$	Fuel costs of energy carrier ec in year y

Variables

$Cap^{Max}_{u,y}$	Maximum installed capacity of generation unit u at the end of year y
$Cap^{Tot}_{u,y}$	Installed capacity of generation unit u at the end of year y
$FL_{no,no',ec,y,t}$	Level of the flow between node no′ and no in time slice t in year y
$FL_{no,no',ec,y}$	Level of the flow between node no′ and no in year y
$K^{new}_{u,y}$	Newly installed capacity of unit u in year y
$K_{u,y}$	Capacity of unit u in year y
$LV^{down}_{pc,ec,y,t-1,t}$	Load variation downwards between time slices t-1 and t in year y
$LV^{down}_{u,t-1,t,y}$	Load variation downwards between time slice t-1 and t in year y
$LV^{up}_{pc,ec,y,t-1,t}$	Load variation upwards between time slices t-1 and t in year y
$LV^{up}_{u,t-1,t,y}$	Load variation upwards between time slice t-1 and t in year y
$PL_{pc,y,t}$	Production level of process pc in time slice t in year y
$PL_{pc,y}$	Production level of process pc in year y
$SL_{u,y,t}$	Storage level of pumped storage units in time slice t in year y
$SOC_{ess,y,t}$	Charging level of storage system ess at the end of time slice t in year y

2018). Overall, GHG emissions of EV depend on the electricity mix used during charging as well as on the emissions from vehicle production and scrappage processes. Many studies (Bauer et al., 2015; Lewis et al., 2014; Nanaki and Koroneos, 2013; Orsi et al., 2016; Qiao et al., 2019; Shen et al., 2019; Casals et al., 2016) have already shown the large advantages of EV in climate change mitigation compared to conventional internal combustion engine vehicles (ICEV) and have confirmed the positive effect of renewable-dominated electricity systems compared to fossil-based ones for EV, even from a life cycle perspective. However, those studies mainly used the national or regional average annual electricity mix to calculate upstream GHG emissions of EV. Most studies consider neither the feedback effect which occurs due to the additional electricity demand by EV nor a timing effect which considers different charging strategies. However, controlled charging of EV affects the electricity mix and emissions considerably and is therefore addressed in the following.

From an energy system point of view, controlled charging is an acceptable demand-side flexibility option to cope with the challenges of an increasingly intermittent electricity generation from renewable energy resources (RES), such as wind and Photovoltaics (PV), and fluctuating demand (Richardson, 2013). The controlled charging strategies can be divided into unidirectional controlled charging, and bidirectional controlled charging (the so-called Vehicle-to-Grid (V2G) approach (Ghofrani et al., 2016)). V2G makes EV mobile storage, which feed electricity back into the grid, whenever possible and necessary from the system perspective.

Depending on the EV charging strategy chosen, the electricity mix generated for EV may vary, and so will the resulting impact on the electricity system and climate change in the future. This calls for an evaluation of GHG emissions of EV with different charging strategies, based on the electricity mix dedicatedly generated for EV. The idea to assess GHG emissions of EV is not new, and different charging strategies have also been considered, such as unidirectional charging (Jochem et al., 2015; Rangaraju et al., 2015) and even V2G (Colmenar-Santos et al., 2019; Lund and Kempton, 2008; Zhao et al., 2016, 2017; Noori et al., 2016). However, these assessments mainly focus on direct CO_2 emissions of electricity production during the vehicle usage phase, while emissions from upstream and downstream processes were neglected. Additionally, additional charging in V2G might cause an accelerated degradation of the EV batteries (Hoke et al., 2011) which may lead to higher GHG emissions. Consequently, it is crucial to consider GHG emissions from EV battery production, too.

This study aims to fill this knowledge gap, i.e. to systematically assess GHG emissions associated with both the generation of electricity mix during vehicle usage and EV battery production including V2G and the feedback effect of EV charging on the European electricity system. For this purpose, life cycle assessment (LCA) is coupled with an electricity system model, PERSEUS-EU. LCA is a holistic quantitative method for assessing the environmental impacts of a product or a service during the entire lifespan, i.e. from raw materials extraction, processing, production, and utilization to final disposal (International Organization for Standardization, 2006). It has been widely applied to evaluate electricity generation systems and generation technologies, especially for their GHG emissions. The PERSEUS-EU model is a bottom-up optimization model which represents the European electricity system (Fichtner et al., 1999). As a base model of the electricity system, it has been developed and applied by many researchers to analyze the integration of EV (Jochem et al., 2015; Babrowski et al., 2014; Heinrichs et al., 2014). Additionally, the environmental assessment framework of energy system analysis (EAFESA) (Xu et al., 2020) is applied as a guideline to couple both models. Consequently, the analysis identifies the effects of different EV charging strategies on climate change.

Although fuel cell electric vehicles (FCEV) are another important electrification option in road transport and hydrogen technology will be important for storage in the future energy system with high shares of RES, FCEV will not be considered by this study. The main reason is the still unclear market penetration of this technology as well as the unknown hydrogen share in the future energy system.

This paper is organized as follows: Section 2 gives an overview of current literature and Section 3 describes the methodologies, including description of models and their coupling, used data, and the scenarios. In Section 4, the results regarding GHG emissions from the generation of the electricity mix and battery production are presented and discussed, Section 5 contains uncertainty analyses of battery development and EV availability. Finally, Section 6 summarizes the main findings of the paper, makes policy recommendations, and presents critical reflections and an outlook.

2. Literature review

A shift from ICEV to EV will, ceteris paribus, increase the demand for electricity and might, consequently, increase installations of power plants (Hadley, 2006). Due to their technically seen high charging flexibilites (Babrowski et al., 2014) this additional load might be scheduled to hours of low demand or high supply of intermittent electricity supply by RES which increases system efficiency with little additional investments (e.g. Jochem et al., 2015; Richardson, 2013; Kristoffersen et al., 2011). This is especially true for V2G applications which decreases curtailment of electricity generation by RES and storage applications in the energy system (e.g. Hajimiragha et al., 2011; Colmenar-Santos et al., 2019). Especially, Colmenar-Santos et al. (2019) shows a comprehensive impact from V2G on the European energy system in the year 2050.

One main impediment to make use of these flexibilities, however, is the still low demand for EV in the large car markets (Vilchez and Jochem, 2020). According to a study of Geske and Schumann (2018), mainly 'range anxiety' and the 'minimum range' are important factors determining the willingness of German EV users to participate in V2G. The study concludes that if these concerns are addressed, e.g. by guaranteeing a certain lower bound for the range throughout the whole charging process, high participation rates might be achieved.

Some studies identified that a smart integration of EV into power markets might be profitable - especially in the long run. According to Li et al. (2020), the total net profit of V2G services in Shanghai is positive, at least for the EV users (in Shanghai power grid operators may not be able to role over the additional costs to their customers).

