Assessing the Environmental Implications of Offshore Wind Energy Advancements on the Future German Electricity Sector

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Abstract

Climate change mitigation requires the rapid defossilisation of the German electricity sector. While energy system models are extensively used to evaluate climate change mitigation strategies, they generally consider environmental aspects in a limited manner, often focusing on direct operational emissions. To overcome this limitation, this thesis aims to investigate how the environmental impacts of energy systems can be evaluated through an integrated approach that combines Life Cycle Assessment into an energy system model. Integrating both methodologies enables a more comprehensive evaluation by including upstream and downstream environmental impacts and indicators related to ecosystems, human health and resources. However, the integration is challenging due to data inconsistencies.

A core contribution of this thesis is developing a systematic process to compile and automate input parameters to ensure a consistent collection of data relevant to both methodologies. The integration approach enables the generation of consistent scenarios that are tested within the model. The modelled use case is a simplified representation of the European electricity system and is built on Calliope, an open-source Python-based framework for energy system modelling.

This thesis conducts a more detailed analysis of Germany within the model, focusing on offshore wind due to its strategic role in the country's renewable energy expansion and the significant technological advancements expected by 2030 and 2050, which existing integration approaches fail to capture. For the first time, this thesis develops and tests an integrated approach that systematically harmonises prospective life cycle, economic, and technical data with the technological, geographical, and temporal scope of both Life Cycle Assessment and the energy system modelling. This approach enables the evaluation of technologies, particularly offshore wind, within a broader electricity system while resolving methodological inconsistencies.

The primary scientific contribution of this thesis lies in the methodological innovation that allows for the systematic alignment of assumptions between environmental and economic indicators and the assessment of trade-offs between cost and environmental impacts. For instance, the results show that while offshore can reduce the impact on greenhouse gas emissions in 2030 by up to 80 % compared to current levels, the associated investment, however, is up to 40 % higher than other technological alternatives. In addition, offshore wind can increase impacts on ecotoxicity, and water use due to its used materials and manufacturing processes.

This integrated modelling approach facilitates not only the assessment of trade-offs between cost and environmental indicators, but also the provision of deeper insights into the implications of future technologies and supports more informed decision-making for a sustainable energy transition.

Kurzfassung

Eine rasche Dekarbonisierung des deutschen Stromsektors durch den Verzicht auf fossile Energieträger ist notwendig, um die klimarelevanten Emissionen zu reduzieren und die nationalen sowie internationalen Klimaziele zu erreichen. Energiesystemmodelle werden zwar oft eingesetzt, um Strategien zur Eindämmung des Klimawandels zu evaluieren, aber sie berücksichtigen Umweltaspekte meist nur begrenzt und konzentrieren sich oft auf direkte Emissionen aus der Verbrennung fossiler Rohstoffe. Um das zu verbessern, wird in dieser Arbeit untersucht, wie die Umweltauswirkungen von Energiesystemen durch einen integrierten Ansatz bewertet werden können, der die Methode der Lebenszyklusanalyse in ein Energiesystemmodell einbindet.

Die Integration beider Methoden ermöglicht eine umfassendere Bewertung, da vor- und nachgelagerte Umweltauswirkungen sowie Indikatoren in Bezug auf Ökosysteme, menschliche Gesundheit und Ressourcen berücksichtigt werden. Die Integration ist jedoch aufgrund von Dateninkonsistenzen schwierig. Ein zentraler Beitrag dieser Arbeit ist die Entwicklung eines systematischen Prozesses zur Zusammenstellung und Automatisierung von Eingabeparametern, um eine konsistente Erfassung aller relevanten Daten für beide Methoden zu gewährleisten. Die entwickelte Methodik ermöglicht die Erstellung konsistenter Szenarien, die innerhalb des in dieser Arbeit entwickelten Modells getestet werden.

In einer Fallstudie wird eine vereinfachte Darstellung des europäischen Stromsystems analysiert. Dieses basiert auf Calliope, einem Open-Source-Framework für die Modellierung von Energiesystemen auf Python-Basis. Der Schwerpunkt der Fallstudie für Europa ist eine detailliertere Analyse Deutschlands, wobei der Schwerpunkt auf Offshore-Windenergie liegt. Diese Technologie besitzt eine strategische Rolle für den Ausbau der erneuerbaren Energien in Deutschland, und ein bedeutender technologischer Fortschritt ist für die Jahre 2030 und 2050 zu erwarten. Die bestehenden Ansätze erfassen jedoch diese Aspekte nicht. Daher wird in dieser Arbeit erstmals eine integrierte Methodik entwickelt und getestet, die prospektive Lebenszyklus-, Wirtschafts- und technische Daten systematisch mit dem technologischen, geografischen und zeitlichen Untersuchungsrahmen sowohl der Lebenszyklusbewertung als auch des Energiesystemmodells für die Jahre 2030 und 2050 in Einklang bringt. Dieser Ansatz ermöglicht die Bewertung von Technologien, insbesondere der Offshore-Windenergie, innerhalb eines breiteren Stromsystems und beseitigt gleichzeitig methodische Inkonsistenzen.

Der wichtigste wissenschaftliche Beitrag dieser Arbeit liegt in der methodischen Innovation, die eine systematische Angleichung der Annahmen zwischen Umwelt- und Wirtschaftsindikatoren sowie die Bewertung von Zielkonflikten zwischen Kosten und Umweltauswirkungen ermöglicht. Die Ergebnisse zeigen zum Beispiel, dass Offshore-Windenergie zwar die Treibhausgasemissionen bis 2030 um bis zu 80 % gegenüber dem aktuellen Niveau senken kann, die damit verbundenen Investitionen aber bis zu 40 % höher ausfallen als bei anderen technischen Alternativen. Außerdem kann Offshore-Windenergie aufgrund der eingesetzten Materialien und Herstellungsprozessen Probleme in Bezug auf Ökotoxizität und Wasserverbrauch mit sich bringen.

Der in dieser Arbeit entwickelte integrierte Modellierungsansatz erleichtert nicht nur die Bewertung von Zielkonflikten zwischen Kosten- und Umweltindikatoren, sondern ermöglicht auch eine Abschätzung Auswirkungen zukünftiger Technologien und unterstützt dadurch fundiertere Entscheidungen für eine nachhaltige Energiewende.

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Abbreviations

APOS	Allocation at the Point of Substitution
APS	Announced Pledges Scenario
BEE	In German Bundesverband Erneuerbare Energien
BG	Background Systems
BWMK	In German Bundes-Ministerium für Wirtschaft und Klimaschutz
CAPEX	Capital Expenditures
CCGT	Combined cycle gas turbines
CHP	Combined Heat and Power
COP	Coefficient Of Performance
CSP	Concentrated Solar Power
EF	Environmental Footprint
Ef	Emissions Factor
ESM	Energy System Model
EV	Electric Vehicle
FG	Foreground Systems
GAMS	General Algebraic Modelling System
GHG	Greenhouse Gas
GHI	Global Horizontal Irradiance
GWP	Global Warming Potential
HAWT	Horizontal Axis Wind Turbine
IAM	Integrated Assessment Model
IEA	International Energy Agency
ILCD	International Reference Life Cycle Data System
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
LCA	Life Cycle Assessment
LCIA	Life Cycle Impact Assessment
LCOE	Levelized Cost of Electricity
LHV	Low Heating Value
LP	Linear Programming
MILP	Mixed Integer Linear Programming
MRL	Manufacturing Readiness Level
NZE	Net Zero Emissions
OPEX	Operating Expenditures
PB	Planetary Boundaries
PEST	Political, Economic, Social and Technological
pLCA	Prospective Life Cycle Assessment
PP	Power-only Plants
PV	Photovoltaics
RCP	Radiative Concentration Pathways
RER	Region of Europe
SIMPL	Scenario-based inventory Modelling for Prospective LCA
SSPs	Shared Socioeconomic Pathways
STEPS	Stated Policy Scenarios

TRL	Technology Readiness Level
VAWT	Vertical Axis Wind Turbine
WEO	World Energy Outlook
WG	Working Group

1 Introduction

The ambitious climate goal is to keep greenhouse gas (GHG) concentrations at levels that limit global temperature rise to 1.5 °C IPCC (2023b). However, records from 2024 indicate that this threshold has already been reached (ECMWF, 2025). Rising global temperatures pose significant risks to humanity, with consequences worldwide. In Europe, extreme weather events—such as heatwaves, droughts, and heavy rainfall—are associated to climate change (IPCC, 2022d). Climate mitigation refers to efforts to slow climate change, including strategies such as expanding renewable energy sources (UNFCCC, 2024). However, evaluating mitigation strategies is a complex task that requires quantifying GHG emissions coming from human activities across various economic sectors, which is necessary to estimate atmospheric concentrations of GHG and to develop climate projections for assessing climate change (IPCC, 2023a, 2023b). Although climate change has a global reach, mitigation strategies are enforced at sectoral and national levels. In this context, the electricity sector is the most prone to reduce GHG emissions (BMUB, 2016; Prognos et al., 2021), as it is considered less challenging to transform, primarily due to the availability of mature low-carbon technologies, well-established infrastructure, and relatively centralised systems that facilitate large-scale integration of renewables.

Germany as Europe's largest economy and GHG emitter (UBA, 2024a), and is leading efforts towards climate mitigation (EUROSTAT, 2023; Sulich & Zema, 2023), with the defossilisation of the electricity sector being a key strategy (Prognos et al., 2021). This term refers to the process of phasing out fossil fuels from energy systems and replacing them with low carbon technologies (The Royal Society, 2025). Between 1990 and 2023, Germany achieved 46 % reduction in GHG emissions (UBA, 2021) and reached approximately 190 GW of installed renewable energy capacity, out of which 9 GW corresponds to installed offshore wind capacity (Bundesnetzagentur, 2025). Germany has set an offshore wind capacity target of approximately 70 GW (Agora Energiewende et al., 2020). Furthermore, the expansion of offshore wind energy is accompanied by technological development in the sector, which is reflected in the production of larger components for offshore wind turbines (Deutsche WindGuard, 2023; Pierrot, 2023). Therefore, offshore wind emerges as a relevant low-carbon technology that supports the defossilisation of the electricity sector.

While low-carbon technologies such as offshore wind are crucial for the its defossilisation (WFO, 2023), its operation within the energy system is complex due to their dependence on variable weather conditions, particularly wind speed and direction. This variability introduces challenges for grid stability and energy forecasting, as electricity generation cannot be perfectly controlled or predicted. They are part of complex and interconnected systems (Azeem et al., 2021). Consequently, assessing technologies in isolation can overlook relevant system-level interactions. Additionally, large-scale structural transformations require short, medium, and long-term planning. Therefore, energy scenarios are an invaluable tool for strategic planning (Prina et al., 2020; Witt et al., 2020). In this regard, scenarios provide narratives or storylines that describe key driving forces (e.g., technological change, demographics, socioeconomic development) (IPCC, 2012, 2022b; Witt et al., 2018). Accordingly, the generation and quantification of scenarios requires models that consider socio-technical, environmental and economic aspects of human activities at several levels of detail and aggregation. Energy system models (ESMs) represent in a simplified form real-world relationships of components related to the production, conversion, delivery, and use of energy (Verbruggen et al., 2011) and serve to generate and evaluate energy scenarios from a technical, economic and environmental perspective (IPCC, 2022b).

However, while ESMs incorporate environmental considerations, they typically focus on direct emissions occurring during the operation (Laurent et al., 2018). In this context, Life Cycle Assessment (LCA) is a comprehensive methodology to evaluate environmental impacts not only during the operation of a technology, but throughout its life cycle. LCA strives for science-based indicators, considering several environmental concerns, human health and resources (Hauschild, 2018). Therefore, LCA enables a thorough evaluation of the interplay between technology and environment. *This thesis aims to investigate how an integrated approach that combines LCA with an ESM can evaluate the environmental aspects of an energy system*. Such approaches support a more robust estimation of emissions across sectors by capturing upstream and downstream GHG.

Several approaches to integrate LCA and ESM exist (Baumgärtner et al., 2021; Junne et al., 2020; Reinert et al., 2022), differing in ESM scope, sector coverage, and LCA approach. The evaluation of these integration approaches reveal key challenges, particularly structural data inconsistencies and the lack of tools for managing LCA inventories (Vandepaer & Gibon, 2018). Data inconsistency arises from methodological differences between ESM and LCA. The former is dynamic, whereas LCA is static as it relies on inventories representing existing technologies at a given time (García Gusano et al., 2016). Although ESM and LCA require the definition of input parameters that include geographical, technical, and temporal information, they hold different levels of aggregation. As a result, extensive data handling is necessary to ensure data consistency. Recent advancements in tools to manage LCA inventories, such as the Python-based framework PREMISE (Sacchi et al., 2022), facilitate aligning LCA data to match ESM technical, geographical, and temporal scope by generating prospective inventories. However, this tool primarily focuses on updating life cycle inventory data. Effective ESM-LCA integration still requires managing large, complex datasets relevant to both modelling domains. Therefore, to achieve a consistent integration, there is a necessity for the systematic handling of relevant input parameters for both LCA and ESM. *For this reason, this thesis develops a pioneering approach that automatically compiles collected data, ensuring that input parameters—such as economic, environmental, and technical—are integrated consistently*. This systematic approach allows for the generation of scenarios that will be tested in an ESM-LCA model developed in this thesis. The ESM-LCA model represents a simplified version of the European electricity system. The present thesis places particular emphasis on Germany. Additionally, this thesis makes a significant contribution by integrating technical developments in the offshore wind sector into the ESM-LCA approach, an aspect that is overlooked in previous studies.

Given the complexity and extension of the thesis's topic. Five research questions are guiding this thesis and will be answered:

1. How can environmental impacts of energy systems be effectively assessed through the integration of environmental assessment frameworks such as Life Cycle Assessment into energy system modelling?

The answer involves two key aspects. First, assessing the environmental impacts of energy systems through an integrated LCA–ESM approach requires a systematic process to collect, manage, and harmonise relevant input data. This step is essential to resolve inconsistencies and support the generation of scenarios, defined by varying ranges of input parameters aligned with specific narratives. Secondly, it is necessary to develop an integrated ESM–LCA model capable of quantifying and testing those scenarios.

The integration of LCA and ESM is inherently interdisciplinary, requiring competence in several domains such as data science, modelling, engineering, and environmental science to reconcile geographical, temporal and technological data mismatches. For this reason, Chapter 2 provides an overview of the relevant background knowledge needed to support the integration process, including scenario classification, scenario narratives, and reviews of both global and national energy scenarios, with particular attention to climate mitigation strategies in Germany and the role of offshore wind. Consequently, Chapter 2 revisits the relevant aspects of offshore wind technology. Moreover, the chapter examines climate mitigation modelling frameworks, which inform the selection of the energy system model applied. Building on these foundations, the following questions guide Chapter 2:

2. Which solutions are proposed in energy scenarios to reduce greenhouse gas emissions? What role does offshore wind energy play in these scenarios? Which modelling frameworks are available to assess climate mitigation solutions?

Subsequently, Chapter 3 reviews existing approaches for integrating LCA and ESM to identify key challenges, potential solutions, and the contexts in which such integration is most effective. The chapter also examines the types of ESM suitable for integration, highlighting the strengths and opportunities of each methodology. Furthermore, the chapter explores existing methods and tools that facilitate the incorporation of future technological developments, such as those in the offshore wind sector. Based on these findings, the following chapter delves into the steps towards a consistent implementation of the integration approach. Therefore, Chapter 3 explores these questions:

3. How can the integration of Life Cycle Assessment into energy system models improve the representation of emissions and enhance the evaluation of climate mitigation strategies? What are the current approaches for integrating LCA and ESMs?

In the following chapter, the implementation of the integration approach developed within the scope of this thesis is presented. Chapter 4 outlines the main assumptions and details the derivation of all relevant input parameters, including electricity demand, capacity factors, and technical, economic, and environmental data. It also describes the methodological approach adopted to enable the integration of Life Cycle Assessment into the energy system model. Furthermore, geographical and temporal considerations are discussed in relation to the capacity factors for wind and solar technologies. Overall, Chapter 4 provides a comprehensive overview of the modelling assumptions, and the scenario narratives developed for this thesis. The discussion and content presented in Chapter 4 constitute the basis for developing a systematic approach to collect and harmonise relevant input data for both LCA and ESM. The following question guides this chapter:

4. How can future input parameters, particularly those related to offshore wind, be derived and applied within an integrated ESM-LCA modelling approach?

In the next chapter the quantification of the scenarios is conducted. Therefore, Chapter 5 introduces the case study, which consists of an energy system model representing a simplified version of the European electricity sector, with a particular emphasis on Germany and the evaluation of technological advancements in offshore wind turbines. The case study relies in the implementation of the scenario methodology when conducting the LCA of the technologies that are part of the system and when designing the narratives of the scenarios to be quantified in the model. The reference scenario reflects the current state of technological development, while additional scenarios are developed for the years 2030 and 2050. These future scenarios assess the impacts of varying, costs, and environmental performance indicators—particularly those related to offshore wind turbines. The case study is designed to address the following research question:

5. How can technological changes such as in offshore wind technology be investigated from a technical, economic and environmental perspective within the context of an integrated energy system?

Finally, the last chapter discusses the findings of this thesis in the context of the above-mentioned research questions. Overall, the structure of the thesis is illustrated in Figure 1.1.

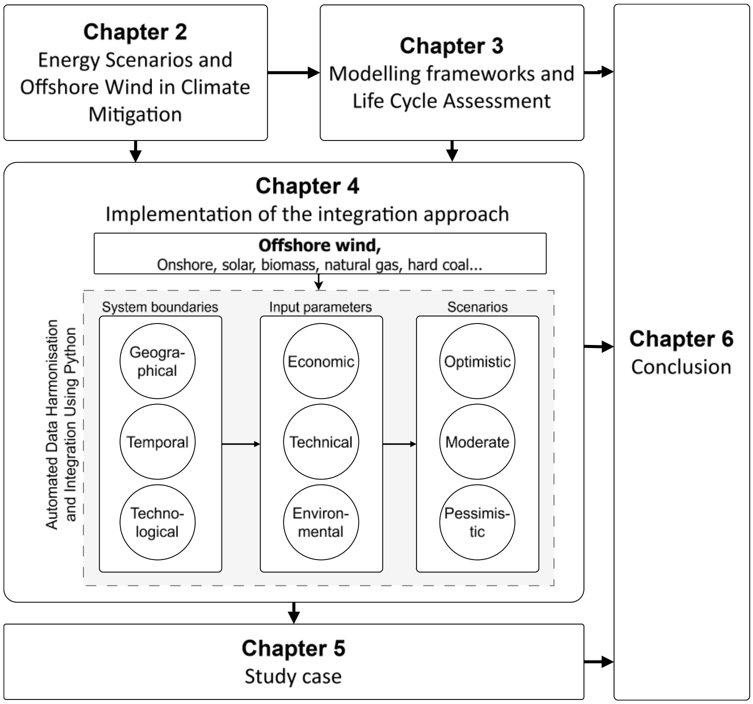


Figure 1.1 Thesis structure overview

Source: Own representation

2 Energy Scenarios and Offshore Wind in Climate Mitigation

Several scenarios show German strategies for mitigating climate change. These strategies rely on the increasing share of renewable energy sources in the electricity sector, for example, offshore wind energy. However, scenarios show disparities in expansion rates, resulting in notable variations in power capacity. Chapter 2 examines recent energy scenarios and the role of scenario typology in shaping different outcomes for the German power sector. In addition, this chapter clarifies scenario narratives and their intended use as well as the implications of the most recent scenarios for the German power sector. Specifically, this chapter addresses the questions:

- Which solutions are proposed in energy scenarios to reduce greenhouse gas emissions?
- What role does offshore wind energy play in these scenarios?
- Which modelling frameworks are available to assess climate mitigation solutions with regard to offshore wind?