While the impact of EV on transmission grids seems rather unproblematic (e.g. Heinrichs and Jochem, 2016), the impact on distribution grids depends on many framework conditions (Held et al., 2019). Technically, a smart controlled charging could allow market penetrations of 100% and even improve the power quality in most distribution grids (cf. Ghofrani et al., 2016; Habib et al., 2015; Ma et al., 2012). An uncontrolled charging may, however, lead to increased line losses, transformer overloads and voltage limit violations (Habib et al., 2015; Gong et al., 2011).

Controlled charging strategy could also be an essential component of environmentally friendlier road transport, since charging with electricity from fossil power plants makes the environmental impact by EV worse than those of ICEV - especially, if the LCA impact from EV are included. Furthermore, different charging management strategies could facilitate the integration of intermittent RES into electricity grids (cf. Ghofrani et al., 2016; Huijbregts et al., 2017; Dallinger and Wietschel, 2012). But the impact of such strategies is strongly dependent on different assumptions such as technical limitations or socio-economic parameters as well as many others. Some studies try to estimate concrete economic and environmental effects. E.g. Szinai et al. (2020) analyzed for California a scenario with a share of 50% RES grid and the 5-million-EV target and quantify the added value from controlled charging in 2025. The study concluded that compared to uncontrolled charging with 0.95 million vehicles an expansion to 5 million "smart" EV reduces the total system costs by up to 10% and declines the amount of RES curtailment by up to 40%. In addition, it is found that, residential smart charging supported by overnight time-of-use tariffs with added daytime periods are important policies which help to reach California's EV and RES goals. Similarly, Jochem et al. (2015) assessed CO_2 emissions of EV in Germany in 2030 for uncontrolled charging and optimized unidirectional controlled charging strategies. These studies do not consider V2G.

According to most studies, bidirectional controlled charging enhances these advantageous effects further. E.g. Kawamoto et al. (2019) analyzed the life cycle CO_2 emissions of EV in the U.S.A., European Union (EU), Japan, China, and Australia using country-specific parameters such as the vehicle's lifetime, driving distance, and CO_2 emissions associated with battery production. They emphasize, similar to other studies (e.g. Ellingsen et al., 2016; Helmers et al., 2020; Mayyas et al., 2017), that though the CO_2 emissions for the production process of EV outbalance those of ICEV, the excess can be compensated by the vehicle consuming electricity from clean energy sources. These findings are generally supported by Lund and Kempton (2008) who modeled the impact of V2G on the national energy system of Denmark in 2020. The analyses reveal that EV with overnight charging and even more with V2G, enhance the efficiency of the electrical energy system, reduce CO_2 emissions, and improve the ability to integrate wind power.

From this literature review it follows that there are still several research gaps with regard to several issues. We try to fill some of these gaps in the following by applying a comprehensive modeling approach which considers many of the already mentioned dimensions together:

1. Empirically-based and detailed controlled unidirectional and bidirectional charging strategies are implemented.
2. The expansion of RES is modeled endogenously in the energy system model and depends on the electricity demand by EV.
3. The geographical scope is extended to Europe and the time horizon to 2050.
4. While many studies consider only CO_2 emissions during the vehicle usage phase associated with the combustion of fossil fuels for electricity generation, we focus on GHG emissions and consider the life cycle perspective of EV (i.e. emissions from battery production and disposal), too.

3. Methodology

For the analysis of GHG emissions with different charging strategies, a model coupling concept is applied to combine LCA with an electricity system model. In Section 3.1 the used electricity system model PERSEUS-EU is presented, Section 3.2 focuses on the implementation of the EV module in PERSEUS-EU. Section 3.3 presents the LCA model. In Section 3.4 the coupling concept is demonstrated. Afterwards, the data are described in Section 3.5 and finally, the analyzed scenarios are presented in Section 3.6.

3.1. Electricity system model

The PERSEUS-EU model (Heinrichs, 2014) represents all power plants and energy flows of the electricity sector in 28 European countries (EU28 without the islands of Cyprus and Malta, but including Switzerland and Norway) using a linear optimization approach. The main decision variables of the optimization problem are the production level of existing electricity production capacities, investments in new capacities, and electricity exchange between neighboring countries.

The objective of the optimization problem is to minimize total system costs under a set of technical, ecological, and political constraints. The time horizon until 2050 is modeled. The base year 2015 is used for model calibration with historical data. Due to the computational restrictions, the characteristic years of 2015, 2020, 2030, 2040 and 2050 are calculated. An inner-year time resolution with 6 representative weeks in hourly resolution is applied to each year. A method, based on neural networks, presented in Yilmaz

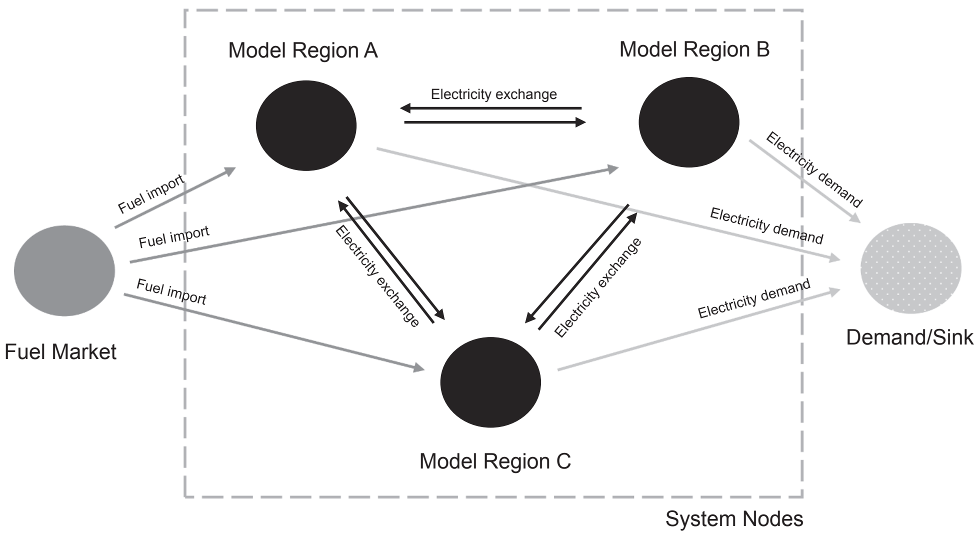

Fig. 1. PERSEUS model structure.

et al. (2019), is used to select the representative weeks and to create the time structure of the model.

In this study, the PERSEUS-EU model was further developed to analyze the different EV charging strategies. The implementation of the EV charging strategies and the main structure of the model are described in Section 3.2. The model equations can be found in the supplementary material of Appendix A and further details as well as a discussion in Heinrichs (2014). PERSEUS-EU is implemented as a linear program in GAMS and is solved with the CPLEX solver.