The aim of this chapter is to outline key concepts for integrating Life Cycle Assessment (LCA) into energy system models (ESM). The concepts include scenario classification, scenario narratives, and a review of global and national scenarios, with the latter focusing on Germany. Such scenarios emphasize climate mitigation strategies involving low-carbon technologies, thereby supporting the thesis's focus on offshore wind energy. Accordingly, the chapter revisits essential aspects of offshore wind relevant to the development of this thesis. Moreover, the present work explores available tools for generating scenarios in the context of climate mitigation, which are important for justifying the selection of the ESM applied in this thesis.

The structure of the chapter is as follows: Section 2.1 presents scenario typologies. The subsequent section discusses the role of scenario classifications in describing different futures to facilitate the interpretation of various scenarios for the energy sector in Germany. In addition, Section 2.3 discusses the role of offshore wind energy as one low-carbon technology, and its contributions for reducing greenhouse gas (GHG) emissions. Section 2.4 outlines the main energy system models used to generate energy scenarios. Finally, section 2.5 introduces the LCA methodology as a standardized framework enabling the evaluation of the environmental performance of energy scenarios.

2.1 Scenario typology and basic concepts about future scenarios

As philosophical as it sounds, the future is impossible to predict because it simply does not exist. However, our ability as a society to anticipate events has sustained our development over time. While predicting the future is impossible, foreseeing future alternatives is feasible (Gall et al., 2022). Indeed, the field of futures studies aims to anticipate different futures (Roney, 2010). Although future studies cover a wide range of issues, one of the most common topics is technology development. Within future studies, scenario generation is a technique that describes different types of futures. A visual aid for communicating these futures is the cone of plausibility (Gall et al., 2022) or future cone (Voros, 2003). It distinguishes four futures, namely possible, plausible, probable, and preferable futures (see Figure 2.1). These four futures differ in terms of uncertainty. For example, a possible future describes all the events or developments that might occur; therefore, it carries the widest range of possibilities. Similarly, a plausible future illustrates events that could happen, framed by uncertainty, and in accordance with current knowledge. A probable future describes what will happen when events or development follows historical trends; thus, a probable future is the most likely to occur. While a preferable future describes a desirable vision, a preposterous future refers to an implausible or seemingly impossible scenario. Scenario generation is the tool that facilitate the construction of scenarios describing these future alternatives (Gall et al., 2022; Roney, 2010). Additionally, when the future is assumed to follow the current trajectory, it is referred to as a Business-as-Usual (BAU). For example, in the context of climate mitigation, BAU describes the projected concentration of greenhouse gas emissions assuming no additional efforts are made to reduce them (German Council on Foreign Relations, 2025).

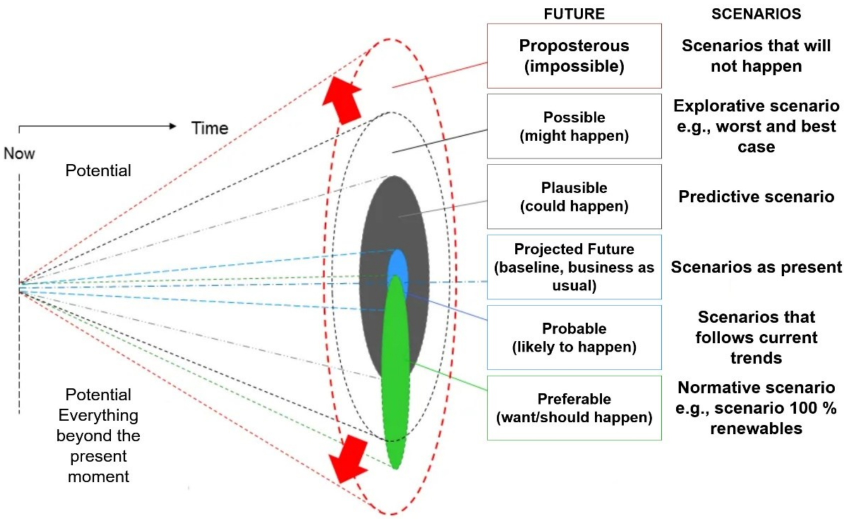


Figure 2.1 Cone of plausibility or the futures cone

Source: Based on (Horvath, 2023; Voros, 2003).

Scenarios are "consistent and coherent descriptions of alternative hypothetical futures that reflect different perspectives on past, present, and future developments, which can serve as a basis for action" (Van Notten et al., 2003). Spaniol and Rowland (2019) have reviewed several definitions of the term and proposed a unified version, integrating shared elements from prior definitions. These features imply that a scenario aligns external forces —such as environmental factors, political conditions, economic trends, technological developments, and social dynamics—with a future-oriented timeframe, ensures plausibility of occurrence under coherent narratives consistently designed to complement each other (Shapiro, 2021). In other words, scenarios contain the narratives that describe a type of future (see Figure 2.1). In the context of combining methodologies such as LCA and ESM, the use of scenarios that reflect possible futures is key to ensuring consistent and meaningful handling of input data. For this reason, the thesis includes dedicated sections to review and contextualize these concepts.

2.1.1 Scenario types and their narratives

In line with the definition of the term scenario, several typologies have emerged proposing different options. For example, Crawford (2019) has identified at least eight scenario typologies In this context, scenario typologies refer to the way scenarios are classified or categorized based on different characteristics (see Table 2.1).

Table 2.1 Scenario typologies

Scenario typologies	Subclassification	Source
DL	exploratory-mixed-anticipatory, descriptive-dynamic-normative, trend-compound-peripheral	(Ducot & Lubben, 1980)
HV	Armchair, Monte Christo, Enterprise, Monte Carlo	(Heugens & van Oosterhout, 2001)
VRVR	Project goal, process design, scenario content	(Van Notten et al., 2003)
BHDEF	Predictive, Explorative, Normative	(Börjeson et al., 2005)
PV	Forecasting, Hedging, Back-casting	(Pulver & Van Deveer, 2007)
VAV	Scenario development, Scenario properties, Scenario applications	(Van de Riet et al., 2008)
WE	problem-focused, actor-focused, and reflexive interventionist or multi-agent-based	(Wilkinson & Eidinow, 2008)
WKM	single client focussed-seeing, single client focussed-seeding, grand challenges-seeing, grand challenges seeding	(Wilkinson et al., 2013)
CSI	Project goals, process design, scenario content, scenario impact	(Crawford, 2019)

DL typology, Ducot & Lubben; HV typology, Heugens & van Oosterhout; VRVR typology, van Notten, Rotmans, van Asselt, & Rothman; BHDEF typology, Börjeson, Höjer, Drebord, Ekvall, & Finnveden; PV typology, Pulver & VanDeveer; VAV typology, van de Riet, Aazami, & van Rhee; WE typology, Wilkinson & Eidinow; WKM typology, Wilkinson, Kupers and Mangalagiu; CSI: Comprehensive Scenario Intervention

Source: Based on (Crawford, 2019)

In the 1980s, Ducot and Lubben (1980) suggested a three-dimensional classification that groups scenarios around three axes, providing a set of 27 scenarios. Potential occurrences belong to the exploratory-mixed-anticipatory type. Descriptive-dynamic-normative illustrates goal-oriented scenarios, while trend-compound-peripheral scenarios group plausible ones. Börjeson et al. (2005) classify scenarios according to their intended use as exploratory, normative, and predictive. The subsequent classification group the scenarios into study categories, such as Armchair, Enterprise and Monte Carlo (Heugens & van Oosterhout, 2001). While the Armchair type ponders potential future contingencies, Monte Christo could serve as a tool for creating a future. Monte Carlo scenarios incorporate a mixture of cognitive and physical elements (e.g., probabilities of success and failure), and the Enterprise type conducts experiments and builds scenarios from them. Later, Pulver and Van Deveer (2007) distinguished between scenarios as products and scenarios as processes. In their view, scenarios as products involve considering what can be inferred (i.e., making an informed decision). For instance, forecasting scenarios predict likely outcomes; hedging scenarios group a range of future alternatives, and back-casting scenarios outline paths to an ideal future. Wilkinson and Eidinow (2008) distinguish three scenario approaches: problem-focused, actor-focused, and reflexive interventionist or multi-agent-based. The first targets on a specific goal or objective. The second focuses on a particular organisation. The last focuses on solving a concrete problem that requires collaborative action. Further on, Wilkinson et al. (2013) point out the benefits of combining complexity thinking and plausible scenarios, proposing a 2x2 typology. Wilkinson et al. (2013) contemplate four potential scenarios cases which considers the purpose (e.g., seeing versus seeding) and the scale of the organization (e.g., single client focusses or problem-centre focus). While *seeding* refers to the scenario intention targeting or making the future, *seeing* means the intent of underscoring a new understanding of a new development. Crawford (2019) comprises all dimensions of existing typologies in a comprehensive scenario intervention typology. Scenario classification has evolved due to the broad application of scenario planning. Some typologies share similarities, as they were created by combining or extending previous versions, while differences aim to enhance scenario planning for specific purposes (Crawford, 2019). As shown above, the existence of multiple scenario classifications highlights the need for application-oriented approaches that enhance clarity and relevance. In the context of this thesis, Börjeson's scenario classification is well aligned with the objectives of this thesis.

2.1.2 Predictive, Explorative and Normative scenarios

The scenario typology proposed by Börjeson et al. (2005) is frequently utilized for environmental research (Ballesteros et al., 2023; Langkau et al., 2023). Therefore, this section outlines their most relevant aspects (see Figure 2.2). Furthermore, this section emphasises the importance of using scenarios in this thesis. They are crucial for addressing uncertainty, aligning assumptions between LCA and ESM, exploring alternative strategies and facilitating informed decision-making. As Gall et al. (2022) discussed, different futures outlined in the cone plausibility are described by generating predictive, explorative and normative scenarios.

According to Börjeson et al. (2005), *predictive scenarios*, such as forecasts and what-ifs, estimate the likelihood of events and reply to "*What will happen?*". Predictive scenarios offer future alternatives by taking the present as a starting point. While forecasts focus on predicting events based on the most likely unfold developments, what-ifs are based on the occurrence of specified events. Although predictive scenarios could find application in long-term planning, forecast and what-if scenarios are better suited for short-term planning, as these scenarios employ external factors as inputs. External factors are those occurring outside the organization, they can be economic events, natural phenomena and organization statistics (Börjeson et al., 2005). Forecast scenarios provide a single probable outcome, while what-if could provide more than two potential events; thus, what-ifs illustrate potential outcomes if a specific near-future event of great relevance happens. Probabilistic scenarios are a sub-set of what-ifs scenarios, and they estimate the probability of occurrence of relevant events. Predictive scenarios describe probable futures, given that they assess a future that follows historical trends.

Explorative scenarios illustrate future plausible alternatives, regardless they seem desirable (Ballesteros et al., 2023). Therefore, explorative scenarios reply to *"What can happen?".* They often come in sets, where the reference scenario is the alternative lacking surprises, and have a long-term future oriented temporal frame. Explorative scenarios are suitable for long-term planning and for estimating deeper changes than what-ifs scenarios. In addition, the reference year of explorative scenarios can be any time in the future, unlike what-ifs that take the present as their starting point (Börjeson et al., 2005). Explorative scenarios are suitable when the development of input parameters is unknown or highly uncertain, or when the actual operation of a system is well-known (Börjeson et al., 2005).

Explorative scenarios are classified as external scenarios, answering to *what can happen to the development of external factors* and strategic scenarios that answer *what can happen if we act in a certain way*. External scenarios focus on factors out of the control of relevant actors, and depending on the complexity of the model, they might require the expertise of many participants. Knaut et al. (2016) evaluated a low-fuel scenario, considering as external factors fossil fuel prices (e.g., natural gas, crude oil, and coal). Their low-fuel scenario classifies as explorative-external type because it replies to what can happen if fuel costs vary in the future. Strategic scenarios consider the development of internal factors, those that are under the control of relevant actors, and their aim is the evaluation of strategic decisions. Therefore, while external scenarios omit policies, strategic scenarios evaluate the effect of policy intervention.

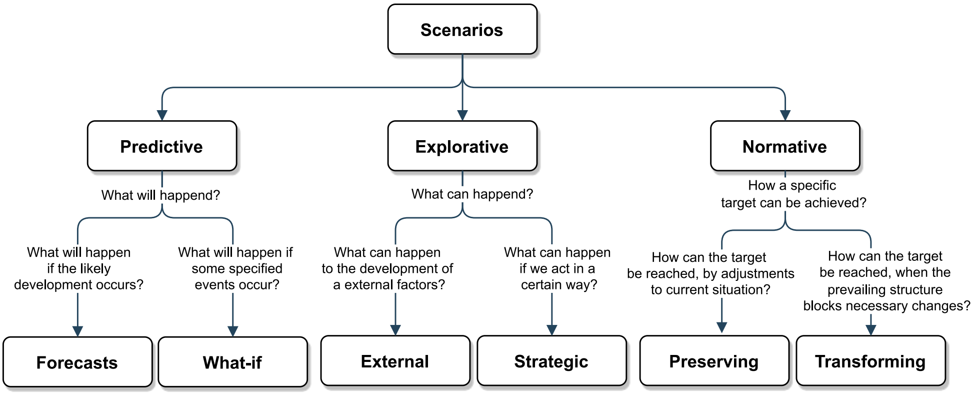


Figure 2.2 Scenario typology

Source: Based on Börjeson et al. (2005)

Scenarios describing plausible and probable futures provide a wider range of outcomes, as the interest is to explore changes. Both plausible and possible future are rooted in changes originated from external sources. These visions of future are described by scenarios (i.e., explorative scenarios) which explore the impact of external changes, such as increase in prices, efficiency improvement etc.

Determining the achievement of a specific goal is done by *Normative scenarios*, which replay *to how a specific target can be achieved*. They explore specific starting points and privilege the occurrence of specific events related to a particular interest. Normative scenarios classify in two sub-categories, such as preserving scenarios when with the current system structure the targets could be achieved or transforming when achieving a specific target requires structural changes (Börjeson et al., 2005). Normative scenarios outline ways to achieve a concrete goal that may be theoretically feasible but improbable in practice. They could play a fundamental role in communicating challenges to a general audience and raising awareness of specific problems. Normative scenarios are rooted in the values that users aspire to uphold. Consequently, they guide the design of a desirable future, facilitating strategies to align societal efforts with these visionary outcomes.

Table 2.2 Application of scenarios typologies. Classification of energy scenarios

Scenario	Narrative	Application (useful for)
Predictive	Predictive Forecast: *What will happened with the global temperature in 2100 if the concentration of greenhouse gases continues increasing? e.g., Radiative concentration pathways (RCP) scenarios*	to aid governments to demonstrate to their citizens the importance of climate change mitigation.
	Predictive Forecast: *What will happen if natural gas prices remain high?*	to aid political decisions. E.g., extend or not operation of nuclear or fossil power plants.

	Predictive What-if: *What will happen with the gas prices in Germany if the War in Ukraine continues?*	to help the government its responses to geopolitical situations, aid to develop policies to cope with existing constraints.
	Predictive What-if: *What will happen with the evolution of energy systems if governments around the world meet their climate targets?*	Useful to provide a sense of how countries may deliver on climate targets (IEA, 2023e).
Explorative	Explorative external: *Given the present consumption levels of natural gas in the German electricity sector, what can happen to the German trade balance (deficit or surplus) if natural gas prices remain high in the next ten or 15 years? What can happen to the German power sector if prices of natural gas vary ± 15 %? e.g., Fuel Cost Low scenario (Knaut et al., 2016)*	to aid political decision. E.g., programs for developing fuel alternatives. To estimate impacts of fuel cost variations.
	Explorative Strategic: *What can happen if the electricity sector in Germany phase-out hard coal power plants in 2030? e.g., Keles-Phaseout scenario (Keles & Yilmaz, 2020) What can happen with the evolution of energy systems if no additional policies are implemented? What can happen to the oil demand if the market penetration of electric cars reach 70 %? e.g., Stated Policies Scenario (STEPS) from the IEA energy-outlook 2023.*	Useful to provide a sense of the prevailing direction of energy system progression and to aid policy makers in realizing where are leading current efforts (IEA, 2023e). To evaluate impact of policies, e.g., the cost and benefits of long-term climate goals (van Vuuren et al., 2011).
Normative	*Normative: How can the German power sector achieve climate neutrality by 2045?*	to identify plausible pathways to achieve climate neutrality, for instance which technologies might require investment
	Normative Preserving: How can the German power sector achieve climate neutrality by 2045 if storage capacity remains constant? e.g., BWMK scenario.	to help raise public awareness of the challenges of achieving climate neutrality.
	Normative transformative: How can the Germany power sector achieve carbon neutrality by 2045 if domestic green hydrogen can meet the demand?? e.g., BEE scenario.	to support the investment decision, identify challenges, find optimal solution.

Source: Based on Börjeson et al. (2005), Ducot and Lubben (1980)

To clarify the concepts explained above, Table 2.2 presents the narratives and the intended use of the Börjeson scenario typology (Börjeson et al., 2005) to address different aspects of energy-related issues. It can be inferred from Table 2.2 that scenarios facilitate the communication, interpretation, and scope of the results of a study.

For this thesis, it is essential to have a clear understanding of the differences between normative, exploratory and predictive scenarios. This distinction facilitates data collection and the alignment of input parameters, ensuring coherent assumptions when integrating LCA into ESMs.