3.2. Implementation of the EV module in the PERSEUS-EU model

The model structure is based on a directed graph in which the system nodes are connected with each other by energy flows (see Fig. 1). In addition, we have a sink and a source node.

In PERSEUS-EU, each system node is a country. Several power plant technologies are available at the system nodes to generate electricity from different energy sources, e.g. gas. Exchange flows between the system nodes represent electricity exchange between the European countries. The sink node contains the energy demand of the modeled countries, which is to be covered by the inflows to this node. The source node supplies the graph with fuel from outside the system (e.g. gas imports from the world market). The energy inflows and outflows are balanced for each system node.

The electricity demand is represented by $FL_{no,si,el,y,t}$. The demand is the electricity (*el*) flow from each system node (*no*) to the sink node (*si*) in every year (*y*) and in each model time slice (*t*). An additional controlled EV demand ($FL^{ev}_{no,si,el,y,t}$) is added to the model.

We define and formulate the calculation of the additional controlled EV demand ($FL^{ev}_{no,si,el,y,t}$) as follows. Index t' denotes the original time slice of the uncontrolled demand and index t denotes the rescheduled time slice of that uncontrolled demand.

Eq. (1) defines the controlled charging strategy. Within a time span (the time between the time slice t' and $t' + shift^{max}$), charging and discharging are both allowed but the summation of the charging solutions ($Ctrl^{ch}_{no,si,el,y,t',t}$) and discharging solutions ($Ctrl^{dis}_{no,si,el,y,t',t}$) for time t' in time t must be equal to the uncontrolled demand of the starting time slice t'.

$$d^{ev}_{no,si,el,y,t'} = \sum_{t \in P_{t'}} (Ctrl^{ch}_{no,si,el,y,t',t} - Ctrl^{dis}_{no,si,el,y,t',t}) \quad \forall\ no \in NO^{sys},\ \forall\ y \in Y,\ \forall\ t' \in T,\ P_{t'} = \{t',\ t'+1,\ ...,t'+shift^{max}\} \tag{1}$$

This implies that:

- The uncontrolled charging demand ($d^{ev}_{no,si,el,y,t'}$) must be covered within the considered time span, i.e. the next $shift^{max}$ hours.
- Discharging ($Ctrl^{dis}_{no,si,el,y,t',t}$) is allowed, but the discharging amount must be compensated before or after and within the same time span.

The net controlled EV demand ($FL^{ev}_{no,si,el,y,t}$) from the grid perspective is then defined by Eq. (2). After the uncontrolled EV charging demand is rescheduled to the next $shift^{max}$ hours by Eq. (1), we calculate the controlled net EV demand ($FL^{ev}_{no,si,elec,y,t}$). The net demand EV ($FL^{ev}_{no,si,elec,y,t}$) in time slice t is the summation of the charging and discharging solutions for the previous $shift^{max}$ hours. $FL^{ev}_{no,si,elec,y,t}$ is a free variable in the model and can be positive, zero, or negative.

$$FL^{ev}_{no,si,el,y,t} = \sum_{t' \in Q_t} \left(\frac{Ctrl^{ch}_{no,si,el,y,t',t}}{\eta_{ev}} - Ctrl^{dis}_{no,si,el,y,t',t} \cdot \eta_{ev} \right) \quad \forall\ no \in NO^{sys},\ \forall\ y \in Y,\ \forall\ t \in T,\ Q_t = \{t - shift^{max},\ t - shift^{max} + 1,\ ...,t\} \tag{2}$$

In Eq. (3), the total amount of charging ($Ctrl^{ch}_{no,si,el,y,t',t}$) and discharging ($Ctrl^{dis}_{no,si,el,y,t',t}$) demand in one time slice is limited by the total charging power ($Ctrl^{max}_{no,si,el,y,t}$) of EV available at time t. This power depends on the EV usage pattern, access to charging infrastructure, and user acceptance of controlled charging.

$$Ctrl^{max}_{no,si,el,y,t} \geqslant \sum_{t' \in Q_t} \left(\frac{Ctrl^{ch}_{no,si,el,y,t',t}}{\eta_{ev}} + Ctrl^{dis}_{no,si,el,y,t',t} \right) \quad \forall\ no \in NO^{sys},\ \forall\ y \in Y,\ \forall\ t \in T,\ Q_t = \left\{ t - shift^{max},\ t - shift^{max} + 1,\ ...,t \right\}. \tag{3}$$

In Eq. (4), the total discharging amount of a country (*no*) within every 24 h is limited by the amount of electricity available in the batteries of all EV in that country. This restriction is applied in a rolling window fashion and t^{start} is the starting time slice.

$$Discharge^{max}_{no,si,el,y} \geqslant \sum_{t \in R_{t^{start}}} \sum_{t' \in Q_t} Ctrl^{dis}_{no,si,el,y,t',t} \quad \forall\ no \in NO^{sys},\ \forall\ y \in Y,\ \forall\ t^{start} \in T,\ R_{t^{start}} = \{t^{start},\ t^{start}+1,\ ...,t^{start}+23\},\ Q_t = \{t - shift^{max},\ t - shift^{max} + 1,\ ...,t\}. \tag{4}$$

3.3. The LCA model

LCA converts material and energy inputs into environmentally relevant outputs per functional unit associated with all the stages of the life cycle of a product or service. Different environmental impact categories are distinguished, e.g. climate change. The functional unit is the utility of a product or service and is given in a physical unit (Cooper, 2003). The general formulation of an LCA model on the technological scale is described in Eq. (5):

$$h_{u,y,l} = \sum_{k\in K}\sum_{i\in I}\sum_{i'\in I} Q_{u,y,l,k}B_{u,y,k,i'}A_{u,y,i',i}\cdot f_{u,y,i} \quad \forall\, k\in K, \forall\, i\in I, \forall\, i'\in I \tag{5}$$

where $h_{u,y,l}$ represents the potential environmental impact in category l over the life cycle of technology u in year y in a functional unit, $Q_{u,y,l,k}$ is the characterization factor which reflects the relative contribution of emission k to the environmental impact in category l for technology u in year y, $B_{u,y,k,i'}$ represents the environmental output in emission k from process i' for technology u in year y. $A_{u,y,i',i}$ represents the linkage between the processes i' and i that shows how many products from the process i' are required in process i for technology u in year y. $f_{u,y,i}$ denotes the final demand in process i which specifies the functional unit for technology u in year y. K represents the set of all emissions, while I is the set of all processes.

Based on the above LCA model, Eq. (6) is used subsequently to assess a system containing multiple technologies.

$$Z_{y,l} = \sum_{u\in U} h_{u,y,l}\cdot E_{u,y} \quad \forall\, u\in U \tag{6}$$

where $Z_{y,l}$ is the total environmental impact in category l over the life cycle of all considered technologies in year y. $E_{u,y}$ equals the electricity generation or electricity charging amount from technology u in year y.