2.2 Energy scenarios in the context of climate change

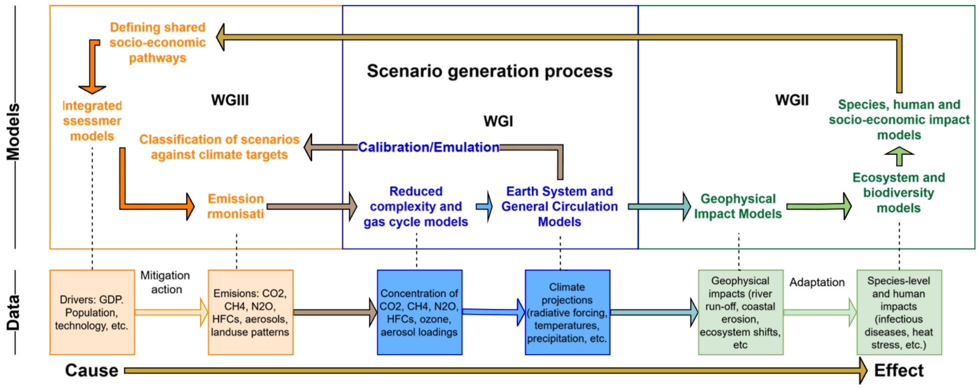
Assessing the impact of human activities on climate change is a complex endeavour that requires multidisciplinary collaboration. This complexity means that the same problem must be analysed from different perspectives, requiring the expertise of different disciplines, methodologies and models. The definition of scenarios with clear narratives has become crucial to facilitate data exchange, the interpretation of results and the formulation of recommendations. This section elucidates the role of scenarios as a supporting tool for assessing climate change. Due to their intrinsic value and frequent use, this section prioritizes scenarios used in the Intergovernmental Panel on Climate Change (IPCC) reports and the International Energy Agency's (IEA) energy outlook. This is followed by a more detailed focus on Germany and its strategies for climate change mitigation.

Moreover, IPCC scenarios provide a science-based context for understanding future technological developments, decarbonization targets, and shifts in the global energy mix. Similarly, IEA scenarios highlight global trends in technology deployment. Together, these scenarios offer valuable context for LCA studies by indicating potential technological advancements. This is particularly relevant for this thesis, as such insights support the integration of LCA into ESM. Therefore, this section examines the assumptions and methodologies behind these scenarios to inform their incorporation into this thesis.

2.2.1 Context of the scenarios in the IPCC and energy outlooks

As part of the United Nations, the IPCC has the task of enhancing scientific understanding of anthropogenic climate change (IPCC, 2024a). The IPCC regularly publishes assessment reports on climate change to provide governments with scientific evidence on potential consequences. Given the complexity of climate systems and the global scope of the assessments, three Working Groups (WG) (IPCC, 2024a) cover aspects such as the physical science basis of climate change (WGI), impacts, adaptation and vulnerability related to climate change (WGII), and the mitigation of climate change (WGIII), see Figure 2.3. In addition, the Task Force on national green gas Inventories (TFI) is dedicated to developing and improving methodologies for estimating net emissions (IPCC, 2024d).

Both interdisciplinary and multidisciplinary approaches are essential for investigating the impact of human activities on the environment. Interdisciplinary collaboration facilitates the integration of knowledge from different disciplines (e.g., methods, concepts) of the scientific community, while a multidisciplinary approach allows a better understanding of a complex problem from the perspective of different experts. In this regard, scenarios are essential to facilitate communication and comparability of results between different studies, ensuring consistent results across disciplines (van Vuuren et al., 2011). For instance, measuring anthropogenic emissions requires the expertise of energy system modellers, to understand how key drivers such as population, income, and technological development relate to emissions that contribute to environmental impacts (Moltensen & Bjørn, 2018) such as climate change. Anthropogenic emissions include greenhouse gases (GHG), their precursors and aerosols caused by human activities. These activities include the burning of fossil fuels, deforestation, land use and land-use changes (LULUC), livestock production, fertilisation, waste management and industrial processes (IPCC, 2018). These emissions are the basis for calculating GHG concentration levels in the atmosphere. Climate modellers use this information to develop climate projections and evaluate the potential long-term effects that fluctuations in concentration levels of GHG could have on global scale. From the perspective of the modellers, this means that the results obtained by one group of experts (e.g., WGIII) may be the input for another research group (e.g., WGI), (see Figure 2.3). Furthermore, different fields require specific data sets at a particular temporal or geographical resolution. It is therefore essential to establish a consensus on how data and results will be produced and shared. According to IPCC (2022b), climate change scenarios have four main purposes. *First*, scenarios examine potential changes in socio-economic developments, energy and land use, and their interconnections with greenhouse gas emissions. Furthermore, they assess the impact of those emissions on the composition of the atmosphere and their role in climate change. *Second*, climate change scenarios facilitate the evaluation of long-term climate goals and the potential implications of policy interventions. Thus, scenarios contribute to developing pathways, which are useful to evaluate actions and to identify trade-offs. *Third*, climate share scenarios facilitate the exchange of knowledge between different disciplines. For this reason, the IPCC developed the Representative Concentration Pathways (RCPs) scenarios, which aim to inform about potential trajectories of the main drivers of climate change and facilitate the exchange between climate modellers and energy system modellers (Clarke, 2022). Consequently, working groups can work in parallel, following consistent narratives, and speeding the generation of results (van Vuuren et al., 2011). And *fourth*, climate change scenarios seek to inform society, raise awareness, and contribute to science-based decision-making (IPCC, 2022b).



The circular set of arrows at the top indicates the main set of models and workflows used in the scenario generation process, with the lower level indicating the datasets.

Figure 2.3 A simplified illustration of the scenario generation process within the IPCC Working Groups

Source: Based on (IPCC, 2023a)

Regarding the third goal of climate change scenarios, and although the RCPs scenarios have grouped more than 300 scenarios to describe the four trajectories of greenhouse gas concentration, the assumption of drivers such as population and economic growth was set by each of those scenarios independently (van Vuuren et al., 2011). Therefore, to enhance the analysis of future climate impacts and the integration among working groups, the shared socioeconomic pathways (SSPs) were defined (IPCC, 2022b; O'Neill et al., 2014). According to O'Neill et al. (2014), the SSPs depict plausible trends in the evolution of society and natural systems, ultimately, the goal of SSPs is to support the inclusion of socioeconomic and environmental aspects affected or not by both climate change and climate policy (IPCC, 2022a, 2022b; Riahi et al., 2017).

The SSPs and RCPs scenarios are essential in assessing global climate change, as established by the IPCC (Hausfather, 2018). They facilitate the harmonization of data exchange and maintain consistent narratives that aid the interpretation of results. Understanding socioeconomic and technological development, as captured in these scenarios, is crucial to estimating the environmental impacts of human activities. For instance, the WGIII employs Integrated assessment models (IAMs) to evaluate these scenarios. Section 2.4.1 introduces the main characteristics of IAMs.

The IPCC's Sixth Assessment Report (AR6) includes results coming from the three working groups, which employ different models to evaluate the scenarios, as shown in Table 2.3 (IPCC, 2023b). The working group I (WGI) focussed on climate models, physical models and they determine potential pathways for greenhouse gas (GHG) emissions. These pathways are summarized in four scenarios that depict potential concentration levels of GHGs by 2100, and radiative forcing, illustrating the world at global mean temperature increases above preindustrial level of 1.5 °C, 2.2 °C, 3.5 °C and 4 °C. These global temperatures are dependent on the concentration of greenhouse gases associated with anthropogenic activities. The global temperature has remained approximately 1.1 °C above preindustrial levels (IPCC, 2023b). However, 2024 marked the first year in which the global mean temperature exceeded a 1.5 °C increase above preindustrial levels (ECMWF, 2025). Should this trend continue, the hottest day of the year could vary between 0 °C and 7 °C, depending on the region and the scenario (IPCC, 2023b). In South America, for example, countries such as Paraguay, where the hottest day of the year in 2022 already exceeded 40 °C (DINAC, 2022), could reach 47 °C in a scenario with a global mean temperature of 4 °C. For certain regions, changes in precipitation might be more problematic than the temperature rise, as changes in soil moisture and precipitation patterns are also expected (IPCC, 2023b). For instance, April 2024 was significantly warmer and wetter than the long-term average in Germany, according to the German Weather Service (DWD, 2024). Similarly, the second working group (WGII) has identified potential risks associated with a rise in the global mean temperature. For instance, in Europe, these risks are linked to an increase in heat waves, droughts, and water scarcity in southeastern Europe, while precipitation and floods increase in the north (IPCC, 2022d). WGII relies on specific models (e.g., economic, geophysical, ecosystem and biodiversity) to estimate the impact on humans and ecosystems of increases in the concentration of greenhouse gases. The WGIII evaluates the implication of human activities, technology development and focuses on describing emissions caused by human activities, which are converted into concentration levels to elaborate climate projections (IPCC, 2022b). WGIII has estimated current greenhouse gas concentration levels, and evaluate the results of recent efforts, and potential technological solutions to mitigate climate change. For instance, the AR6-WGIII indicates that current mitigation efforts are insufficient to limit the global mean temperature below 1.5 °C by 2100. Even though low-carbon energy sources provide over 37 % of the world's electricity, meeting the 1.5 °C target would require a 95 % reduction in coal usage by mid-century. Meeting this target is challenging, given the increase of 7.5 % in new coal power plants and oil consumption by 5 % in 2019 (IPCC, 2024c). Table 2.3 shows the main aspects of the three IPCC working groups.

Table 2.3 Summary IPCC working groups.

Teams	Research area	Answered questions	Models	Based on

Working Group I	The physical science bases	What will happen to the World if the global temperature reaches 1.5 °C, 2 °C, 3 °C or 4 °C by 2100? How will the World look like at this temperature?	Regional climate models, earth system models and general circulation models for climate projection.	(IPCC, 2021, 2023b)
Working Group II	Impacts, adaptation, and vulnerability	What would be the possible effects on ecosystems, the economy, sea levels and the energy sector if global temperatures were to rise to 1.5 °C, 2 °C, 3 °C or 4 °C by 2100? What are the dangers that society must face?	Geophysical impact models; ecosystem and biodiversity models; species, human and socio-economic models.	(IPCC, 2022d, 2022f)
Working Group III	Mitigation of climate change	How can the effects of global temperatures at 1.5 °C, 2 °C, 3 °C or 4 °C by 2100 be mitigated? How technology, policies or international collaboration could help? Is the speed of change sufficient?	Integrated assessment models; energy system models	(Clarke, 2022; IPCC, 2022c, 2022e)

In the aftermath of the 1970s energy crisis, the International Energy Agency (IEA) initiated the coordination of action to mitigate oil supply disruption. Over time, the IEA's initial objective has shifted towards data provision and policy recommendations for a sustainable future, the evolution of technologies, and the potential effects of abrupt events (e.g., war, conflicts) in the short and medium term (IEA, 2023b; IPCC, 2022b; Moltensen & Bjørn, 2018; van Vuuren et al., 2011). While the IPCC publishes comprehensive reports every five to seven years (IPCC, 2024b), the IEA's annual World Energy Outlook (WEO) turns to the energy security of the global energy system, proposing three scenarios: the Stated Policies Scenario (STEPS), the Announced Pledges Scenario (APS) and the Net Zero Emissions by 2050 (NZE) scenario (IEA, 2023e). The STEPS could be classified as an explorative scenario, as it portrays the prevailing trends in energy systems and responds to the question of what can happen if a set of likely developments occurs, such as 16 members of the European Union having coal phase-out commitments, or Germany tightening offshore wind deployment targets, etc. While, the STEPS assists policymakers in understanding the direction of current efforts (IEA, 2023e), the APS scenario evaluates the impact of new policies. Consequently, the APS describes an explorative-strategic scenario, which assumes that all existing climate commitments will be achieved in a timely manner. For instance, those made by the G7, which is a forum on climate, energy, and the environment composed by seven heads of state (e.g., Canada, France, Germany, Italy, Japan, and the United Kingdom) (BMUV, 2023). G7 members are committed to phasing out fossil fuels. For example, the complete decarbonisation of the electricity sector in 2035 by the United States and Europe (IEA, 2023e). Finally, the NZE scenario is a normative-transformative scenario that addresses how to achieve net zero emissions when a broad portfolio of clean energy technologies is deployed (IEA, 2023e).

In addition, the WEO 2023 discusses the effects of conflicts (i.e., the war in Ukraine) that caused turmoil in the energy sector. In this context, key findings assume further disruptions in the energy market and prices. Although rapid expansion of renewables (more than 500 GW added worldwide in 2023), the supply chain for wind energy is under pressure (IEA, 2023e). In 2023, one in five cars sold was electric, demonstrating a significant step towards the electrification of sectors. However, while the share of fossil fuels (i.e., coal, oil, natural gas) could fall to 73 % in 2030 from 80 % (current share), efforts seem to be insufficient to achieve the climate goal that limits global temperature increase at 1.5 °C, according to the STEPS scenario. Furthermore, STEPS scenario points out the importance of the heating sector and suggests heat pumps as a potential solution to achieve targets depicted in the NZE scenario (IEA, 2023e). In conclusion, IEA scenarios are critical for identifying geopolitical risks and opportunities in the global energy landscape. They highlight challenges and encourage international cooperation.

International agencies such as the IPCC and IEA have been set up to provide comprehensive scenarios for a holistic understanding of the interaction between geopolitics, energy security and climate change. Achieving climate goals could face delays due to supply chain disruptions affecting steel and rare earth materials in the case of wind energy (Bettoli et al., 2023). Additionally, other challenges are the lack of international engagement, as six members of the European Union have no official coal phase-out discussion (Beyond Fossil Fuels, 2025), conflicts (e.g., the war in Ukraine, Palestina) and other events (e.g. pandemics, economic crises). However, implementing policies (and their monitoring) is more likely to occur at the lower levels (e.g., region, nation, sector); therefore, stakeholders need scenarios describing those levels for planning more concrete actions (Blaufuß et al., 2019; Geldermann et al., 2007).

In the context of integrating LCA into ESM, scenarios derived from the IPCC are relevant for contextualizing LCA data, as they enhance future-oriented analysis and provide insights into innovation. For this reason, this section is important for the development of this thesis.

2.2.2 Scenarios in the context of the German energy transition

Several German institutions explore ways to mitigate climate change, emphasizing the energy sector due to its complexity and relevance in reducing emissions. The previous section highlighted the role of scenarios in anticipating the future and scenario generation as a powerful tool for decision making and strategy design. The complex and large-scale structural transformations require short, medium, and long-term planning. Decision-makers, therefore, rely on energy scenarios as an invaluable tool to guide their decisions (Prina et al., 2020; Witt et al., 2020). However, the variability of the outcomes described in the scenarios is related to their narratives, which follow a discourse based on the purpose of the scenario. It is, therefore, essential to clarify their intended use from the outset. This section explores scenarios for the German energy transition, as Germany is one of Europe's largest economies and greenhouse gas (GHG) emitters, and is leading efforts towards climate mitigation (EUROSTAT, 2023; Sulich & Zema, 2023).

Two main aspects characterise the German electricity mix. First, its cumulative capacity is significantly higher, with over 200 GW in 2024, compared to France (150 GW), Italy, Spain, and the UK, which are nearly 100 GW (ENTSO-E, 2024a). Second, Germany has significantly expanded renewable energy sources, with wind and solar accounting for 60 % of the total installed capacity (ENTSO-E, 2024a). One reason for this high installed capacity is the inherent volatility of renewable energy sources, which requires greater capacities to ensure reliability and balance in the electricity system. While France relies on nuclear power and Italy on gas, Germany has a well-diversified technology mix. However, despite efforts to reduce reliance on fossil fuels, they account for almost 30 % of total installed capacity in 2024 (Directorate-General for Energy, 2023). According to UBA (2023), the German energy industry is the largest contributor to greenhouse gases, accounting for 34 % of the total national GHG emissions in 2022. The energy industry includes public power plants, heating plants, refinery furnaces, gas pipelines, etc (Harthan et al., 2023). At the same time, the sector is the most prone to reduce emissions (BMUB, 2016; Prognos et al., 2021). The Renewable Energy Act 2023 sets a target of generating 80 % of the electricity from renewable energy sources by 2030 (Agora Energiewende, 2022; BMWi, 2021). However, implementing energy policies faces the dilemma of ensuring a secure, affordable, and clean energy supply (Schmidt et al., 2019). For example, while a system reliant on renewable energy sources provides energy with low carbon emissions, it is prone to weather conditions and high prices. Hence, designing an optimal solution requires understanding the complexity of energy systems at various levels, making energy scenarios a crucial tool for guiding experts (Prina et al., 2020).

German scenarios evaluate strategies for climate mitigation from different perspectives. For example, although green hydrogen serves many purposes, the national hydrogen strategies advocate for application of green hydrogen in several sectors (e.g., transport, industry, buildings, etc.) (BMWK, 2024; Rasul et al., 2022). One potential application of hydrogen is as a fuel in gas-fired power plants to ensure security of supply (Prognos et al., 2021). The implementation of energy-efficient measures, the augmentation of storage capacity, and the acceleration of renewables, with a particular emphasis on photovoltaics, would result in a 30 % decrease in natural gas consumption (Mueller et al., 2022). The Ariadne project focuses on developing target-oriented measures and explores the effects of energy transition strategies (Kopernikus Projeckte, 2024), and it suggests six climate-neutral scenarios that assume massive expansion of renewables, in particular onshore wind, through the entire exploitation of the country's energy potential and significant imports of hydrogen and synthetic fuels (Luderer et al., 2021). The project employs various modelling approaches, including systemwide and sector-specific analyses, which addressed several issues and facilitated the comparison of outcomes generated by different energy system models. The Bundesministerium für Wirtschaft und Klimaschutz (BMWK, currently Bundesministerium für Wirtschaft und Energie) envisions the Long-term Scenarios III, which provides projections of the expansion of solar photovoltaics and onshore wind power. Furthermore, the scenarios consider high shares of imported hydrogen. Similarly, the Bundesverband der Deutschen Industrie (BDI) proposes the Climate Path 2.0 scenarios, which anticipate climate neutrality by 2050 but at the cost of escalating imports of natural gas, hydrogen, and minimal storage capacity. The Climate Path 2.0 scenarios count on offshore wind energy (BCG & Klimapfade, 2021). To ensure security of supply, the scenarios proposed by the German Bundesverband Erneuerbare Energien (BEE) focus on new electricity markets design and rely on domestic hydrogen. Their scenarios suggest approximately 100 GW of electrolysis capacity by the year 2050 (Stark et al., 2021). The German Energy Agency proposed the DENA KN 100 scenario (Jugel et al., 2021), which limits hydrogen production inside Germany. Among the scenarios discussed, DENA KN 100 estimates the highest amount of imported hydrogen, almost twice the amount projected by Agora-Prognos and Climate Path 2.0 scenarios. However, the viability of this scenario requires the immediate development of the infrastructure to transport hydrogen and synthetic fuels (Ballesteros et al., 2023).