Several life cycle impact assessment (LCIA) methods are available to identify impact categories, category indicators, and characterization factors. The ReCiPe method (Huijbregts et al., 2017) is applied in this study. The impact category concerned is climate change, and the category indicator is GHG emissions (kg CO_2 eq.). The electricity generation technologies and EV battery technologies are included in the system under review, which defines the set of U. In addition, the geographical boundary is assumed to be a global market for the upstream processes and a European market for use and downstream disposal processes.

3.4. Model coupling

As already mentioned, the PERSEUS-EU model is used for modeling the European electricity system. The results, such as the electricity mix produced are then analyzed using LCA. In this case, the Environmental Assessment Framework for Energy System Analysis (EAFESA) is applied as a guide for coupling both models to overcome the challenges due to the differences of both models in terms of the system boundaries, databases, and assumptions (Xu et al., 2020). There are four steps in EAFESA, i.e., goal and scope definition, inventory analysis, impact analysis, and policy implication, which are inspired by ISO LCA guidelines (International Organization for Standardization, 2006). Fig. 2 presents the framework used for this paper.

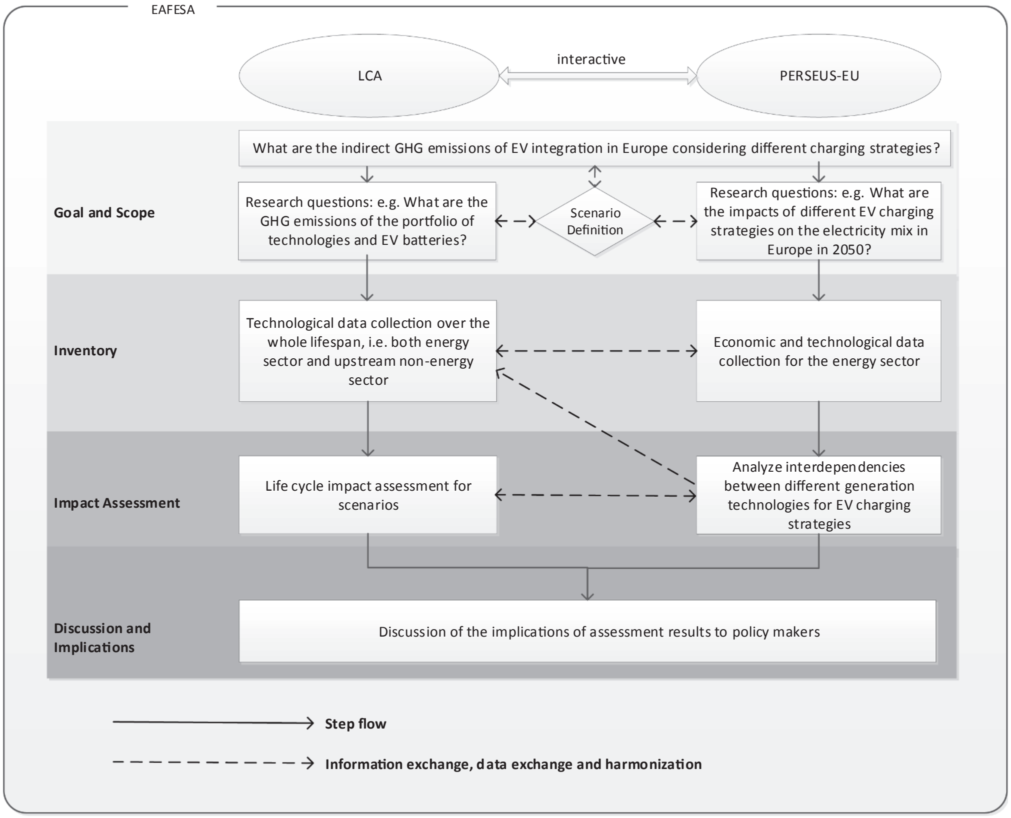

Fig. 2. Applying the EAFESA framework to guide model coupling between LCA and PERSEUS-EU.

In general terms, the technologies expected to exist in Europe by 2050 are defined first and matched between LCA and PERSEUS-EU considering technological development and progress. Secondly, some technologies aggregated in PERSEUS-EU are broken down in LCA, based on literature and expert knowledge. Technologies on the laboratory scale are not included. In this case, wind and PV energy technologies are especially relevant. Electricity generation from wind turbines is achieved by a mix of technologies: Asynchronous generators and synchronous generators. The latter are further subdivided into electrically excited direct drive, permanent magnet and high-temperature superconductors. PV technologies are conventional technologies based on crystalline cells and advanced technologies using thin-film cells. All assumptions about specific breakdowns of electricity generation technologies are obtained from Xu et al. (2020). Additionally, data are harmonized in terms of electricity mix, efficiencies, capacities, as well as life times.

3.5. Data

The power plant data are based on the WEPP database (Platts, 2015). For the techno-economic parameters of future power plant investment options, data based on DIW (2013) are applied. The development of electricity demand for EU countries is based on the EU Reference Scenario 2016 (Capros et al., 2016). The discount rate in the target function is set to 5%.

We make optimistic assumptions regarding RES in order to achieve high shares of RES in 2050. The CO_2 emission price path is based on the 450 ppm scenario of World Energy Outlook (International Energy Agency, 2016), which reaches 160 Euros per ton in 2050. Furthermore, investments in coal-fired power plants are not allowed, which leads to a phase-out of coal-fired power plant capacities over time.

The strongly growing development of EV for the 28 European countries from 2015 to 2050 is derived from the centralized high-RES scenario of the REFLEX project (Reiter et al., 2017). The average mileage of a car is based on the constant assumption of 12,000 km/year and the empiric average gross electricity efficiency is assumed to be 20 kWh/100 km (Jochem et al., 2015). The uncontrolled EV charging load curve is adopted from the Reference Scenario of Babrowski et al. (2014) with an assumption of 6.3 kWh charging power on the average. The EV can be charged at home or at the workplace. Additionally, a plug-in of every other day is assumed (i.e. 50% availability of EV). The daily discharge limit of each connected EV is set to a maximum of 10 kWh for V2G.

The life cycle inventory (LCI), i.e., data for both the technologies under review as well as upstream and auxiliary systems for the generation of electricity mix, is taken from Xu et al. (2020). The LCI of the EV battery is obtained from Notter et al. (2010), which is based on lithium-ion batteries. The EV battery life time is set to guarantee 150,000 km in Notter et al. (2010). Considering V2G will increase the battery charge and discharge volumes, the original battery life in terms of mileage (150,000 km, cf. Notter et al. (2010)) is not guaranteed anymore. Hence, we limit the lifetime of the battery in terms of energy throughput (i.e. 30,000 kWh, which equals 150,000 km without V2G). The battery survives for the whole lifetime (i.e. 30,000 kWh) and dies at 30,001 kWh. Consequently, V2G leads in our model to higher battery demand. The weight of the 40 kWh battery is 300 kg (Notter et al., 2010).