In addition, Thimet and Mavromatidis (2022) examined 47 scenarios conducted by independent researchers for the German energy sector (i.e., heat and electricity), out of which 28 scenarios look exclusively into the electricity sector and its interconnection with neighbouring countries. They classified the scenarios depending on the share of low-carbon sources in *low*, *moderate*, and *ambitious* scenarios. The authors noticed that by 2030, most scenarios with a lower share of renewables kept coal-based and gas power plants as core suppliers, with some variation in the coal generation attributed to the coal phase-out target year. The *Low* scenarios envision an increase in wind and solar, with generation shares like natural gas and minimal generation from biomass. *Moderate* scenarios rely more on wind energy than solar, and by 2030, they require less natural gas compared to the current demand because wind energy fills the gap left by coal and nuclear. The *Ambitious* scenarios depict a substantial increase in solar and wind energy and a minor contribution of natural gas. The evaluation of these scenarios shows a clear pattern regarding the role of renewables and natural gas in the German electricity sector. Most scenarios agree to assign a relegated role to bioenergy and lack clarity regarding energy imports and exports, presenting divergent outcomes – from Germany potentially becoming a net energy exporter to an importer.

Although a direct comparison among the scenario outcomes could mislead conclusions, they highlight trends regarding technologies that might require incentives, the crucial role of wind and solar energy, and natural gas. In most scenarios, the role of bioenergy in the electricity sector is minimal. However, the scenarios provided scattered results regarding strategies to deal with fluctuating energy, energy import and export and electricity demand. For instance, both Thimet and Mavromatidis (2022) and Doms (2022) underscore the substantial variability in storage capacity and the strategies employed to integrate renewables into the system, such as battery, hydro pumped storage, power to gas (most specifically hydrogen production through electrolysis), and demand side management. Most scenarios evaluated by Doms (2022) support hydrogen and synthetic fuel imports due to lower generation costs, while BEE scenarios project domestic hydrogen production. However, over half of the scenarios evaluated by Thimet and Mavromatidis (2022) omit energy import and export. Regarding the future electricity demand, those scenarios that consider the electrification of the sectors project significant increase of the electricity demand. By 2045, on average the gross electricity consumption[1] might reach about 1000 TWh (Ballesteros et al., 2023).

The previous discussion is crucial for integrating LCA into ESM, as it provides detailed insights into the technological pathways, energy mixes, and infrastructure developments projected in various scenarios. Understanding the diversity and assumptions within these scenarios facilitates more precise modelling of environmental impacts across the life cycle of energy systems.

[1] "A country's gross electricity consumption is defined as the entirety of the electricity that is used in a country. It's called 'gross' electricity consumption because it includes electricity that gets lost on the way and never makes it to the end user." Source: https://www.bmwk-energiewende.de/EWD/Redaktion/EN/Newsletter/2016/01/Meldung/direkt-answers-gross-electricity-consumption.html

Table 2.4 Key Insights from Climate-Neutral Scenarios for the German Energy Transition. Gross electricity consumption for 2045

Study (scenario)	**Agora-Prognos (CN 2045)**	**Kopernikus-Ariadne (REMIND*)**	**BDI (Climate paths 2.0)**	**BEE (Base 2050)**	**BWMK (TN electricity 2050)**	**DENA (KN 100, 2050)**
Name	Climate Neutral Germany 2045	Germany on the way to Climate Neutrality 2045. Scenarios and pathways in model comparison	Climate paths 2.0. An economic program for climate and the future	New Electricity Market Design for the Integration of Fluctuating Renewable Energies	Long-term scenarios for the transformation of the energy system in Germany (Long-term Scenarios III)	DENA pilot study Towards Climate Neutrality
Scope	Macro and sectoral level GHG neutrality in 2045	Macro and sectoral level GHG neutrality in 2045	Macro and sectoral level GHG neutrality in 2045	Sector level, GHG neutrality in 2045, ensure security of supply	Macro and sectoral level GHG neutrality in 2050	Macro and sectoral level in Germany, GHG neutrality in 2045
Publication year	2021	2021	2021		2021	2021
Gross electricity, TWh	1017	1154	1082	1370	1078	910
Onshore wind, GW	145	218	180	198	155	124
Offshore wind, GW	70	29	70	57	45	50
Solar PV, GW	385	329	230	449	290	260
Storage, GW	59	-	39	96	8	25
Natural gas, GW	70	42	90	15	64	55
Electrolyzes, GW	50	19	-	86	41	24
Share electricity, %	46	69	59	-	53	49
Imported H_2, TWh	265	215	237	-	262	364
Domestic H_2, TWh	96	63	99	300	92	60
Institutions	a)	b)	c)	d)	e)	f)

a) Prognos, Öko-Institut, Wuppertal Institut on behalf of Stiftung Klimaneutralität, Agora Energiewende, Agora Verkehrswende. WISEE-EDM: Wuppertal Institute System Model Architecture for Energy and Emission Scenarios – Energy Demand Model.

b) PIK, MCC, Paul Scherrer Institute (PSI), RWI, Fraunhofer Institute for Systems and Innovation Research (FhG-ISI), German Aerospace Centre - Institute for Networked Energy Systems (DLR-VE), German Aerospace Centre - Institute of Transport Research (DLR-VF), Institute of Energy Economics and Rational Energy Use (IER), German Aerospace Centre - Institute of Vehicle Concepts (DLR-FK), Frauenhofer Institute of Energy Economics and Energy Systems Engineering (FhG-IEE), Helmholtz Centre Hereon, Frauenhofer Research Institution for Energy Infrastructures and Geothermal Energy (FhG-IEG) on behalf of Kopernikus-Projekt Ariadne.*Results obtained with REMIND.

c) Boston Consulting Group (BCG)

d) Fraunhofer Institutes for Energy Economics and Energy System Technology (IEE) and Solar Energy Systems (ISE) and legally reviewed by the law firm Becker Büttner Held (BBH).

e) Corsentec, Frauenhofer Institute for Systems and Innovation Research (Fhg-ISI), Institute for Energy and Environmental Research Heidelberg (ifeu), Technical University Berlin (TU), on behalf of Federal Ministry for Economic Affairs and Climate Action (BMWK).

f) Institute of Energy Economics at of the University of Cologne (EWI), Institute for Technical Building Equipment (ITG), Environmental Energy Law Foundation (SUER), Research Institute for Thermal Insulation (FIW), Jacobs University Bremen (JUB), Wuppertal Institute for Climate, Environment, Energy gGmbH (WI), on behalf of Deutsche Energie-Agentur (DENA).

Source: Based on (Ballesteros et al., 2023)

2.2.3 Scenario Narratives in the Context of Germany's Energy Transformation

The previous section presents Germany's scenarios for achieving carbon neutrality or zero greenhouse emissions within a specific period (see, Table 2.4). They correspond to the normative type, according to the typology of Börjeson et al. (2005). For example, although they all aim to reach the targets through a rapid expansion of renewables, the scenarios differ in their technology choices and required installed capacity to achieve the targets. Moreover, scenarios in Table 2.4 show two types of normative scenario subcategories. For instance, BEE's scenario addresses how Germany can achieve carbon neutrality by producing green hydrogen domestically, requiring higher electricity demand and renewable installed capacity as result. Although theoretically feasible, this scenario would require 86 GW of electrolysers, which may be unlikely in practice due to the current number of electrolysers being less than 80 MW in the European Union (IEA, 2023c), and about 62 MW in Germany (Amelang, 2023). While the European manufacturing capacity for electrolysers was 3.3 GW per year in 2022, the rate should reach 53 GW per year by 2030 to sustain the hydrogen strategy (Hydrogen Europe, 2022). Therefore, bottlenecks in the manufacturing capacity are obstacles to the BEE's vision. However, this scenario serves as a tool to communicate the challenges of reaching this target and exploring alternative options. Regarding BDI, the scenario assumes a preserving-normative approach, as it explores ways to achieve climate neutrality without increasing storage capacity, which could justify higher hydrogen imports. This outcome relies on hydrogen production outside Germany. Nonetheless, this scenario could aid in developing international cooperation programmes for green hydrogen production. Prognos and Kopernikus classify as normative-transformative scenarios, they answer how Germany can achieve climate neutrality developing a hydrogen economy and electrification of the sectors, as result they suggest different requirements of imported hydrogen and installed capacity. The Kopernikus-Ariadne project has developed several scenarios. The scenario depicted in Figure 2.4 corresponds to a normative transformative scenario that achieves carbon neutrality by exploiting all onshore wind potential. In Germany, 2 % of the land area has an energy potential of up to 198 GW from onshore wind (Unnewehr et al., 2021), with 61 GW already achieved in 2023 (ENTSO-E, 2024a). The Kopernikus-Ariadne scenario requires an additional 120 GW in the coming years. DENA is another example of a normative transformative scenario that explores how to achieve climate neutrality. It assumes the highest import of hydrogen, which consequently reflects the lower demand for electricity. However, the origin of green hydrogen, whether domestically produced or imported, holds little significance compared to global electrolyser manufacturing capacity, which remains insufficient to meet net-zero production targets by 2030. For instance, the International Energy Agency (IEA) estimates that global electrolyser production capacity could reach approximately 130 GW/year, while achieving carbon neutrality will require approximately 184 GW/year (IEA, 2023a).

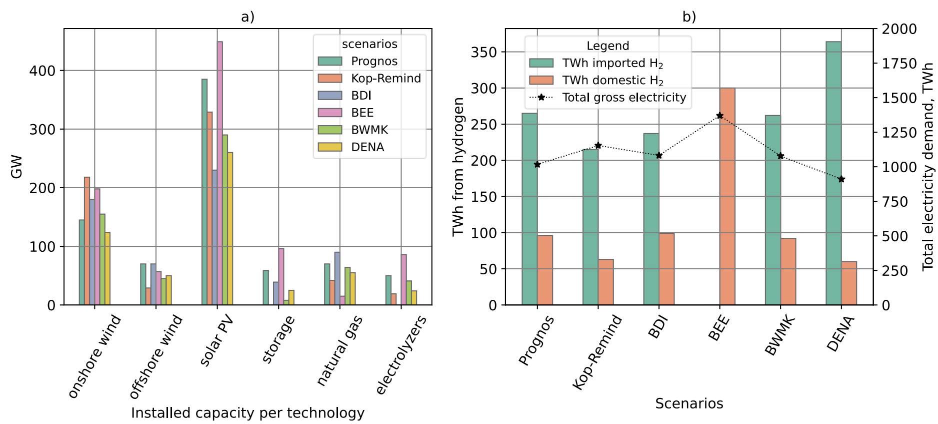


Figure 2.4 Energy scenarios for Germany
a) Installed capacity for different technologies; b) Gross electricity and imported and domestic hydrogen requirements

Source: Based on the scenarios Agora-Prognos (CN 2045), Kop-Remind (Kopernikus-Ariadne REMIND), BDI climate pathway 2.0, BEE Base 2050, BWMK long term 2050, DENA KN 100 2050 (see Table 2.4)

In contrast, Thimet and Mavromatidis (2022) examined a mix of normative and explorative scenarios for Germany, which employs a variety of energy models (see, Table 2.5). For instance, Thimet and Mavromatidis (2022) classified as ambitious scenarios those provided by (Bartholdsen et al., 2019). These scenarios encompass the implementation of policies related to carbon taxes and the phase-out of coal, and are categorised as explorative-strategic scenarios according to the classification of Börjeson et al. (2005). For example, the scenarios answer what can happen with the different rates of carbon taxes and target years for phasing carbon power plants. Hansen et al. (2019) also proposed explorative-strategic scenarios but examined what can happen if 100 % of renewable energy potential is utilized in 2050, using a simulation based energy model (see, Section 2.4). Keles and Yilmaz (2020) focused exclusively on the electricity sector and illustrated a normative-preserving and a normative-transforming scenario. The first replies to how can 80 % of the electricity come from renewable sources without phasing out coal power plants, and the second explores how to generate 80 % of the electricity from renewable sources but phasing out coal power plants by 2040. On the other hand, Knaut et al. (2016) proposed explorative external scenarios that focus on the variation of fuel prices over time. Overall, the projection of the electricity demand is about 600 TWh in 2030, and between 1400 and 600 TWh in 2050. The analysis of German scenarios highlights significant variation regarding the role of photovoltaics, wind energy, and natural gas. For example, on average at least 75 TWh of electricity might be supplied through natural gas, representing between 5 % and 35 % of the total electricity generation in 2050. Additionally, wind energy could provide between 100 and 800 TWh in 2050 (Thimet & Mavromatidis, 2022). The reason of these variation comes from different scenario narratives and modelling frameworks (see Section 2.4).

Furthermore, it can be concluded from the scenarios in Figure 2.4 that the role of wind and solar energy is crucial. To achieve climate neutrality, solar energy might require a capacity of between 200 GW and 450 GW. This means an enormous amount of installed capacity to ensure sufficient electricity generation. Sunshine duration plays a significant role in the generation of electricity, for example, in Germany the sun shines for an average of 4.5 hours per day (Wirth, 2024). Additionally, the global horizontal irradiance (GHI) in Germany has a moderate value of 2.98 kWh/m^2 compared with other regions like Spain (e.g., 4.69 kWh/m^2) (Solargis, 2017). In 2023, 14 GW of new photovoltaic systems were added, representing a 22 % increase in installed capacity and nearly 82 GW of cumulative photovoltaic installations (UBA, 2024b). However, the difference in generation is minimal, rising from 60.3 TWh in 2022 to 61.2 TWh in 2023. Therefore, despite the efforts invested in solar energy, the number of installations requires considerable resources and space, not to mention the necessity for storage solutions (e.g., batteries).

Regarding wind energy, although the growth rate of onshore wind rebounds in 2023 with around 3 GW of additional capacity (UBA, 2024b), the expansion of onshore wind faces potential delays as existing wind turbines reach the end of their life. New projects should replace old wind turbines (repowering) and add new installed capacity (Deutsche WindGuard, 2023). In addition, supply chain issues, increases in the price of critical materials (e.g. rare earth elements used in generators) and bureaucratic hurdles in obtaining permits are challenging the expansion of wind energy. In the onshore sector, the average size of wind turbines increased by a modest 3 % year-on-year, as larger sizes may face social acceptance issues (Deutsche WindGuard, 2023). While 2023 was less sunny than previous years[2], which negatively affected solar electricity generation, it was the windiest year in Germany since 2007 (Wettengel, 2024). The average wind speed reached 6 m/s, exceeding the long-term average—particularly during the winter months of January, November, and December—and reaching the highest level recorded since 2007 (Wettengel, 2024). As a result, wind power generation increased by 14 %, from 124 TWh in 2022 to 142.1 TWh in 2023, due to 3 GW of capacity added and good wind conditions (i.e., in 2023 average wind speed at 100 m above 6 m/s). There is a potential for offshore wind capacity of about 70 GW in Germany, while only 8 GW is currently installed (Agora Energiewende et al., 2020). The remarkable difference in installed capacity between onshore and offshore wind (e.g., 60 GW versus 8 GW in 2024) is mainly due to cost (Stehly et al., 2023), the foundation type, and the need of offshore and onshore substations (Junginger et al., 2020). While onshore wind has achieved a 40 % reduction in capital expenditure, offshore wind has seen a 50 % reduction over the last decade (Sens et al., 2022), in particular after 2015. Yet, the cost of building offshore wind farms remains higher due to increasing water depth and offshore distance. For instance, only the foundation holds about 50 % of the cost and can double depending on the water depth (Hevia-Koch & Klinge Jacobsen, 2019; Oh et al., 2018). However, technology development, and the availability of space allow for enlarger components in offshore wind farms, have resulted in higher capacity factors[3], making offshore wind a more cost-competitive energy source (Junginger et al., 2020). In addition, experts foreseen reductions between 37 % and 49 % in wind energy cost by 2050 (Wiser et al., 2021).

Ultimately, energy scenarios enable analysis at multiple levels. They describe several strategies to achieve climate mitigation. For instance, they assess the implementation of policies such as the phased out nuclear and coal power plants, the adoption of natural gas and storage solution to balance

[2] Sunny June and September and dull November characterized 2023. Additionally, the duration of sunlight is not uniform in all the regions. For example, the South of Germany reached 2000 hours of sunshine, but low mountain regions reached 1600 hours (DWD, 2023).

[3] "Capacity factor is *the actual energy output of an electricity-generating device divided by the energy output that would be produced if it operated at its rated [power output](https://pris.iaea.org/PRIS/Glossary.aspx) for the entire year*" https://pris.iaea.org/PRIS/Glossary.aspx

intermittent renewable energy sources. In Germany, the energy strategy relied on affordable natural gas sourced mostly from Russia, which involved significant investments such as the Nord Stream I and II pipelines. Consequently, the outbreak of the war in Ukrainian has left Germany vulnerable to supply disruptions and soaring gas prices. Therefore, such a turn-over event poses a threat to Germany's security of supply (Doms, 2022). Unforeseeable events are challenging to predict when planning long-term energy strategies, requiring specific approaches to access the impact of these events. For example, the World Energy Outlook 2023 evaluates potential treats such as political tension and how them might affect electricity prices and supply, effects of inflation and rise on interest rates in renewables projects. In the case of Germany, experts are rethinking energy strategies. According to Doms (2022), there is a clear consensus about achieving climate neutrality without extending the operation of nuclear power plants. Moreover, coping with the energy crisis requires diversifying the natural gas supply and restarting coal power plants for short term (from October until March 2024) (Elspas et al., 2023). While the commitment to phasing out coal power plants by 2030 is a crucial aspect of the German energy policy, the current crisis needs to ensure the security of supply (Wiertz et al., 2023). However, with the firm conviction of a rapid and intensive implementation of renewable energy sources, as shown with the release of the Easter packet (Agora Energiewende, 2022). This comprehensive legislative package forms part of the immediate energy action plan and implements many of the energy policy measures. For instance, the amendment of the Renewable Energy Act even tightened the climate goals and emphasized their alignment with the 1.5-degree path of the Paris Agreement (BMWK, 2022; Bundesregierung, 2023).

In a global context, the scenarios proposed by IEA suggested a worldwide increase of electricity demand and the dependency, especially until 2030, of fossil fuels that are necessary for the pathways, including the Stated Policies Scenario, the Announced Pledges Scenario, and the Net Zero Emissions by 2050 Scenario (IEA, 2023e). For instance, the energy outlook 2023 focuses on region-level instead of county level, it is a tool to guide decision-makers regarding which improvement and technology trends are expected, or potential threats in the energy sector, such as increase of geopolitical tensions. For instance, according to the IEA energy outlook, solar energy will grow rapidly in China, the US and Europe, and although Germany is leading the expansion, the European region ranks third in solar capacity annual additions. These scenarios are an important tool that could aid policy makers in developing programs to assess material criticality issues.