3.6. Scenarios

Three scenarios with different charging strategies and a reference scenario without EV is calculated. In all these scenarios, we calculate endogenously the expansion and electricity production of all power plant technologies, including RES. Detailed information

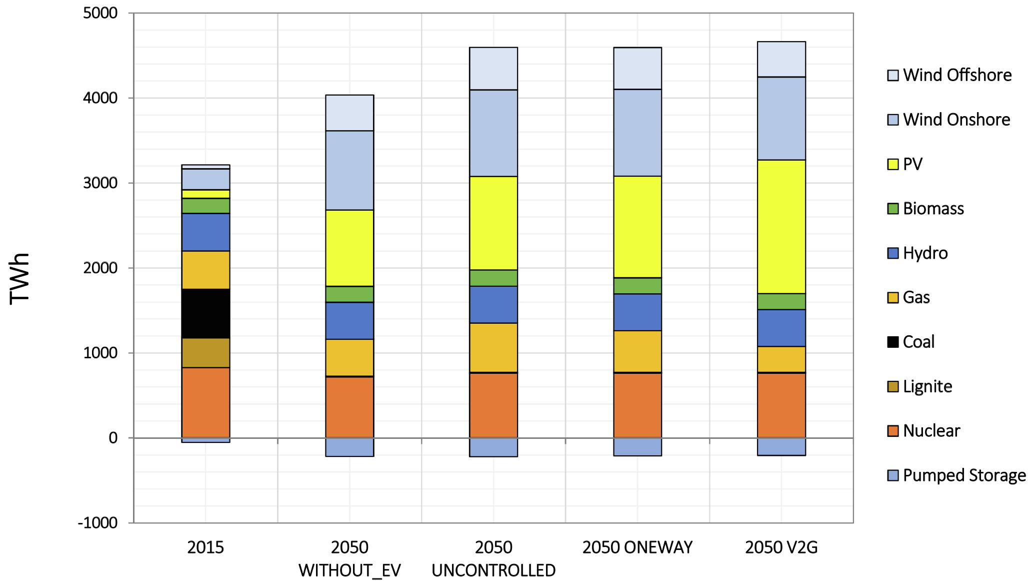

Fig. 3. The electricity mix in 2015 and for different EV charging strategies as well as the WITHOUT_EV scenario in 2050.

on the four scenarios is given below:

- **WITHOUT_EV:** A hypothetical reference scenario without any EV and consequently none charging demand from EV is assumed.
- **UNCONTROLLED:** The EV charging process starts whenever the EV is connected to the grid. For this, a fixed electricity demand curve from the EV is added to the demand curve used in the WITHOUT_EV scenario.
- **ONEWAY:** The charging task at a certain time span is to be accomplished within the next 12 h only.
- **V2G:** Similar to the ONEWAY scenario, the charging task at a certain time span is to be accomplished within the next 12 h but discharging is also allowed during this period. This scenario provides the highest degrees of freedom to the energy system.

4. Results and discussion

This chapter presents and discusses the results of the four Scenarios and mainly focuses on the direct and life cycle related GHG emissions.

Fig. 3 presents the electricity mixes of the different EV charging scenarios as well as the WITHOUT_EV scenario in 2050 and the electricity mix in 2015. Comparing the electricity mixes in all scenarios, the amount of RES in 2050 is higher than in 2015 due to high CO_2 prices, coal phase-out, and declining costs of RES. In 2050, electricity production by coal-fired power plants is close to zero in all scenarios. However, the share of electricity produced by gas-fired power plants is not eliminated in 2050, even increases in the UNCONTROLLED scenario compared to in 2015 due to the need for flexible electricity generation. The amount of renewable and flexible conventional electricity production varies in all scenarios, as the different EV charging strategies allow different levels of flexibility for the system.

In 2050, total electricity production is 15% higher in the UNCONTROLLED scenario than in WITHOUT_EV due to the increased demand by EV. In the UNCONTROLLED scenario, electricity generation from gas is higher despite further investments in RES. This is due to the intermittent characteristic of RES. In the hours when there is no wind and solar, gas-fired power plants are operated predominantly. In the ONEWAY scenario, electricity production from RES is higher than in the UNCONTROLLED scenario. Much cheaper electricity from RES is obtained by shifting the charging time to the hours of higher electricity production from RES. Then, less gas-fired electricity is produced.

Due to the efficiency losses in EV charging and discharging, total electricity production in the V2G scenario is slightly higher than in the ONEWAY scenario, whereas electricity production by gas-fired power plants is much lower. Similar to the ONEWAY scenario, the demand is shifted to the hours of increased electricity production from RES. In addition, the electricity production from PV is significantly higher by about 30%. In return, electricity production not only from gas-fired power plants but also from wind power is declining. PV is cheaper than other technologies and therefore the EV are charged with electricity from PV as much as possible and discharged during the night hours for decreasing electricity generation by fossil fuels.

Fig. 4 demonstrates the direct and life cycle GHG emissions associated with electricity production for the UNCONTROLLED, ONEWAY, and V2G Scenarios compared to WITHOUT_EV in 2050 and the base year 2015. The significant reduction in GHG emissions is due to the high share of renewable power in 2050. However, a shift from direct emissions by the electricity generation to life cycle emissions can be observed. Since there is no direct emissions of RES-based power generation, the share of direct emissions in the life cycle emissions decreases from 75% in 2015 to 23–35% in 2050. Hence, the share of direct emissions in the life cycle emissions decreases along with the shares of RES-based power generation.

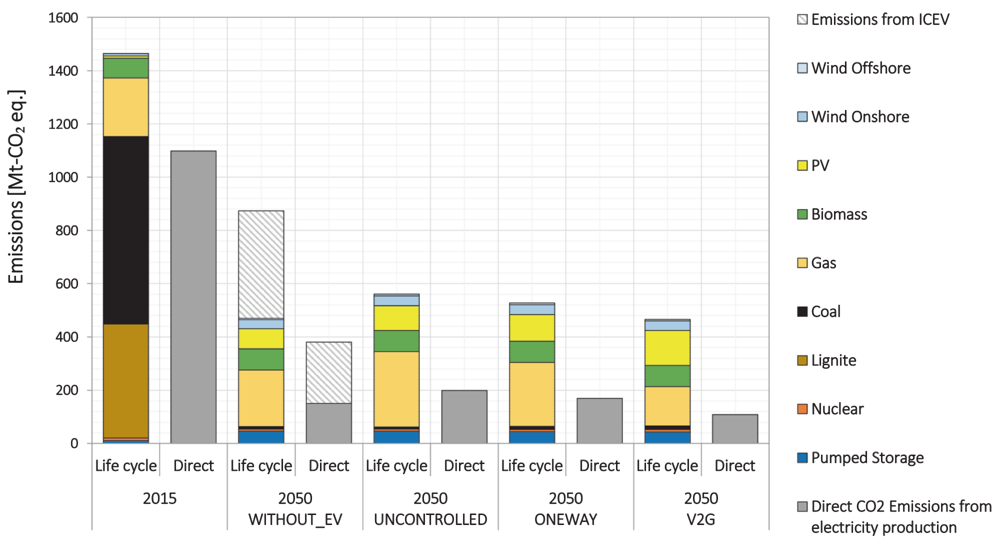

Fig. 4. The direct and life cycle GHG emissions associated with the production of electricity in the UNCONTROLLED, ONEWAY, and V2G scenarios compared to WITHOUT_EV in 2050 and the base year 2015.