The evaluation of the energy scenarios yielded two key takeaways. First, the complexity of the transformation to decarbonize the energy supply necessitates multiple layers of analysis. Consequently, a range of scenarios and energy system models complement each other to tackle many potential issues. While scenarios provide a clear framework for the desired future (e.g., increasing the share of renewables), numerous alternatives exist. The second takeaway pertains to the role of offshore wind as one crucial low-carbon technology. The present thesis focuses on offshore wind because the technology is promising not only for Germany but also for countries that share the North Sea. There is a lack of studies evaluating the performance of offshore wind technology from an economic, technical and environmental perspective and within an energy system model.

2.3 Offshore wind energy within the German power sector

In consideration of the preceding discussion, it is evident that Germany considers offshore wind energy as one key strategy for climate change mitigation. This global trend is reflected in Germany's position as the third-leading nation in installed wind energy capacity (MW), following China and the United Kingdom (see Figure 2.5b) (Benitez et al., 2024). While estimates for offshore wind energy capacity vary by source and are subject to revision as countries update their energy commitments, the International Renewable Energy Agency (IRENA) projects that global wind energy capacity could reach 1,000 GW by 2050 (IRENA, 2019) (see Figure 2.5c). This rapid expansion could lead to cost reductions due to learning effects and economies of scale. Furthermore, the expansion of offshore wind energy is accompanied by technological development in the offshore wind sector, which is reflected in the production of larger components for offshore wind turbines (see Figure 2.5a). For instance, offshore wind turbine nominal capacity has experienced significant growth since their initial deployment , increasing from an average of 5 MW in 2010 to approximately 10 MW in 2024 (Deutsche WindGuard, 2023; Pierrot, 2023).

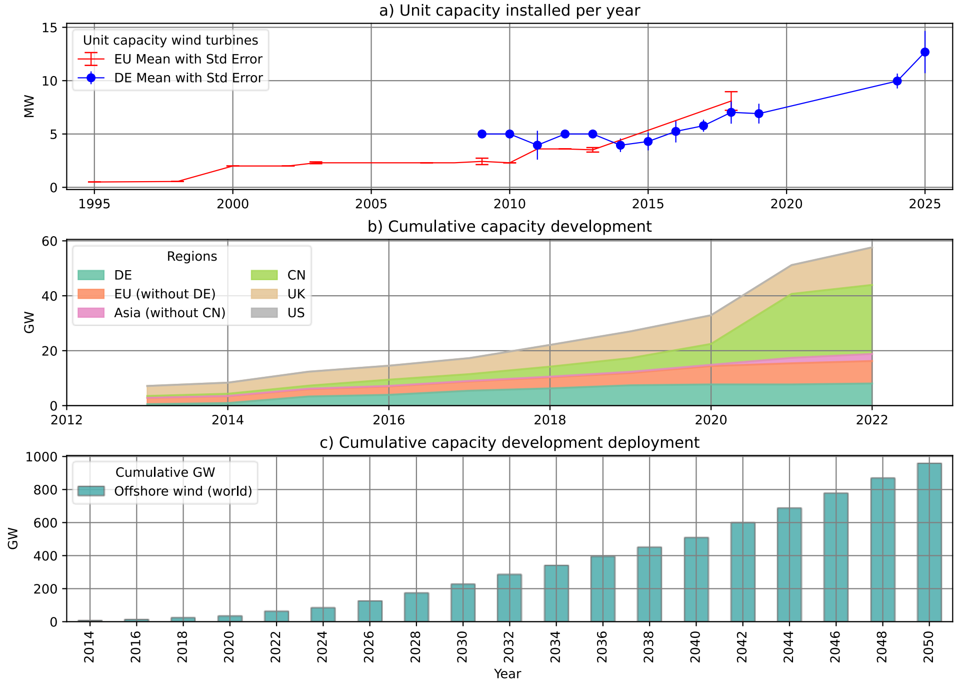


Figure 2.5 Offshore wind in different regions of the world
a) Historical development of offshore wind turbine unit capacity (in MW), red line represents mean values in Europe (without the United Kingdom and Germany), blue line represents average unit nominal capacities (in MW); b) Historical offshore wind cumulative installed capacity in several regions (in GW); c) Expected installed capacity deployment (World)

Source: Based on Benitez et al. (2024), IRENA (2019)

The primary objective of technological development in the field of offshore wind energy is to optimise power output whilst ensuring a more stable and consistent supply. From an economic perspective, the motivation for increasing wind turbine rating and rotor size is to reduce the levelized cost of electricity (LCOE), thereby making offshore wind more cost-competitive (Meißner, 2020). However, as wind turbine sizes grow, the share of infrastructure-related costs within the LCOE also increases, requiring more accurate calculation of costs. Therefore, a comprehensive understanding of the influence of technical advancements on both the cost (e.g., capital and operating expenditure) and environmental impact of wind turbines necessitates a robust grasp of the fundamental principles underlying their operation. These systems are inherently complex, and their design, efficiency, and integration into the energy system are closely tied to engineering innovations that continue to evolve.

The purpose of this section is to briefly recapitulate the fundamentals of wind turbine operation (Section 2.3.1), outline the technological diversity within the offshore wind sector (Section 2.3.2), and discuss the advantages and contributions of offshore wind (Section 2.3.3). A clear understanding of these concepts is essential for the coherent, realistic, and relevant consideration of future developments of offshore wind technologies in the context of integrating LCA into an ESM.

2.3.1 Basic principle offshore wind turbines

Taking advantage of solar and wind energy is crucial to decarbonize the German power sector. Offshore wind energy has the potential to supply annually about 280 TWh of electricity to the German grid (Agora Energiewende et al., 2020). Yet, despite its apparent simplicity, offshore wind technology is complex due to the technical, economic and environmental factors. Depending on the axis of rotation, there are two main types of wind turbines: horizontal axis wind turbine (HAWT) and vertical axis wind turbine (VAWT) (Borg et al., 2012; Letcher, 2023). As HAWTs are the most extensively used, they are the focus of this thesis. The basic principle of wind energy is the conversion of kinetic energy into mechanical energy, which is transformed into electricity (i.e., law of conservation of energy). The energy contained in the wind is captured by rotor blades attached to a hub (see, Equation 2.1). Bernoulli's principle explains the relationship between the pressure and velocity of a moving fluid (see, Equation 2.3); drops in air pressure create a lifting effect (i.e., thrust) when a flow circulates at high speed, causing the blades to rotate. The motion is transmitted to a shaft connected to a generator, which converts the mechanical energy into electricity. However, due to the conservation of mass and energy, there is a maximum amount of available power in the wind that can be extracted by a wind turbine (see, Equation 2.8). Thereby, the equations that governates the basic principle of wind energy can be summarized as follow:

$$E_{kin} = P_{wind} = \frac{1}{2}\dot{m}v^2 \text{ with } \dot{m} = \rho v A \qquad 2.1$$

$$P_{wind} = \frac{1}{2}\rho A v^3 \qquad 2.2$$

The kinetic energy (E_{kin}) contained in the wind (P_{wind}) is expressed in terms of the air mass flow ($\dot{m}$), wind speed (v), and air density (ρ).

$$p_0 + \frac{1}{2}\rho {v_0}^2 = p_1 + \frac{1}{2}\rho {v_0}^2 \qquad 2.3$$

$$\Delta p = p_0 - p_1 = \frac{1}{2}\rho({v_0}^2 - {v_1}^2) = \frac{1}{2}\rho(v_0 + v_1)(v_0 - v_1) \qquad 2.4$$

Bernoulli's principle expressed in terms of pressure drop (Δp), downstream pressure (p_0), upstream pressure (p_1), downstream wind speed (v_0), upstream wind speed (v_1) and air density (ρ).

The Equation 2.5 describes the thrust experienced by the rotor blades. Consequently, the thrust can be expressed in terms of the difference between the downstream and upstream wind speed velocities times the mass flow ($\dot{m}$), or in terms of the pressure drop of the air passing through the area A. The area

A is also called the swept area of the wind turbine, or the area of the circle covered by the radius of the rotor blades (Hyderabad Guruprasad, 2017; Letcher, 2023).

$$T = \dot{m}(v_0 - v_1) = \rho A(v_0 - v_1) = \Delta p A \qquad 2.5$$

The flow velocity at the rotor blades (v) can be expressed in terms of the arithmetic average of the upstream and downstream velocities.

$$v = \frac{1}{2}(v_0 + v_1) \qquad 2.6$$

Then, the power that can be extracted from the wind is equal to the thrust (T) experienced in the rotor blades times the rotor wind speed velocity (v), which can also be expressed in terms of pressure drop (Equation 2.4). Thus, the combination of the Equations 2.4, 2.5 and 2.6 results in Equation 2.7, which expresses the power at the rotor (P_{rotor}).

$$P_{rotor} = Tv = \dot{m}(v_0 - v_1)v = \Delta p A v = \frac{1}{2}\rho({v_0}^2 - {v_1}^2)Av = \frac{1}{4}\rho A({v_0}^2 - {v_1}^2)(v_0 + v_1) \qquad 2.7$$
$$= \frac{1}{4}\rho A(v_0 + v_1)(v_0 - v_1)(v_0 + v_1) = \rho A v^2(v_0 - v_1)$$

The maximum theorical efficiency is defined by the Betz limit, which is maximum when the ratio between upstream (v_1) and downstream (v_0) velocities is 1/3. The Cp factor (i.e., power coefficient or coefficient of performance) is an indicator of how efficiently the wind turbine converts kinetic energy into mechanical energy and cannot exceed 59.2% (Equation 2.8)

$$C_p = \frac{P_{rotor}}{P_{wind}} = \frac{\frac{1}{4}\rho A({v_0}^2 - {v_1}^2)(v_0 + v_1)}{\frac{1}{2}\rho A v_0^3} = \frac{\rho A v^2(v_0 - v_1)}{\frac{1}{2}\rho A v_0^3} = \qquad 2.8$$

$$for \frac{v_1}{v_0} = \frac{1}{3} \rightarrow Cp\ is\ maximum = \frac{1}{2}(v_0 + v_1) = \frac{2}{3}v_0$$

$$C_p = \frac{P_{rotor}}{P_{wind}} = \frac{\rho A v^2(v_0 - v_1)}{\frac{1}{2}\rho A v_0^3} = 2\frac{\frac{4}{9}v_0^2\left(\frac{2}{3}v_0\right)}{v_0^3} = \frac{16}{27} \approx 0.592$$

Thus, the power coefficient could be interpreted as the combination of the different efficiencies. For instance, the aerodynamic efficiency (η_T) describes the losses in the rotor blades when converting kinetic energy into rotating mechanical energy; the mechanical efficiency (η_m) representing the losses along the shaft; and the electrical efficiency (η_e) which represents the losses during the generation of electricity. Despite electrical and mechanical efficiencies exceeding 90 %, the largest loss occurs in the blades during the conversion of kinetic to mechanical energy. Consequently, the aerodynamic efficiency may vary between 20 % and 40 %. And overall, Cp values around 0.32 can be expected.

$$Cp = \frac{P_{out}}{P_{wind}} \approx \eta_T \eta_m \eta_e \leq 0.592 \qquad 2.9$$

Finally, the power output of a wind turbine is described by the equation below.

$$P_{out\ put\ wind\ turine} = \frac{1}{2}\rho A v_0^3 Cp = \frac{1}{2}\rho A v_0^3 \eta_T \eta_m \eta_e \qquad 2.10$$

The power output of a wind turbine is difficult to predict as wind speed depends on the hub height (i.e., the distance from the water surface to the centre of the rotor), and weather conditions. Therefore, power curves are used to express the relationship between wind speed and altitude. Power curves are an intrinsic characteristic of the wind turbine and help to maximise its power output. Additionally, power curves play a fundamental role in forecasting electricity generation, estimating capacity factors, and selection of the proper wind turbine for a specific site (Sohoni et al., 2016). A typical power curve is divided into four regions, which are delimited by wind speeds (see Figure 2.6). Region 1 defines the area below the minimum threshold (cut in) where the power out is zero. Low wind speeds have a direct impact on the mechanical performance, which can lead to component failure. The cut in wind speed depends on the wind turbine design and can vary between 3 and 4 m/s. In Region 2, between the cut-in and rated wind speed, the power output depends on the cube of the wind speed; the rated wind speed (i.e., between 10 and 13 m/s) is close to the average wind speed of the installation site. In the Region 3, between the rated wind speed and cut-off wind speed, the power output is constant and corresponds to the rated capacity of the wind turbine. Above the cut-off wind speed, which ranges between 25 to 30 m/s, the wind turbine is switched off for security reasons. The cut-off wind speed varies between 20 and 25 m/s.

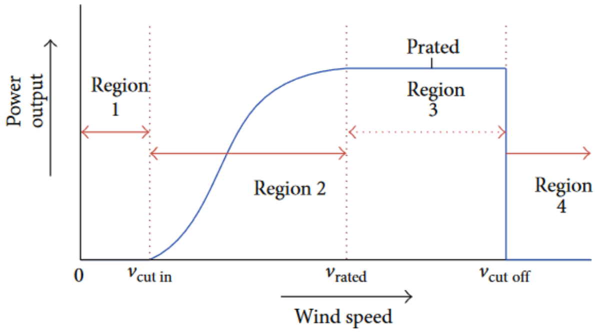


Figure 2.6 Generic power curve of a wind turbine
Prated stands for rated power output

Source: Based on Sohoni et al. (2016)

The swept area, which is determined by the diameter of rotor blades, is another factor that contributes to maximising the power output of a wind turbine. This explains the interest in increasing the size of wind turbines, as this has direct implication for their profitability. Offshore wind energy benefits from the open space, thereby facilitating the transport and installation of larger wind turbine components. Over the past decade, the development of offshore wind turbines has been significant, not only in size but also in technology. This is reflected in an improvement in capacity factor from 30 % to 45 % (Wiser et al., 2021). The capacity factor, which measures how efficiently a wind turbine operates over a period of time, is the ratio of the actual power output to the maximum possible power output over the same period of time (EIA, 2024).

2.3.2 Offshore wind technology diversity

Offshore wind involves the interaction of several components out of which five parts can be highlighted: foundation, tower, nacelle, rotors and hub. Foundations for offshore wind already achieved a mature state, however improvement in design and operation process could allow even larger monopile foundation. Major developments are expected in floating foundation, which find application for water depth beyond 50 m (Edwards et al., 2023).

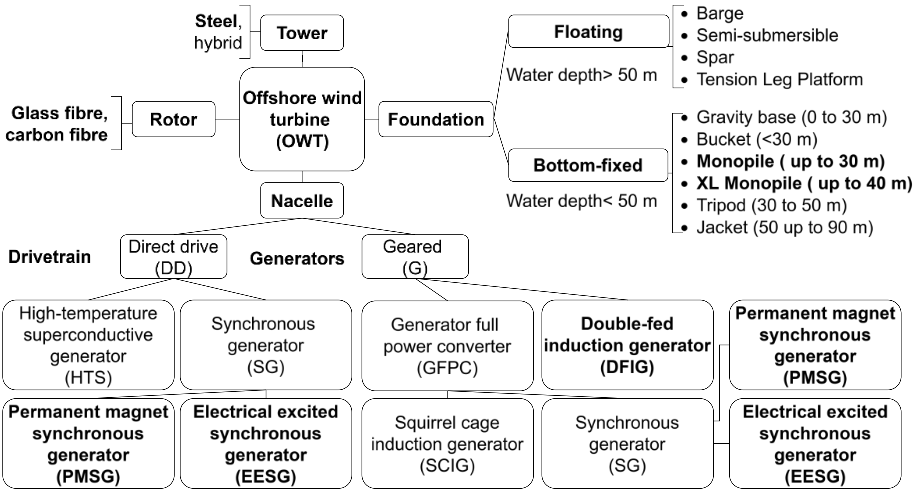


Figure 2.7 Offshore wind technologies

Source: Based on Benitez et al. (2024)

The selection of foundation type is determined by geographical factors. Foundations' cost and environmental impacts could change dramatically based on water depth (Vieira et al., 2019). For Germany and other countries with wind farms located in the southern North Sea, monopile foundations are expected to remain relevant, as water depths range between 15 to 30 m. In contrast, floating foundations are more suitable for the northern part, where the average water depth can reach up to 90 m (BSH, 2024; Maerz et al., 2016). Tubular steel towers are the most widely used structures for offshore wind applications (Damiani, 2016). Regarding the nacelle, depending on the drivetrain system (e.g., direct drive and geared), several generator types are possible. For offshore wind application, a combination of double-fed induction generators and synchronous generators is commonly used, with some synchronous generator requiring permanent magnets (Nejad et al., 2022). While permanent magnets could improve efficiency, the scarcity of rare earths, their cost, and geopolitical aspects impose problems. The selection of the drivetrain conditions the lifetime of the wind turbine, as geared wind turbines are more susceptible to failures. The lifetime of an offshore wind turbine is estimated 20 years (Benitez et al., 2024). The trend in the offshore wind sector is a significant increase in rotor diameters, reaching 200 m. This requires the use of reinforced materials, such as carbon fibre, to ensure strength without compromising weight (Ennis et al., 2019). The technological diversity of offshore wind turbines extends beyond their components design to other critical aspects such as assembly, installation, operation and end of life. Assembly and installation processes often demand increasingly complex procedures, particularly as turbine components continue to grow (Thomsen, 2014). In terms of operation, scheduled maintenance typically requires two to four interventions per year (Garcia-Teruel et al., 2022). However, unexpected failures may necessitate additional interventions that, depending on their severity, can be time-consuming and require the use of heavy machinery (Garcia-Teruel et al., 2022). Regarding the end of life, the deployment of offshore wind turbines has raised concerns about plastic waste, particularly coming from rotor blades (Sommer et al., 2020). These blades are large, voluminous structures composed of resin and fibres, making their disposal challenging. Exploring potential applications for these materials after their lifecycle could offer not only cost benefits but also significant environmental advantages (Beauson et al., 2022). Additionally, retiring turbine components at the end of their life requires the use of heavy machinery, which can contribute to environmental impacts.

In the context of combining LCA into an ESM, assessing the long-term environmental impacts of offshore wind turbines requires accounting for potential technological developments, including new foundation types, larger components (technological diversity), and improved performance. Performance depends not only on wind speed distribution but also on design parameters such as rotor diameter, hub height, and operational speed. These nuances are absent from current commercial LCA databases. In order to address this gap, and as a direct outcome of this thesis, a peer-reviewed publication has been produced (Benitez et al., 2024) that investigates the future environmental impacts of offshore wind technologies.

2.3.3 Offshore wind energy’s contribution to decarbonising the power sector

The installation of 1 GW of offshore wind capacity could displace approximately 3.5 million t of direct CO_2 emissions from fossil fuel power plants (IEA, 2020b). While nuclear and hydropower displace more direct CO_2 emissions (see, Figure 2.8), these technologies are water intensive. Therefore, offshore wind energy is a good solution for countries with coastal areas, where nuclear energy has low political acceptance and problems with water scarcity (Esteban et al., 2011; IEA, 2020b; Junginger et al., 2020).