In 2050, the life cycle GHG emissions of electricity production are 19% (90 Mt CO_2-eq.) higher in the UNCONTROLLED scenario than in the WITHOUT_EV scenario, which is mainly due to the increased electricity demand by EV and the resulting higher gas-fired electricity production. However, in the WITHOUT_EV scenario, a non-electrified equal number of ICEV (approx. 210 million) at 90 g CO_2/km would lead to about 230 Mt CO_2-eq. of direct emissions and about 400 Mt CO_2-eq. of life cycle emissions in 2050, as shown in Fig. 4. So the electrification of the transport sector helps to reduce the emissions in our framework assumptions, even with uncontrolled charging.

The life cycle GHG emissions are lower (by 6% in ONEWAY and 17% in V2G) in the two controlled charging scenarios compared to the UNCONTROLLED scenario, meaning that both controlled charging strategies have a positive impact on global climate change. The V2G Scenario leads to a greater decrease in GHG emissions than the ONEWAY Scenario, with the emissions being even lower than in the WITHOUT_EV Scenario. Considering that the WITHOUT_EV Scenario assumes a world with ICEV only, the V2G scenario shows a significant reduction of GHG emissions.

Fig. 5 illustrates the difference in life cycle GHG emissions for the UNCONTROLLED, ONEWAY, and V2G Scenarios compared to WITHOUT_EV in 2050 without considering the reduction in emissions by replacing ICEV.

Using the WITHOUT_EV scenario as a reference, the life cycle GHG emissions of the UNCONTROLLED and ONEWAY scenarios are higher by 90 Mt CO_2-eq. and 57 Mt CO_2-eq., respectively, whereas emissions in the scenario V2G are 4 Mt CO_2-eq. lower. The lower flexibility of the UNCONTROLLED and ONEWAY scenarios compared to the V2G scenario results in the use of gas-fired power generation technology, which produces most of the emissions in the UNCONTROLLED scenario and the ONEWAY scenario. When looking at the gas-fired power plants from a life cycle perspective, it is found that the most important emission source is the gas combustion process (over 85%), followed by gas leakage during transport via the long-distance pipeline (8%). Compared to the scenario WITHOUT_EV, GHG emissions associated with PV-based power generation increase by 17 Mt CO_2-eq. (UNCONTROLLED), 24 Mt CO_2-eq. (ONEWAY), and 56 Mt CO_2-eq. (V2G). The GHG emissions from PV are mainly due to the processes of PV panel production (65%) and mounting system production (31%).

With increasing flexibility of the charging options, the importance of pumped storage power plants decreases slightly as well with controlled charging. Compared to the scenario WITHOUT_EV, the emissions are higher by 0.3 Mt CO_2-eq. in UNCONTROLLED, but, lower by 1.7 Mt CO_2-eq. in ONEWAY and by 2.3 Mt CO_2-eq. in V2G, respectively.

Considering the potential risk of accelerated battery degradation due to additional charging and discharging in V2G, Fig. 6 illustrates the life cycle GHG emissions associated with both additional electricity production and EV battery production separated. GHG emissions caused by the EV battery are identical in the UNCONTROLLED and ONEWAY scenarios since the power demand of EV is only shifted in the ONEWAY scenario. Obviously, the V2G scenario is associated with an accelerated battery degradation and increased emissions from battery production. The reduced GHG emissions associated with the electricity generation do more than compensate the increased emissions associated with the EV battery and this scenario, consequently, shows the lowest GHG emissions.

5. Uncertainty analyses

To examine the potential impacts of variations of some important inputs on the systematic performance, a series of uncertainty analyses are performed.

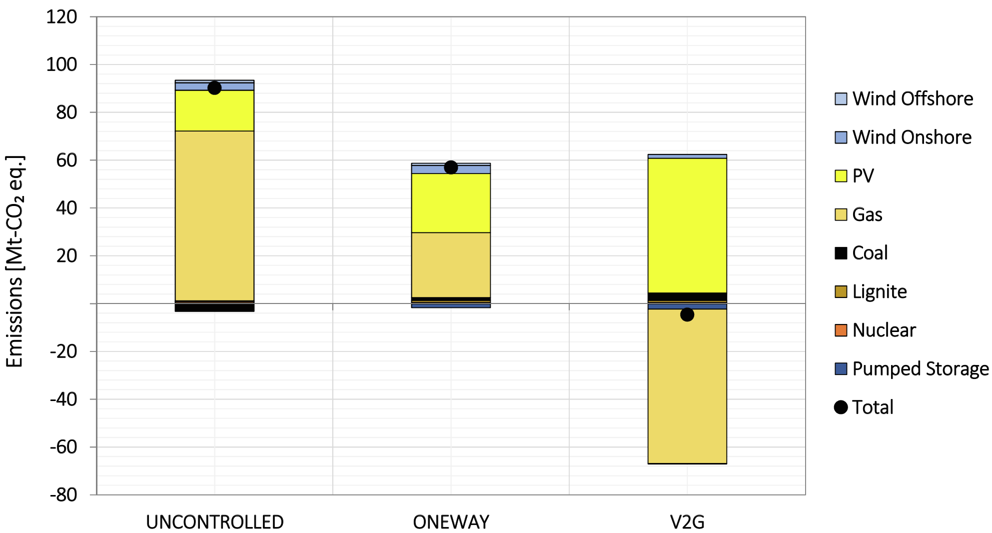

Fig. 5. The differences in the life cycle GHG emissions from electricity production and EV battery production for the UNCONTROLLED, ONEWAY, and V2G compared to the WITHOUT_EV Scenario in 2050.