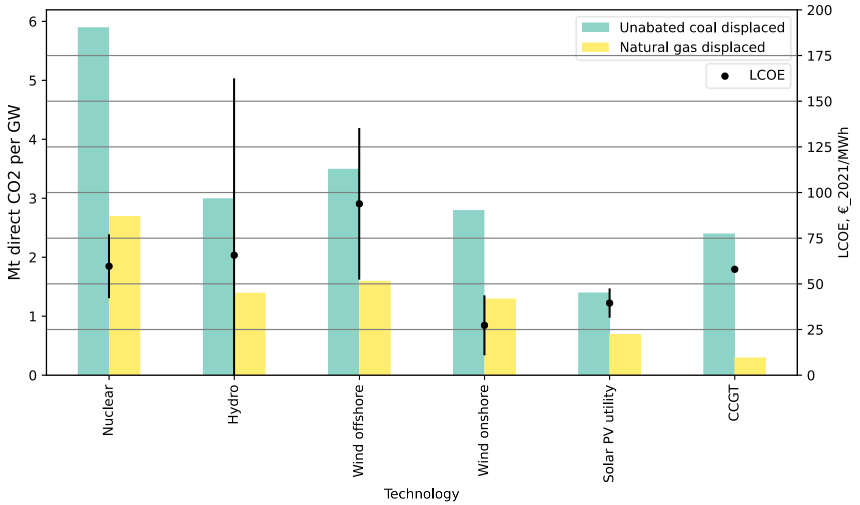


Figure 2.8 Direct emissions displaced by low-carbon technologies versus levelized cost of electricity (LCOE)

Source: Based on IEA (2020b)

In addition to CO_2 reduction, offshore wind contributes to energy independence, and the economy. By reducing a country's dependence on imported fossil fuels, offshore wind makes countries less vulnerable to geopolitical risks and minimises the impact of supply disruptions. Despite fierce competition from Asian companies, European industry is experienced in offshore technology. According to the IEA (2023d), the global demand for offshore wind could reach 180 GW by 2028 (IEA, 2023d), and potentially reaching 560 GW by 2040 (Li et al., 2022b). China, the United Kingdom, and Germany lead offshore wind installed capacity expansion, each with 2030 targets of 66 GW, 50 GW, and 30 GW, respectively (Bilgili & Alphan, 2022; BMWi, 2021; Deng et al., 2022; HM Goverment, 2023; IEA, 2019).

From an economic perspective, over the years offshore wind became more competitive (Meißner, 2020). The LCOE evaluates and compares the cost of electricity production across different technologies (Fraunhofer, 2021). Equation 2.11 illustrates the LCOE in terms of investment expenditure (I_o , in €), annual total cost (A_t, in € per year), produced amount of electricity ($M_{t,el}$ in kWh/year), real interest rate (i), economic lifetime (n, in years) and year of lifetime (t). Figure 2.8 shows LCOE between 50 and 130 Euros per MWh in 2021 (European Commision, 2020; IEA, 2020b). However, assessing offshore wind competitiveness through the LCOE remains complex due to their dependence on weather conditions and site-specific characteristics (Meißner, 2020). While increasing the nominal capacity and rotor size generally reduces the LCOE, it also increases the share of capital expenditure (CAPEX) or investment expenditure (I_o) in the overall cost structure (see, Equation 2.11). For example, key components such as the nacelle, rotor, foundation and blades already account for around 30 % of total CAPEX (CATAPULT, 2019). As these components grow in size, so does the need for additional materials and more complex logistics, such as transportation and installation (Fingersh et al., 2006).

$$LCOE = \frac{I_o + \sum_{t=1}^{n} \frac{A_t}{(1+i)^t}}{\sum_{t=1}^{n} \frac{M_{t,el}}{(1+i)^t}} \tag{2.11}$$

In this context, Shields et al. (2022) highlight variables that have a significant impact on CAPEX. These include global installed capacity, which relates to industry experience and learning effects that help drive down costs; project capacity, as larger projects tend to benefit from economies of scale; water depth, as deeper installations require more robust and expensive foundations; and distance from shore, which influences installation complexity and grid connection costs. In addition, the country in which the project is installed plays a role, as different regulatory frameworks, support schemes and cost structures can have a significant impact on the total investment required.

Understanding these factors is essential for evaluating the economic viability and competitiveness of offshore wind relative to other generation technologies, as the offshore wind expansion entails the installation of wind farms at longest shore distances, and deeper water depths, which in turn requires the development of foundation technologies such as floating foundations. In particular, in those projects located at water depths greater than 50 m (Musial et al., 2022). Other advances imply improvement in the turbine design and size, in turn long-lasting drive-train systems, generators and rotor blades (Goyal, 2024). Overall, at global level installing cost of offshore wind is expected to decrease with values between 3,200 and 1,700 USD/kW in 2,030 to 2,800 and 1,400 USD/kW in 2050, meaning more competitive prices for offshore wind electricity generation.

From the environmental perspective, there are important challenges to overcome regarding offshore wind development. For instance, although during operation offshore wind turbines emit near zero greenhouse gas emissions, impacts during the installation, and maintenance are not well described. Additionally, other impacts related to effects on marine life and ecosystems require better understanding. Therefore, the evaluation of offshore wind from a life cycle perspective is relevant.

Beside challenges related to regulatory frameworks and grid interconnection (Goyal, 2024), social challenges might require better consideration (Skjølsvold et al., 2024).

2.4 Modelling methods for climate mitigation

Climate mitigation refers to the collection of actions oriented toward reducing greenhouse emissions and tackling the consequences of climate change (UNFCCC, 2024), where the transition to low-carbon technologies is one strategy. In Section 2.2, the value of scenarios as tools for assessing global climate change have been discussed. These scenarios emphasize renewable energy sources, such as offshore wind, as part of the climate mitigation strategy. This section focuses on the models that generate these scenarios (e.g., explorative, normative, predictive). Given the broad scope of models for climate mitigation, this section highlights those designed to account for greenhouse gas emissions across economic sectors, in particular, models that evaluate the impact of low-carbon technologies within the energy sector. Understanding the key features of modelling frameworks is essential to this thesis, as it enables the informed selection of the most appropriate model for integrating life cycle assessment.

A fundamental step toward climate mitigation strategies is quantifying emissions from human activities and projecting their future trends. In this regard, scenarios provide narratives or storylines that describe key driving forces (e.g., technological change (Viebahn et al., 2018), demographics, socioeconomic development), and their evolution (IPCC, 2012, 2022b). Yet, quantifying scenarios requires multiple models that consider socio-technical and economic aspects of human activities at several levels of detail and aggregation. Human activities are represented within macro-economic sectors such as energy, building, transport, industry, etc. Overall, models are a representation of these sectors (or real-world systems) through mathematical equations. For instance, energy system models (ESMs) are sets of mathematical equations that represent in a simplified form real-world relationships of components related to the production, conversion, delivery, and use of energy (Verbruggen et al., 2011). Accordingly economic models are mathematical representation of economic processes. Given the complexity of monitoring and measuring climate change, a wide variety of models are needed. In this thesis, these models are categorized based on common traits such as level of detail, mathematical formulation and system boundaries based on (IPCC, 2022b; Nikas et al., 2019; Prina et al., 2020) (see Figure 2.9). A first distinction lies between top-down and bottom-up models, which describes how economic sectors are represented, Prina et al. (2020). Top-down models avoid extensive technological representation. As highly aggregated models, their main goal is to study interactions within the entire global economy. For this reason, top-down models are well-suited for evaluating the impacts of energy policies on socio-economic sectors (e.g., public welfare, employment) and understanding structural changes (IPCC, 2022b). On the other hand, bottom-up models focus on detailed technological analysis within a specific sector, isolating it from other macroeconomic sectors. Bottom-up models provide a comprehensive view of individual technologies and mitigation strategies but omit interactions between macroeconomic sectors (Prina et al., 2020). They offer detailed, sector-specific insights and vary in time frame, solution method, scope, resolution, and mathematical formulation (IPCC, 2022b). Furthermore, models can be classified in partial and general equilibrium models based on the representation of economic agents. In partial equilibrium models, clearing of prices are determined by supply and demand of one market or agent, omitting the interaction of that market with others. General equilibrium models include all economic agents and sectors and study their interaction. The taxonomy of bottom-up models also depends on the purpose, solution method, scope, resolution, or mathematical formulation. The purpose refers to the research question being addressed. In the context of energy system models these question could address aspects such as resource availability, transmission grid design, system operation and dispatch, and energy system planning (Boyd, 2016b).

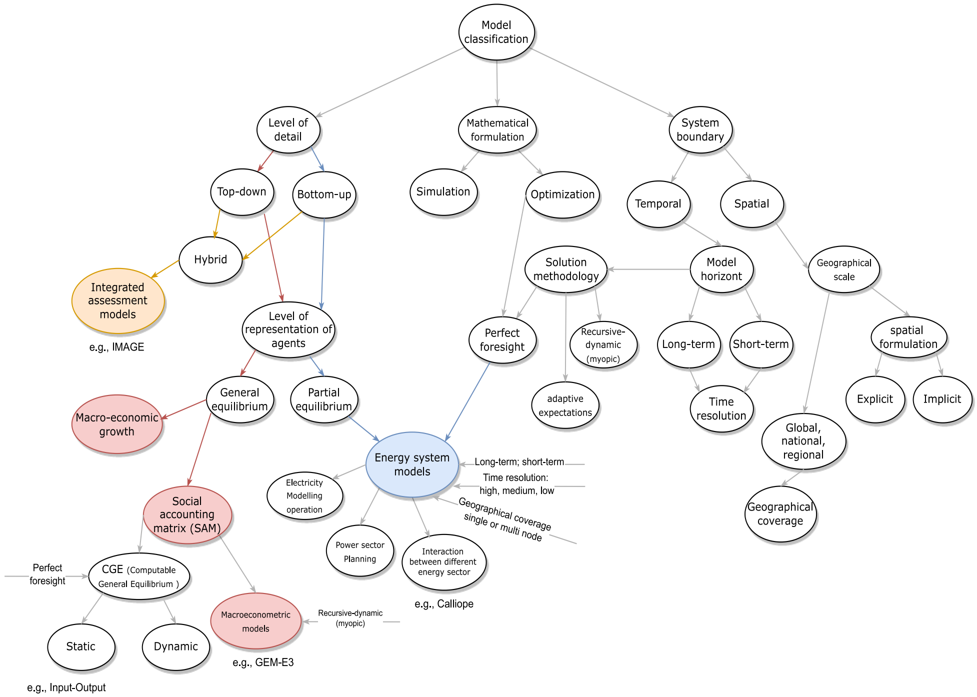


Figure 2.9 Classification climate mitigation modelling methods

Source: Based on IPCC (2022b); Nikas et al. (2019); Prina et al. (2020)

The mathematical formulation (programming technique or mathematical approach) indicates how variables (e.g., input data) are defined and relates with the solution mechanism adopted by the model. A first distinction is between simulation models and optimization models (IPCC, 2022b). The former focuses on the dynamic behaviour of the system. Optimization models define an objective function that can be either maximized or minimized based on a set of constraints, with the objective typically being total cost or revenue (Sayyaadi, 2021b). In optimization approaches, models may assume perfect foresight, meaning that the optimal solution is estimated over a given time horizon. However, perfect foresight requires specifying future parameters in advance, such as demand and available technologies, allowing the model to choose the optimal option based on these predefined input parameters for a single optimization problem. On the other hand, recursive-dynamic models (myopic) make decisions incrementally, meaning the solution disregards information about future conditions. Myopic approaches perform a series of optimizations year by year, making the process dynamic. This methodology avoids the need for complete knowledge of the entire transition pathway or the future state of technologies. Instead, decisions are based on the information available at each step, providing a more realistic reflection of how decisions are made in practice (Prina et al., 2020). As part of the mathematical formulation, the most adopted approaches are linear programming (LP), mixed integer linear programming (MILP), dynamic programming and heuristic technique (IPCC, 2022b; Prina et al., 2020). System boundaries describe aspects such as spatial and temporal resolution. Regarding the level of details, hybrid models combine features of both top-down and bottom-up approaches, with integrated assessment models (IAMs) falling within this category (see Figure 2.9). From the perspective of ESM/IAMs, the geographical coverage refers to the number of locations, regions or countries considered in the model, whereas geographical resolution or spatial resolution refers to the level of detail in which a location is depicted (Esri, 2022).

2.4.1 Integrated assessment models

As outlined in Section 2.2.1, Integrated Assessment Models (IAMs) are utilised for the generation and quantification of climate change scenarios. A discussion of these models, extending beyond the scenarios they produce, is imperative, as the type of IAM influences the outcomes of the scenarios. These aspects are crucial when estimating environmental impacts through Life Cycle Assessment, since the results of climate change scenarios are used to contextualise inventory data. These aspects will be further examined in Chapter 3. However, it is first necessary to acknowledge the similarities and differences among existing IAMs and how these can affect scenario outcomes. For this reason, the present section offers a concise synopsis of the primary characteristics of IAMs.

IAMs are "simplified representations of complex physical and social systems, focusing on the interaction between economy, society and the environment" (IAMC, 2024). Thanks to the increase in computation capacity, IAMs have become capable of performing sophisticated analyses, particularly for studying global challenges such as climate change. IAMs combine knowledge of several domains into a single framework (IPCC, 2022b). For example, they combine general equilibrium models with at least one bottom-up model, coupling energy, land, economy and climate. This integration makes IAMs especially effective for examining interactions between human activities, earth systems, climate and policy, as the model benefits from information coming from many scientific disciplines.

IAMs are comprised of different modules, which can be either soft linked or hard linked. In both cases, the output of one module serves as the input for another. However, in the soft linked approach, the transfer of data and parameters is done manually, whereas in the hard linked approach, the transfer is automated (Prina et al., 2020). A first module contains an energy-economy component, which focuses on energy flows, emissions and costs. The energy-economy component includes energy system models that account for the emissions coming from the energy sector, which includes the electricity, heat, transport, industry sectors. These energy models could operate either as partial equilibrium or general equilibrium models. The partial equilibrium models link the interaction between sectors using external demand drivers (e.g., population growth, technology development, lifestyle, etc.) to account for final energy demand. In contrast, the general equilibrium models determine the final energy demand endogenously, based on the adopted economic growth model. A second module focuses on the land system component, which integrates sectors related to land use, such as agricultural and forestry sectors, along with their associated emissions. This component is increasingly important as it incorporates the effect of carbon sinks, and examines the role of bioenergy, afforestation, and other land-based mitigation efforts. The third module includes the climate system component, which is essentially a simplified version of a climate model, also known as an emulator. The purpose of this module component is to model climate trajectories due to several emissions (IPCC, 2022b).

Examples of relevant IAMS include IMAGE, REMIND and the IIASA IAM framework (also known as MESSAGE*ix*-GLOBIOM). IMAGE (Stehfest et al., 2014) simulates the environmental consequences of human activities on global scale, and consists of two interlinked systems: the socio-economic systems, which simulates long-term developments, and the Earth Systems, which describes environmental changes. The Regional Model of Investments and Development (REMIND) integrates the economy, climate system and energy sector in a multi-regional model (Luderer G, 2020). The IIASA IAM framework provides a comprehensive assessment of energy and environmental policies and combines five models including Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE), with aggregated macroeconomic, air pollution, land-use models and a climate emulator (Krey et al., 2020).

IAMs are classified into two main types. The first type is cost-benefit IAMs, which combine socio-economic models with a simplified climate modules or emulators. These models are designed to account for mitigation costs and damages caused by climate change and are used for assessing the social cost of carbon. The second type is process-based IAMs, which focus on analysing transformation processes. Process-based IAMs describe the interconnections between activities driven by socioeconomic developments, land use and pollution (IAMC, 2024). These models are particularly effective for generating emissions scenarios that create climate projections. Their process-based nature allows for a fair representation of emission sources, making them valuable tools for investigating the effects of policies, synergies and trade-offs of climate mitigation strategies (IAMC, 2024; IPCC, 2022b). For instance, the IMAGE model (Stehfest et al., 2014) falls into the process-based IAMs category, whereas the REMIND (Luderer G, 2020) model is a general equilibrium growth IAM, placing it in the cost-benefit IAMs category (Dekker et al., 2023). IAMs are suited to different applications depending on their type, yet both are extensively used for assessing global climate change. When the goal is to measure trade-offs and evaluate the cost-benefit implications of policies, cost-benefit IAMs are the preferred choice. On the other hand, process-based IAMs are more effective when the focus is on achieving fair accounting of emissions to develop future climate projections. As a result, significant differences in outcomes can arise when quantifying the same scenario. These differences stem from variations in model structure, mathematical formulation, solution approach, geographical representation, and other factors (Henke et al., 2023). For this reason, it is essential to broaden the scope of results and incorporate as many perspectives as possible. This approach explains why more than 30 IAMs[4] participated in the evaluation for the IPCC's Sixth Assessment Report (IPCC, 2022b).

Despite the strengths of IAMs, Guivarch et al. (2022) identify four main limitations. First, IAMs often struggle to capture the dynamics between economic benefits, technology development, and climate mitigation. For instance, as most IAMs rely on cost-optimization approaches, their solutions may fail to reflect what is practically achievable due to technological, social, or political constraints. This is particularly evident when evaluating net-zero technologies or demand-side strategies, where models assume that end-users will adopt more efficient devices or adjust their energy consumption to align with system optimization. Such assumptions often fail to reflect real-world behaviour or feasibility. Second, transparency is often a concern because of the complexity of these models and the extended timeframes they address. Uncertainty is another significant issue. While IAMs are designed to analyse interactions between energy systems, land use, and climate, they often inadequately incorporate social factors, such as disruptive events. Lastly, the limited range of future scenarios considered by IAMs may

[4] https://www.iamcdocumentation.eu/IAMC_wiki

lead to conclusions that steer society toward specific pathways without adequate scrutiny or exploration of alternatives.

Understanding these limitations is instrumental in identifying areas for improvement in the use of IAMs. For example, efforts have been directed toward enhancing documentation and promoting the use of open-source models. These steps improve transparency and accessibility, allowing for broader scrutiny and collaboration. Additionally, refining the design of scenarios has emerged as a key focus. Well-constructed scenarios are essential for effectively communicating model outcomes and providing clarity about the assumptions and expectations underlying the results. Furthermore, advancements in model development have aimed to address these limitations, ensuring IAMs better capture the complexities of real-world systems and provide more robust and actionable insights for policymakers.

This thesis acknowledges the importance of understanding the differences between IAMs, since the results for the same scenario can vary depending on the model used, and IAM outputs are often used to contextualise prospective life cycle inventory data.