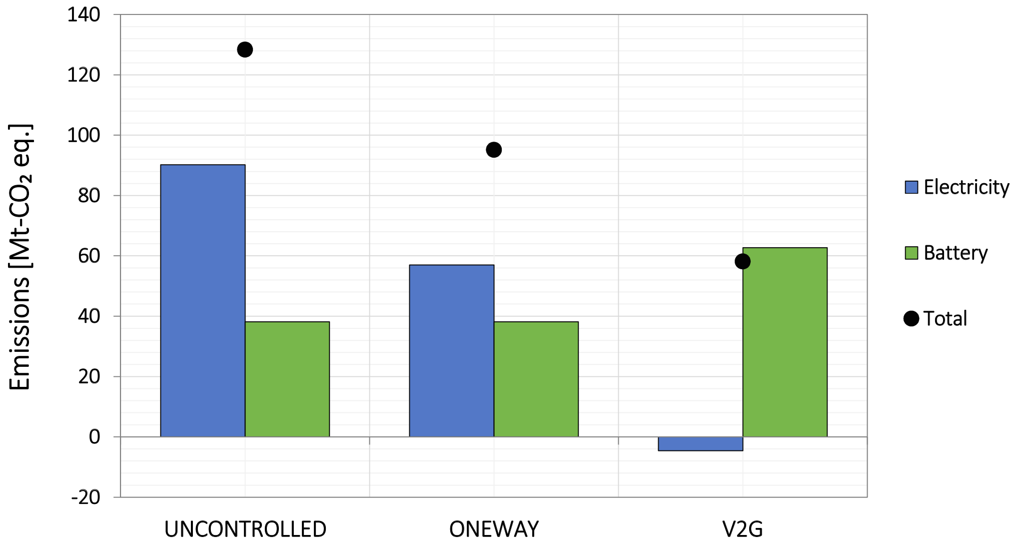

Fig. 6. The difference in the life cycle GHG emissions from electricity generation (blue) and EV battery production (green) for UNCONTROLLED, ONEWAY and V2G Scenarios compared to WITHOUT_EV in 2050. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Lithium-ion batteries are normally considered the best energy storage technology for EV and are already widely applied in EV. Even though post-lithium battery technologies attracted attention in recent years, they still face tremendous challenges in their realization. In this context, the present study is based on the assumption that the future EV will depend highly on lithium-ion batteries.

However, technological development and progress of lithium-ion batteries are required to improve energy security, reduce petroleum dependence, and lower GHG emissions. An important parameter characterizing technological development is a higher energy density in the future compared to the current situation. The battery's energy density is projected to increase by about 140% to around 320 Wh/kg by 2030 (Thielmann et al., 2013). This higher energy density will reduce the GHG emissions of the EV batteries to 42% compared to the current situation, when assuming that this development will continue in a linear way until 2050. This would further enhance the positive effects of EV charging strategies in reducing GHG emissions. Battery life time is another important parameter to characterize technological development. Although lithium-ion batteries are considered mature, attempts to achieve a better cycle life are continuing. In Virya and Lian (2017), a good cycle life (over 10,000 cycles) is demonstrated with the development

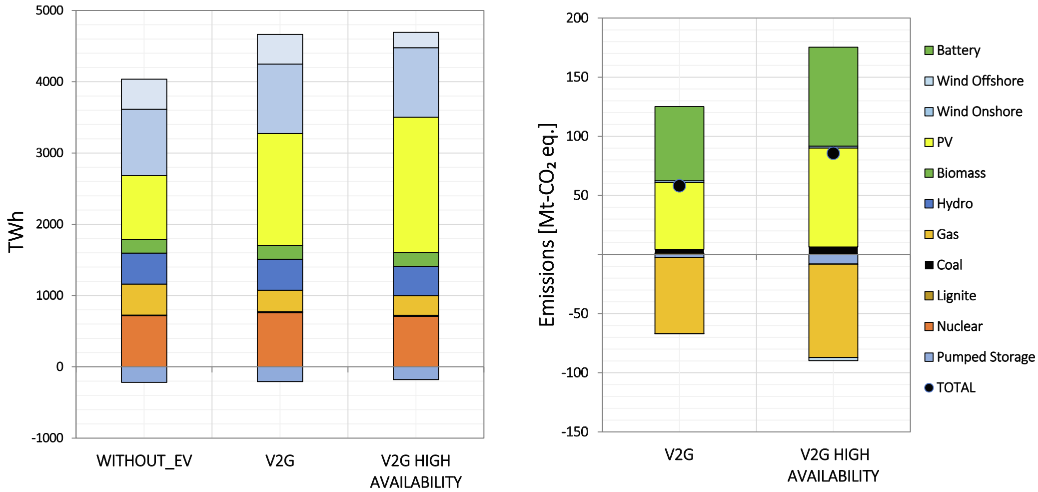

Fig. 7. The electricity mixes (left) and the difference in life cycle GHG emissions (right) in the V2G scenario with different EV availabilities compared to the WITHOUT_EV Scenario in 2050.

of a neutral polymer electrolyte containing lithium chloride and polyacrylamide. The state-of-the-art achievement (Virya and Lian, 2017) is still in the experimental stage, but shows a significant improvement compared to our assumption, i.e., 30,000 kWh of the total battery charge amount for a 40 kWh battery, which is basically in line with the 1,000 full cycle equivalents with 90% Depth of Discharge (DoD). In case of a longer cycle life (from 1,000 cycles to 10,000 cycles), the GHG emissions of batteries should reduce by up to 90%, assuming a constant scaling effect.

Apart from the technological development and progress of lithium-ion batteries, another important uncertainty analyzed is the EV availability. As mentioned before, 50% of all the EV are assumed available everyday. Increasing the availability of EV from 50% to 100% would provide more flexibility with the same number of EV. In this case, maximum discharge into the grid also doubles.

Fig. 7 illustrates the electricity mixes and the life cycle GHG emissions in V2G in 2050 for the different EV availabilities. At a higher EV availability, electricity production from gas-fired and offshore wind power plants decreases while more electricity is produced by PV (see Fig. 7, left). Compared to the original V2G scenario with a lower EV availability, GHG emissions from gas-fired power plants decrease in the scenario with higher EV availability. However, there is not a large decrease associated with gas-fired electricity production, as there are still days when not enough electricity is generated from RES even with more EV availability. In our framework assumptions, V2G can advance or postpone the demand for 12 h. To further reduce gas-fired power generation, long-term storage technologies, such as hydrogen, are required.

Furthermore, total emissions increase in the higher EV availability scenario (see Fig. 7, right). This is caused by two reasons. The first one is due to the higher usage of the batteries. The second is that more electricity production from wind technologies is shifted towards PV technologies. From the LCA-based analysis, PV technologies produce more emissions than wind technologies, when generating the same amount of electricity.

6. Summary and conclusions

Electric vehicles might be a corner stone in the energy transition of passenger transport. For this reason, greenhouse gas emissions and the impact from controlled charging strategies hereon are already widely discussed in academia. This study focuses on different charging strategies, namely, uncontrolled charging, unidirectional controlled charging, and bidirectional charging (Vehicle-to-Grid), and their impacts on greenhouse gas emissions caused by electricity production and electric vehicle batteries in Europe in 2050. For the analyses, life cycle assessment is combined with an energy system model, PERSEUS-EU. To our knowledge, this is the first attempt to analyze the Vehicle-to-Grid charging strategies in the European electricity system and their greenhouse gas emissions by a coupled approach.