2.4.2 Energy system models

In contrast to IAMs, energy systems models (ESMs) focus on the energy sector or sub-sectors of it, investigating technology deployment options, investment cycles, and detailed system operation of individual countries or sub-national regions (Pfenninger et al., 2018). ESMs address various aspects of the energy sectors (i.e., electricity, transport, heat, industry, building, etc.), including resource availability, planning, operation, and network reliability (Boyd, 2016a). This section examines bottom-up models, as the focus of this thesis is on how to assess the environmental aspects of technologies (e.g., offshore wind) within the electricity sector. Bottom-up models are extensively used to address topics related to electricity system operation and planning, particularly in the context of large-scale renewable energy penetration. These models are characterized by their highly detailed representation of the system components. This means bottom-up models assess the evolution of technologies and the impact of different technological choices. As bottom-up ESMs focus on specific isolated sectors, they are called partial equilibrium models. However, they might be able to assess interactions between different energy vectors or commodities such as electricity, heat, hydrogen, fuel, etc, which is relevant for evaluation sector-coupling. In general, models are classified as shown in Figure 2.9. This classification also applies to bottom-up ESMs and can be extended to energy sectors covered.

A key distinction among bottom-up ESMs is their time horizon or the study’s time frame, which can be categorized into short-term (static or snapshot) and long-term approaches (Prina et al., 2020; Thimet & Mavromatidis, 2022). Short-term models focus on potential alternatives or configurations of the energy system for a specific target year (e.g., 2030 or 2050). In this case, input parameters like electricity demand are assumed to already reflect the target year's conditions, and aspects as the end of life or decommissioning might be modelled externally. In contrast, long-term models examine the development of the energy system over time (e.g., 2020 to 2050), considering the life cycle of technologies, residual capacity, and decommissioning.[5] For instance, frameworks built upon Calliope are examples of ESMs with short term horizon (Díaz Redondo & van Vliet, 2015; Jesse et al., 2020; Tröndle et al., 2020; Verrascina, 2022). Calliope is a Python-based framework that provides the building

[5] These types of bottom-up models are also known as capacity expansion models.

blocks for constructing bottom-up energy system models from scratch (Calliope contributors, 2020). It is specifically designed to support ESMs with a high share of renewables, as it enables time-series analysis. Despite its focus is a single sector, it enables the analysis systems with different commodities such electricity and heat, or natural gas. Calliope can perform planning and operational analysis, and its short horizon allows the definition of technical, economic and environmental parameters aligned to the target year. Its objective function is predefined and follows a single-objective approach, targeting total cost minimisation. Additionally, the model allows environmental indicators to be defined as costs, enabling system optimization based on either monetary values or emission levels. Moreover, because Calliope is open source, it facilitates documentation and data exchange, offers flexibility in handling high temporal and geographical resolution, and provides optimal solutions based on cost or emissions for annual dispatch and investment.

In long-term models, the horizon is divided into periods (e.g., five, ten years) because the simulation is performed for those periods, rather than each year, to reduce computational effort. In short-term models, the simulation year coincides with the time horizon. The simulation year is then divided in time-steps, which defines the resolution of the model. A common practice in long-term models is to divide the simulation year into time steps, specifically into time-slices, which are a stylized representation of these time steps used to model the simulation year (Prina et al., 2020). For example, in models that implement 12 or 16 time-slices, the simulation year is divided into four seasons, each with either three or four representative days. These representative days include typical demand patterns for the morning, night, and peak periods. Long-term horizon models are suitable for assessing energy transition pathways and are widely used. Bartholdsen et al. (2019) explore low-carbon energy transformation in Germany using the linear, cost-optimizing Global energy system model (GENeSYS-MOD) (TU Berlin, 2021). Reinert et al. (2022) develop the long-term, cost optimization model SecMoD, based on the General Algebraic Modelling System (GAMS) (GAMS Development Corporation, 2021), to assess multi-sector energy systems at national level. Rafaj et al. (2005) assess carbon mitigation policies with the Global Multi-regional MARKAL (GMM) (Turton et al., 2013). As such, MARKAL (IEA-ETSAP, 2022) is a generic model (model generator) that adjusts input data to represent the evolution of a specific energy system over long periods, at national, regional, state, provincial, or community levels and is used to build several models (Krzemień, 2013; McDowall et al., 2018; Rafaj & Kypreos, 2007).

Despite low time-slides working well for systems with constant electricity production like nuclear and fossil-fired power plants, systems with a high share of variable technologies like solar and wind, which are highly time- and weather-dependent, require more flexibility in time resolution. This becomes even more crucial when storage technologies and demand-side management are introduced. However, higher time resolution means higher computational cost. Therefore, short-term models focused on a target year can handle more flexible time resolution without significantly compromising accuracy. Regarding geographical coverage, bottom-up ESMs use single or multiple nodes to represent regions. In the case of single nodes, transmission constraints are neglected, while in multiple nodes regions are connected by transmission grid and the model can consider transmission constraints (Prina et al., 2020). As for the solution methodology, simulation models aim to test the operation of future energy systems and can incorporate environmental aspects. Simulation models are particularly relevant due to the unpredictability of weather and demand behaviour. Yet, dispatch and investment optimization models are most used, as they allow for detailed analysis of short-term operational decisions and long-term capacity planning. According to Thimet and Mavromatidis (2022), only 20 % of 171 scenarios were generated with simulation-based models. For instance, Hansen et al. (2019) evaluate the impact of transitioning to a 100 % renewable energy system using the short-term horizon model EnergyPLAN (Aalborg University, 2024), which simulates the operation of the German energy system in 2050. Classifying ESMs has become increasingly challenging in recent years due to advancements in computational capacity, allowing ESMs to combine and expand their approaches, sometimes overlapping in functionality (see Table 2.5). Therefore, understanding the differences among available options can help modelers make well-informed decisions about which ESMs are best suited to address their research questions.

Table 2.5 Examples of energy systems models

Scenario type	**Explorative-strategic**		**Explorative-strategic**	**Normative**
Scenario name	European Island [a]	Green Democracy [b]	100% RE & Elec. Transp. [c]	Variant E [d]
Demand projection	endogenous		endogenous	exogenous
Level of detail	Top-down		Hybrid	Bottom-up
System coverage	electricity, heat, and transport		electricity, heat, transport, industry	electricity
Energy vectors	electricity, heat, fuels		electricity, heat	electricity
Mathematical formulation	Optimization		Simulation	Optimization
Objective function	Total cost minimisation		-	Total cost minimisation
Geographical coverage	Multi-node, Germany divided in 16 nodes connected to neighbouring countries		Germany	Switzerland
Temporal coverage	2030, 2050		1 year	2030, 2050
Horizon	long-term (evolution)		short-term (snapshot)	short-term (snapshot)
Time resolution	5 years - 16 time-slices		hourly	hourly
ESM	GENeSYS-MOD (TU Berlin, 2021)		EnergyPLAN (Aalborg University, 2024)	Calliope (Pfenninger & Pickering, 2018)
Application in	(Bartholdsen et al., 2019)		(Hansen et al., 2019)	(Díaz Redondo & van Vliet, 2015)

Narratives: a) What can happen if carbon taxes increase from 5 € in 2015 to 35 € in 2030 and lignite power plants are phase-out in 2035? b) What can happen if carbon taxes increase from 5 € in 2015 to 35 € in 2030 and lignite power plants are phase-out in 2025? c) What can happen if 100 % of renewable potential is used and 80 % of cars are electrical, 20 % rest covered with hydrogen? d) How can the domestic electricity demand in Switzerland be covered if imports increased by 13 % in 2050?

Source: withdrawn from Thimet and Mavromatidis (2022)

2.4.3 Projection of future demand

Depending on the modelling framework, the future demand of various sectors can be calculated based on the external drivers such as population and gross domestic product (endogenously) or user-defined and treated as input (exogenously). IAMs such as IMAGE and REMIND, as well as ESMs like GENeSYS-MOD and MARKAL, determine the demand endogenously. In contrast, ESMs such as MESSAGE, EnergyPLAN, and Calliope rely on exogenous demand projection (e.g., electricity). In this thesis, electricity demand (kW) refers to the maximum power consumption at a given moment, and load represents the hourly average power absorbed by all installations connected to the transmission network, including network losses but excluding pumped storage and generating auxiliaries (ENTSO-E, 2015).

The nature of the electricity requires that at any given instant supply must equal demand (Almeshaiei & Soltan, 2011). Thus, with models becoming more complex due to the penetration of fluctuating renewable energy sources, and the increasing electrification of sectors, load forecasting and projection of future electricity demand constitute an important part in the planning and operation of ESMs (Khuntia et al., 2016; Zhou et al., 2023). Load forecasting refers to short to medium term prediction of electricity demand, while projection of electricity demand focus on the long-term estimation of electricity consumption. Load forecasting (LF) involves the analysis of the historical behaviour, trends and factors associated with the load and the prediction of future load demand (Azeem et al., 2021). Depending on the duration of the planning horizon (e.g., short, medium and long term), different approaches exist (Figure 2.10). For example, very short and short term correspond to the period of up to one hour up to one week and are relevant for operational planning (e.g., scheduling of generation and transmission of electricity); medium term implies planning one year ahead, which is relevant for scheduling of maintenance or purchase of fuel; long term is more than one year planning period, which is relevant for financial and expansion planning (Almeshaiei & Soltan, 2011; Khuntia et al., 2016; Tsivras, 2019). However, the definition of long term might vary. Steinborn (2022) considers long term forecasting for time frame above three years.

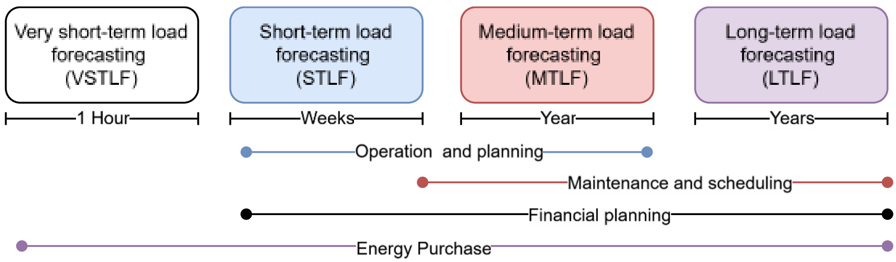


Figure 2.10 Types of load forecasting based on different planning horizon

Source: Based on Azeem et al. (2021)

The integration of a high share of renewable energy within ESMs poses a significant challenge to load forecasting. This complexity is due to non-linear and non-stationary load behaviour, rapid changes of consumption patterns, and a strong dependence on meteorological variables (e.g., irradiance, rain, temperature, humidity, wind speed) (Azeem et al., 2021). Furthermore, user behaviour and environmental factors are hard to predictable and highly random. Improving the accuracy of load prediction is crucial for both economic and technical reasons. Accordingly, even a 1 % error could result in millions of dollars in losses (Azeem et al., 2021). Enhancing load prediction techniques could assist in maintaining a stable supply, thereby reducing the need for frequent grid interventions, as they can stress the grid and lead to black out, jeopardising the security of the power supply (Saha et al., 2023; Steinborn, 2022). However, there are no universal forecasting techniques, they vary depending on the application and planning horizon (Nti et al., 2020). Classical approaches include regression methods and data-driven methods such as artificial intelligence. Short-term load forecasting relies on artificial intelligent models such as artificial neural networks (ANN), support vector machines (SVM, particle swarm optimization (PSO) and fuzzy logics (Nti et al., 2020). For instance, ANN combines historical weather data as input parameters, and mean absolute error or root-mean-square error as performance metrics and focusses on the prediction of energy consumption in the range of minutes up to one day (Nti et al., 2020). In contrast, long-term forecasting techniques rely on regression models, which are used to find relationship of load and weather conditions, day types, customer classes. (Singh et al., 2013). Long-term forecasting also employs the autoregressive integrated moving average (ARIMA), which uses past values to predict future ones and captures seasonality (Nti et al., 2020). For instance, Gotzens et al. (2021) use ARIMA to predict hourly load adjusted to future temperature values. Other classifications divide forecasting techniques into three main groups: correlation, extrapolation, and a combination of both (Singh et al., 2013). For instance, extrapolation techniques (trend analysis) identify a trend-fit function using historical data of electricity demand and forecast future values using the estimated trend curve function. Correlation involves using economic models and incorporating economic and demographic factors, such as population, employment, building permits, heating, and weather data.

For this thesis, it is crucial to acknowledge how modelling frameworks address electricity demand. In user-defined demand models, electricity demand is treated as an external input parameter, requiring careful consideration of its underlying assumptions for a consistent integration. Moreover, modelling frameworks suitable for high-renewable systems are typically flexible in handling time resolutions, which could influence the selection of demand projection methods.

2.5 Life Cycle Assessment

The previous section presents modelling frameworks used in climate mitigation, such as IAMs and ESMs (IPCC, 2022b). However, these models require emissions data of the technologies or sectors they represent. One option to consistently account for these emissions is Life Cycle Assessment (LCA). For this reason, this section outlines the main aspects of the LCA methodological framework.

LCA is a standardized method that quantifies environmental burdens throughout the life cycle of a good or service (product) (Joint Research Center-European Commission-Institute for Environment and Sustainability, 2010), including raw materials extraction, construction, operation and end of life (e.g., recycling, final disposal). LCA covers a wide range of environmental issues related to climate change, ecosystems, human health, and resources, enabling the evaluation of trade-offs or burden-shifting effects, particularly when assessing renewable technologies (Laurent et al., 2018). The ISO standards 14040 and 14044 (ISO, 2006, 2009) define the main principles, vocabulary and methodological framework of LCA studies, which will be discussed in the next section.

Regarding LCA modelling principles, Attributional Life Cycle Assessment (ALCA) and Consequential Life Cycle Assessment (CLCA) are the most relevant approaches. While ALCAs aim to describe impacts of a product, CLCAs focus on the consequences of decision or changes implemented due to product life cycle (IPCC, 2022b). ALCA relies on historical, measured and measurable data, where uncertainties are either known or can be reasonably estimated. For this reason, other terms used to define ALCA are accounting, retrospective, or descriptive LCA (Schuller et al., 2020). It includes all relevant processes within the modelled system, depicting it in its current, past or expected state (Schuller et al., 2020). In contrast, CLCA does not depict actual or forecasted systems but instead models hypothetical scenarios to assess the broader impacts of specific decisions. Accordingly, other terms used to define CLCA are change-oriented, effect-oriented, or decision-based LCA (Schuller et al., 2020). Due to their distinctive modelling principles, attributional LCA was historically referred to as retrospective, while consequential LCA was considered prospective (Schuller et al., 2020). However, these terms more accurately describe the temporal aspects of an LCA study rather than being strictly tied to a specific modelling approach. For instance, it is a common practice to conduct attributional LCA with a prospective approach, particularly by incorporating the development of technical parameters. In recent years, there has been growing interest in future-oriented LCA analyses (Arvidsson et al., 2018; Cucurachi et al., 2022; Langkau et al., 2023). The term prospective LCA (pLCA) encompasses all studies that focus on future scenarios, regardless of the maturity level of the technology being assessed (Arvidsson et al., 2023). Therefore, pLCA considers factors such as the evolution of supply chains and technological advancements. Conversely, retrospective LCA is any LCA that relies on historical or current data. A key distinction between both approaches is that conventional (retrospective) LCA evaluates products in the past or present, and pLCA focuses on future technologies, regardless of the modelling approach (e.g., consequential or attributional) (Arvidsson et al., 2018).

Overall, LCA models are built upon existing databases, which provide detail information on materials, energy and processes. One of the most widely used database is ecoinvent (Wernet et al., 2016). Yet, ecoinvent provides different types of databases depending on the allocation approach such as APOS (i.e., Allocation at the Point of Substitution) and cutt-off (ecoinvent, 2023). The main difference between these two databases lies in the consideration of allocation of environmental burdens: cut-off provides burden-free inventories for waste and recycled flows, while APOS distributes these burdens along the supply chain. The choice between APOS and cut-off depends on the study's objectives. For instance, if recycling rates are explicitly considered in the model, APOS may be the better option, as suggested by Baumgärtner et al. (2021).

2.5.1 LCA methodology framework

According to the ISO 14040 (ISO, 2009), the LCA methodology framework consists in four phases: goal and scope definition, inventory analysis, impact assessment and interpretation. These phases remain consistent in all LCA studies, although each approach (e.g., attributional, consequential, prospective, etc.) may require adjustments.

In the goal and scope definition the functional unit of the study is set. Geographical and temporal coverage are important aspects of the goal and scope definition. In retrospective LCA, the definition of functional unit is direct, as the system modelled is mostly well known as well as its functions. However, in the case of prospective LCA, especially when assessing emerging technologies, the function of the technology being assessed is not always completely clear. In the early stages of development, the final application, operational context, and performance characteristics are unknown or highly uncertain. This absence of clarity poses challenges for establishing a functional unit (Cucurachi et al., 2022). According to Arvidsson et al. (2023), prospective LCA which focus emerging technologies are referred to as anticipatory or ex-ante LCA. The goal and scope definition phase should state the level of maturity expressed by Technology Readiness Level (TRL), potential counterparts, in addition to lifetime, location, timeframe and system boundaries (de Souza et al., 2023). This means identifying a technology that might be replaced by the novel one. Furthermore, the scenario-based approach for prospective

LCA advises defining the research question and specifying the type of scenario (e.g., normative, predictive, or exploratory) during the goal and scope definition phase (Langkau et al., 2023).

The inventory analysis phase or Life Cycle Inventory (LCI) is the most extensive part of an LCA study (Heijungs, 2024), because it involves the collection and quantification of all relevant input and output data for the system such as energy inputs, raw material inputs, and all physical inputs as well as products, co-products and waste, emissions to the biosphere (air, water, soil). In this phase, the practitioner (i.e., the person or team conducting the LCA) must identify all processes relevant to the system, plan and initiate data collection, identify missing information, and scale the data according to the functional unit. Since inventory analysis is an iterative process, an initial iteration of the model can highlight the most relevant data and provide guidance for further refinement (European Commission - Joint Research Centre - Institute for Environment and Sustainability, 2010).

Once all relevant physical flows (i.e., inputs and outputs within the system boundaries) are identified and quantified, they must be associated with their corresponding environmental impacts or in other words translated to an environmental impact score (Joint Research Center-European Commission-Institute for Environment and Sustainability, 2010; Rosenbaum et al., 2018). This is done in the Life Cycle Impact Assessment (LCIA) phase. Thus, life cycle impact assessment methods describe characterization models that represent the environmental mechanism linking each physical flow to a characterization factor, which represents the contribution of that physical flow to a specific environmental impact category (Rosenbaum et al., 2018). Different environmental flows cover LCIA methods based on areas of protection. Generally, existing LCIA methods address three main areas of protection: the environment, human health, and natural resources. The LCIA methods are grouped into impact categories (Geldermann et al., 1999), each represented by environmental indicators or LCA indicators. The selection of impact assessment methods is therefore closely tied to the goal and scope definition. While LCA practitioners typically use pre-existing methods provided by LCA software, it is crucial to adhere to guidelines when selecting an LCIA method (European Commission, 2020; Joint Research Center-European Commission-Institute for Environment and Sustainability, 2010).