The framework assumptions made with respect to renewable energy sources are optimistic, e.g. high CO_2 costs, cost reduction of renewable technologies and phase-out of coal-based electricity production. In 2050, all scenarios reach a very high share of renewable energy sources and deep decarbonization. The results show uncontrolled charging increases electricity production from natural gas slightly. The two controlled charging strategies, however, reduce dependence on gas-fired electricity production and increase the amount of electricity produced by renewable energy sources (mainly photovoltaic). Flexibilites from Vehicle-to-Grid exceeds that of unidirectional charging, as charging cannot only be postponed, but electric vehicles can be used as mobile storages in the electricity system.

Emissions from uncontrolled charging are higher than those of both controlled charging strategies. The emissions are lower in unidirectional charging, and even further decreased by Vehicle-to-Grid, due to the increasing use of electricity from renewable energy sources. Taking into account the degradation of electric vehicle batteries, however, Vehicle-to-Grid may cause more emissions only due to enhanced battery degradation. Nevertheless, in our scenario bidirectional charging still outperforms the unidirectional charging in terms of greenhouse gas emissions at least when the overall flexibility is restricted.

The results of the uncertainty analysis reveal that further technical progress in electric vehicle batteries is of particular needed to increase the benefits of reducing life cycle greenhouse gas emissions. A complete elimination of emission-intensive generation, such as electricity generation from gas, is not possible due to the days and longer periods without sufficient electricity generation from RES. Further scenario analyses may integrate hydrogen as an additional storage system, which may lead to further decreasing greenhouse gas emissions but may show other disadvantages as a lower system efficiency and lower benefits from Vehicle-to-Grid.

Still, our work is subject to the following limitations: Not every single EV or EV fleet is modeled in detail. The EV are represented by aggregated loads or flexibilities for each country. In addition, the costs of EV batteries are not taken into account, as this study focuses on GHG emissions. Another important limitation is that network restrictions are not considered. For charging of the EV, mechanisms in distribution and transmission grid level should be in place to avoid network congestion or even collapse. A detailed analysis with a network model should be performed. The degradation level of a battery is assumed to depend linearly on the accumulated amount of charge. This assumption is applied to all batteries. However, the battery life is significantly affected by a variety of complex factors, e.g. temperatures at which a battery is charged, the state of charge, the charging rate, etc. (Hoke et al., 2011). Differences in battery life result in different life cycle emissions. These factors are usually not considered in macro-scopic energy system models, and, hence, might be an interesting topic for further studies. Hydrogen in the energy system model in combination with fuel cell electric vehicles might even lead to stronger decarbonization effects. However, market success of hydrogen is still subject to several uncertainties, which is why fuel cell electric vehicles have not been considered in this study.

Appendix A. PERSEUS equations

Objective function

$$min \sum_{y \in Y} (\frac{1}{1+r})^{y} \cdot \left(\begin{array}{l} \sum_{so \in SO} \sum_{no \in NO} \sum_{ec \in EC} FL_{so,no,ec,y} \cdot c^{fuel}_{so,no,ec,y} \\ + \sum_{u \in U} (K_{u,y} \cdot c^{fix}_{u,y} + K^{new}_{u,y} \cdot c^{inv}_{u,y}) \\ + \sum_{pc \in PC} \left(\begin{array}{l} PL_{pc,y} \cdot c^{var}_{pc,y} \\ + \sum_{t \in T} \left(\begin{array}{l} LV^{up}_{pc,y,t-1,t} \\ + LV^{down}_{pc,y,t-1,t} \end{array} \right) \cdot c^{lv}_{pc} \end{array} \right) \end{array} \right)$$

Energy balance restrictions

$$\sum_{no' \in NO} FL_{no',no,el,y,t} + \sum_{pc \in PC_{no}} PL_{pc,y,t} = \sum_{no' \in NO} \frac{FL_{no,no',el,y,t}}{\eta_{no,no',y}} \quad \forall\ no \in NO^{sys}, \forall\ y \in Y, \forall\ t \in T$$

$$\sum_{no' \in NO} FL_{no',no,ec,y} + \sum_{pc \in PC_{no}} PL_{pc,y} \cdot \lambda_{pc,ec} = \sum_{no' \in NO} \frac{FL_{no,no',ec,y}}{\eta_{no,no',y}} + \sum_{pc \in PC_{no}} \frac{PL_{pc,y} \cdot \lambda_{pc,ec}}{\eta_{pc,y}} \quad \forall\ no \in NO^{sys}, \forall\ ec \in EC, \forall\ y \in Y$$

$$PL_{pc,y} = \sum_{t \in T} PL_{pc,y,t} \quad \forall\ pc \in PC, \forall\ y \in Y$$

$$FL_{no',no,el,y} = \sum_{t \in T} FL_{no',no,el,y,t} \quad \forall\ no', no \in NO, \forall\ y \in Y$$

Capacity restriction

$$K_{u,y} \cdot av_{u,y,t} \cdot h_t \geqslant \sum_{pc \in PC_u} PL_{pc,y,t} \quad \forall\ u \in U, \forall\ y \in Y, \forall\ t \in T$$

Capacity expansion restriction

$$K_{u,y} = k^{exist}_{u,y} + \sum_{y'=y-\tau_u}^{y} K^{new}_{u,y'} \quad \forall\ u \in U, \forall\ y \in Y$$

Load variation restriction

$$LV_{pc,y,t-1,t} = \left| \frac{PL_{pc,y,t}}{h_t} - \frac{PL_{pc,y,t-1}}{h_{t-1}} \right| \cdot tr_{t-1,t} \quad \forall\ pc \in PC, \forall\ y \in Y, \forall\ t \in T$$

Storage restrictions

$$SL^{pss}_{u,y,t} = SL^{pss}_{u,y,t-1} + \frac{PL^{pump}_{pc,y,t}}{h_t} - \frac{PL^{turb}_{pc,y,t}}{h_t} \cdot \frac{1}{\eta^{turb}} \quad \forall\ pc \in PC_u, \forall\ u \in U^{pss}, \forall\ y \in Y, \forall\ t \in T$$

$$SL^{pss}_{u,y,t} \leqslant s^{max}_{u} = \frac{K_{u,y}}{\kappa^{max}_{u}} \cdot s^{max,0}_{u} \quad \forall\ u \in U^{pss}, \forall\ y \in Y, \forall\ t \in T$$

Generation adequacy restriction

$$max(FL_{no,si,el,y,t}) \cdot sf \leqslant \sum_{u \in U^{conv}_{no}} (K_{u,y} \cdot av_{u,y}) + \sum_{u \in U^{re}_{no}} (K_{u,y} \cdot sc_u) \quad \forall\ no \in NO, \forall\ y \in Y, \forall\ t \in T$$

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