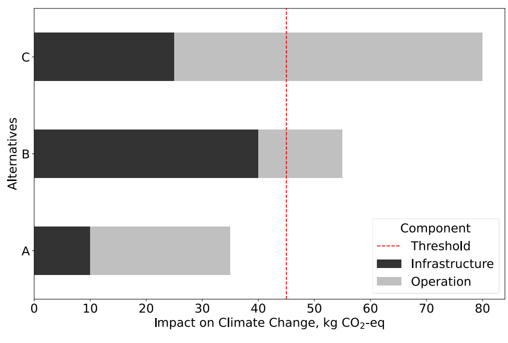
The final phase is the interpretation of results, where the findings from the previous phases are analysed (Hauschild et al., 2018). During this phase, the relative nature of LCA studies must be considered, along with all the limitations outlined in the earlier phases. The term relative nature indicates that LCA results are specific to a defined function and system boundaries. As such, the interpretation of LCA results should consider this context to avoid invalid comparisons with studies that vary in scope and boundaries (Bjørn et al., 2018b). Additionally, uncertainty should be addressed using appropriate tools or methods, such as sensitivity analysis or Monte Carlo simulation.

To ensure a clear understanding of the methodology applied in this thesis regarding LCA, it is necessary to clarify certain terms. LCA examines the physical flows associated with each stage of a product's life cycle. Therefore, the term product system refers to the collection of processes considered to fulfil the function of the assessed product (Bjørn et al., 2018b). For example, the function of an offshore wind turbine is to generate electricity. To achieve this purpose, several industrial processes occur at different life cycle stages. A unit process is the smallest element of an LCA, which quantifies input and output flows (Bjørn et al., 2018b). Product systems consist of a collection of all the unit processes within the system boundary of the LCA study. However, there is a difference between those unit processes belonging to the foreground and background systems. The foreground systems comprise those unit processes that are specific to studied object of an LCA, while the background systems include processes that supply the foreground system and may not be directly accessible. The foreground system often relies on first-hand data, giving the LCA practitioner some degree of flexibility to modify or explore foreground unit processes, such as selecting different suppliers, or introducing a new unit process. In contrast, the background system contains aggregated datasets in which individual processes are not identified (EPA, 2006). In the example of the wind turbine, part of the foreground system includes the amount of steel or energy required to manufacture a specific component, with data typically sourced from manufacturers, experts, or literature. In contrast, unit processes that describe steel and electricity production belong to the background system, with data often provided by commercial databases such as ecoinvent (Wernet et al., 2016). Understanding the structure of an LCA model is crucial not only for conducting a thorough inventory analysis but also for performing future-oriented or prospective LCAs.

2.5.2 Relative and absolute LCA assessments

As mentioned previously, LCA traditionally follows a relative approach, meaning it evaluates the environmental impacts of a product, process, or system in comparison to alternatives rather than in absolute terms (Bjørn et al., 2018a; Moltensen & Bjørn, 2018). As the outcomes of an LCA are relative to a functional unit, it is well-suited for comparing technologies with similar functions (ISO, 2009). However, this relative nature makes it challenging to incorporate external constraints or environmental limits directly into LCA results (see Figure 2.11).

A key criticism of conventional LCA is that it lacks a benchmark for sustainability, meaning that it quantifies environmental impacts without assessing whether they remain within safe ecological limits or not (Moltensen & Bjørn, 2018). To address this limitation, researchers have explored absolute LCA approaches, which incorporate external environmental constraints into LCA assessments. Two major concepts in this context are carrying capacities and planetary boundaries (Rockström et al., 2013). Carrying capacities refer to the maximum level of environmental pressure that a system can endure while maintaining its functionality (Bjørn & Hauschild, 2015). In LCA, this concept can help define



thresholds for resource consumption or emissions beyond which environmental degradation becomes critical (Bjørn et al., 2020).

Figure 2.11 LCA and its relative nature

Source: Based on Vargas-Gonzalez (2018)

Planetary boundaries (PB) define limits for key Earth system processes that, if exceeded, could lead to irreversible environmental changes (Rockström et al., 2009). Incorporating planetary boundaries into LCA can help assess whether a system operates within the Earth's ecological limits. The framework

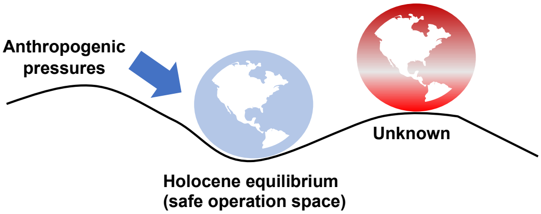


Figure 2.12 The concept of Planetary Boundaries

Source: Based on (Rockström et al., 2009)

establishes a safe operating space by defining nine planetary boundaries such as ocean acidification, biochemical flows, freshwater change, land-system change, biosphere integrity, climate change, novel entities, stratospheric ozone depletion and atmospheric aerosol loading (Rockström et al., 2009). These boundaries serve as sustainability thresholds that should not be exceeded to maintain ecological balance (see Figure 2.12). These boundaries express clear, measurable limits; however, applying them at a national level requires downscaling to account for regional differences (Ryberg et al., 2020; Steffen et al., 2015). Additionally, although there are similarities between the PB framework and impact assessment methods in LCA, they are not entirely equivalent. The approach of PB requires the development of a new set of impact categories based on its concept, as proposed by (Ryberg et al., 2018). However, this approach is still emerging and lacks robustness.

Absolute sustainability approaches are beyond the scope of this thesis, their relevance warrants discussion, particularly due to their potential in improving sustainability communication and decision-making. Future research could explore how to systematically integrate these approaches into LCA-ESM/IAM frameworks to provide meaningful sustainability benchmarks alongside impact assessments.

2.6 Chapter summary

This chapter discusses the role of scenarios, the challenges of offshore wind energy as a low-carbon technology solution, and the modelling frameworks used to assess climate mitigation strategies. The first sections highlight the crucial role of scenarios in preparing for a wide range of possible futures, aiding policymakers, researchers, and industry stakeholders in navigating climate mitigation uncertainties. Beyond strategic planning, scenarios facilitate interdisciplinary communication, fostering collaboration between experts in energy systems, environmental science, and policy. In the context of climate mitigation, they provide a structured approach exploring technological pathways and their implications for achieving low-carbon transitions. Scenario results can vary widely depending on their typology, yet they often complement each other by addressing different aspects of a problem. In energy-related studies, clearly defining the scenario's purpose from the outset ensures the selection of appropriate parameters and system boundaries, enhancing result transparency and communication.

In Germany, various energy scenarios have been proposed to reduce greenhouse gas emissions. While these scenarios suggest different technological combinations, they consistently identify offshore wind energy as a key low-carbon solution. Offshore wind offers high energy yields, scalability, and the ability to complement other renewables like solar and onshore wind. However, large-scale deployment poses challenges, including high initial investment, environmental concerns, and supply chain dependencies.

To assess low-carbon technologies and their role in energy transitions, different modelling frameworks are employed. Integrated Assessment Models (IAMs) provide a macro-level perspective, linking energy, economy, and climate policies. Energy system models (ESMs) offer a more detailed representation of energy supply and demand dynamics, optimizing or simulating technology choices under various policy and economic conditions. Life Cycle Assessment (LCA) complements these approaches by evaluating the environmental performance of technologies across their entire life cycle. Together, these modelling tools enable a comprehensive assessment of offshore wind energy as a climate mitigation solution, identifying both its benefits and trade-offs.

3 Modelling frameworks and Life Cycle Assessment

Understanding how climate mitigation modelling frameworks handle emissions is crucial for drawing reliable conclusions when assessing emission reduction pathways, evaluating policy impacts, and informing decision-making processes. Modelling frameworks such as energy system models (ESMs) and Integrated Assessment Models (IAMs) are often used in these assessments by representing energy production, demand, and their associated emissions. However, given the vast number of modelling approaches, variations in emission representation are expected, which can influence scenario outcomes and policy recommendations.

This chapter examines the state of the art regarding integration approaches between Life Cycle Assessment (LCA) and ESMs and discusses how these methodologies complement each other. Specifically, it seeks to address the following key questions:

- How do energy system models account for emissions?
- What are the current approaches for integrating LCA and ESMs?
- How do these integration methods improve the representation of emissions and enhance the evaluation of climate mitigation strategies?

By addressing these questions, this chapter aims to provide a comprehensive understanding of emission representation in climate mitigation models and highlight the benefits of combining ESMs and LCA for more holistic environmental assessments. These integration approaches are explored in detail in Section 3.1. While studies emphasize the potential of the integration, the combination of LCA and ESMs presents significant challenges (see, Section 3.2) that must be addressed on two fronts. First, through discussions on methodologies (see, Section 3.3), and second, through the development of suitable tools (see, Section 3.4). Overall, this chapter aims to provide recommendations based on the insights and experiences from published works.

3.1 Integration approaches

ESM/IAMs serve different purposes and have been essential tools for evaluating energy transition pathways from economic, technological, and environmental perspectives. However, the environmental dimension is often incorporated in a limited manner, typically focusing primarily on direct CO_2 emissions (Baumgärtner et al., 2021; Blanco et al., 2020; Reinert et al., 2021). Consequently, it is crucial to clarify how modelling frameworks approach emissions and assess their impacts. In contrast, LCA provides a comprehensive understanding of environmental burdens. As such, integrating ESM/IAMs and LCA could provide a more holistic assessment of energy systems. In recent years, several attempts have been made to incorporate both methodologies, demonstrating that LCA can be integrated into various modelling frameworks.

3.1.1 Emissions within ESMs

One of the main arguments for integrating LCA into ESM/IAMs is the limited representation of greenhouse gases (GHGs), with climate change as the primary concern. As shown in Table 3.1, these frameworks typically calculate emission factors based on few GHGs and estimate the environmental impacts of technologies or sectors. Despite apparent similarities, the terms *direct CO_2 emissions*, *emission factors (EFs)*, and the *LCA indicator Global Warming Potential (GWP)* refer to distinct concepts. While the latter two are expressed in CO_2 equivalents (CO_2-eq), they differ in scope. These differences are clarified in the following section.

Table 3.1 Greenhouse gases evaluated in energy system models

Type of GHG emissions evaluation	Global IAMs: IMAGINE 3.0 & 3.2	Global IAMs: REMIND 2.1 - MAgPIE 4.2	Global IAMs: MESSAGEix-GLOBIOM 1.1	Global ESMs: GENeSYS-MOD	Global ESMs: GMM
CO_2 energy	dark green	dark green	dark green	dark green	dark green
CO_2 industrial process	dark green	orange	dark green	white	orange
CO_2 land use	dark green	dark green	dark green	white	white
CH_4 combustion	dark green	dark green	dark green	white	white
CH_4 fugitive	dark green	blue	dark green	white	white
CH_4 biogenic	dark green	orange	dark green	white	white
N_2O	dark green	dark green	dark green	white	white
HFCs	dark green	white	orange	white	white
PFCs	dark green	white	white	white	white
SF6	dark green	white	orange	white	white
SO_2	dark green	dark green	dark green	white	white
Black carbon	dark green	dark green	dark green	white	white
Organic carbon	dark green	dark green	dark green	white	white
NMVOC	dark green	dark green	dark green	white	white

dark green	EF linked to explicit technology w/ fuel representation
light green	EF linked to evolution of other emissions
blue	Average EF for technology class
orange	EF for sector
white	not represented

Source: Based on (IPCC, 2022b)

In most ESM/IAMs, *direct CO_2 emissions* are those released during the combustion of fossil fuels (e.g., in a power plant) or industrial activities. According to the IPCC, GHGs are atmospheric gases that contribute to warming the Earth, with CO_2 being one of the most significant. However, the list of GHGs is extensive (Ehhalt et al., 2001), with certain gases being specifically linked to human activities and contributing significantly to the warming effect due to their high radiative efficiency and long residence time in the atmosphere. These GHGs include carbon dioxide (CO_2), methane (CH_4), nitrogen oxides (N_20), and synthetics gases such as chlorofluorocarbons (CFCs), hydrofluorocarbons (HFCs), hydrochlorofluorocarbons (HCFCs), perfluorocarbons (PFCs) and sulphur hexafluoride (SF_6) (Ehhalt et al., 2001; Penman et al., 2006). Since GHGs differ in how long they stay in the atmosphere and the amount of energy they can absorb, their global warming potential (GWP) is expressed in terms of carbon dioxide equivalents (kg CO_2-eq).

According to IPCC (2022b), there are differences in how emissions are considered in different modelling frameworks. As Table 3.1 shows, carbon dioxide coming from the energy sector is the most well represented. Modelling frameworks estimate the environmental impacts of GHGs by calculating *emission factors (EFs)*, which are coefficients that quantify the amount of a specific pollutant released into the atmosphere per unit of activity or fuel consumed. For example, IMAGE (see Section 2.4.1) estimates emission factors for specific technologies, considering a broader range of GHGs, while REMIND (see Section 2.4.1) estimates EFs linked to sectors and includes fewer GHGs. Although EF and LCA indicators quantify the warming potential of GHGs, the IPCC and ISO (2006) define and apply the term differently (EPA, 2025). EFs offer a conservative estimate of emissions, relying on literature or average values while excluding emissions from upstream processes.

In contrast, ISO (2006) defines GWP as the total greenhouse gas emissions associated with a product's entire life cycle, including upstream activities such as raw material extraction and transportation. Thus, the *LCA indicator of GWP* strives for a detailed and reliable estimates of a technology's environmental performance related with climate change.

Additionally, despite the consideration of air pollution, Table 3.1 highlights climate change as the main environmental concern addressed in ESM/IAMs. Few exceptions exist—for example, the IAM IMAGE also considers the impact of nutrient flows, such as phosphorus and nitrogen, as well as resource use (Stehfest et al., 2014).

In the case of IMAGE, emissions accounted are explicitly defined and related with an activity. EF in IMAGE describe "past and future developments in anthropogenic emissions are estimated on the basis of projected changes in activity and emissions per unit of activity" (Stehfest et al., 2014). The EFs are time-dependent, representing changes in technology and air pollution control and climate mitigation policies (Stehfest et al., 2014). In contrast, the IAM REMIND (see Section 2.4.1) simulates emissions from long-lived GHGs (CO_2, CH_4, N_2O), short-lived GHGs (CO, NO_x, VOCs), and aerosols (SO_2, BC, OC), accounting for these emissions with varying levels of detail depending on their types and sources of emissions. For instance, REMIND calculates CO_2 emissions from fuel combustion, CH_4 emissions from fossil fuel extraction and residential energy use, and N_2O emissions from energy supply based on sources (Luderer G, 2020). Regarding ESMs, while GENeSyS-MOD (see Section 2.4.2) considers direct emissions estimated based on carbon content of fuels from the energy sector only (Burandt et al., 2018), GMM (see Section 2.4.2) also includes direct emission from the industrial sector.

3.1.2 Status of integration approaches of Life Cycle Assessment and energy system models

As discussed in Chapter 2, a wide range of modelling frameworks exits, including those based on optimization, simulation, and general equilibrium. Continuous advancements in computational power have led to increasingly complex and sophisticated models such as integrated assessment models. In principle, LCA can be integrated to all of them (Vandepaer & Gibon, 2018), yet not without challenges. This section discusses the most important features and properties found in studies dealing with the integration of LCA into energy systems models, published since 2015.

Among the vast range of modelling possibilities, the most common attempts at integrating LCA have been centred around bottom-up energy system optimization models (Berrill et al., 2016; García-Gusano et al., 2016; Reinert et al., 2022; Volkart et al., 2018) and integrated assessment models (Arvesen et al., 2018; Boubault et al., 2019; Pehl et al., 2017; Tokimatsu et al., 2016), with a primary focus on the energy sector. However, integration approaches are also applied in the building sector or using top-down models. For example, Guarino et al. (2016) combine LCA indicators with an energy system to simulate the environmental performance of buildings. Additionally, LCA and economic input-out analysis can be found. For instance, Daly et al. (2015) developed a hybrid approach combining a bottom-up energy system, and input-out model and LCA. In addition, Dandres et al. (2011) evaluate consequences of bioenergy policy using a computable general equilibrium model and LCA.

Regarding sector coverage, both multi-sector and single-sector models are used for evaluating environmental performance at the global, regional, or national level. For instance, Volkart et al. (2018) integrate LCA indicators into a global energy system optimization model, while García-Gusano incorporate LCA indicators into the models LEAP (Long-range Energy Alternatives Planning systems) and TIMES-MARKEL, to evaluate the electricity sector in Spain and Norway (García-Gusano et al., 2017; García-Gusano et al., 2016). With the expected increase in the electrification across sectors such as transport, heating, and industry, addressing their environmental impacts from a life cycle perspective have been proposed by Baumgärtner et al. (2021) and Reinert et al. (2022).

Regarding the instances in which LCA is integrated into modelling frameworks, studies propose endogenous and exogenous approaches. In the exogenous approach, LCA is included in the post-processing stage, meaning that LCA indicators do not directly contribute to a target function or constraint (Berrill et al., 2016; Blanco et al., 2020; Hertwich et al., 2015; Xu et al., 2020). For instance, applying LCA at a post-processing stage is useful to evaluate environmental performance of pre-existing scenarios (Luderer et al., 2019). One way to include LCA indicators as part of the decision-making, in other words the endogenization of LCA indicators, is through their monetization and subsequent inclusion in optimization models (Krieg et al., 2013). According to Blanco et al. (2020), the inclusion of emissions in the objective function should be performed through the monetisation of externalities, which means assigning economic values to the environmental damages caused by emissions. However, the monetization of LCA indicators is not entirely straightforward, as well as the definition of constrains (García-Gusano et al., 2018). Another approach proposes the concept of Planetary Boundaries (Rockström et al., 2013) as constraints (Algunaibet et al., 2019), based on (Ryberg et al., 2018). Another alternative is to treat LCA indicators as costs, integrating them as an additional objective. An example of this approach is the work of Junne et al. (2021), who propose a multi-objective optimization to evaluate trade-offs between climate mitigation measures and costs in the energy sector across Europe and North Africa. Junne et al. (2021) develop two objective functions: one based on cost and other based on LCA indicators.

Another important aspect concerns the level of integration, which can be categorized as either soft-linked or hard-linked approaches. The terms describe the degree of automation when exchanging information between models. However, few studies explicitly clarify their level of integration. For instance, García-Gusano et al. (2017) provide examples of soft-linking approaches, while identifying hard-linking approaches remains more challenging. If hard-linking implies that input parameters in both methodologies are fully interconnected—allowing any change in one method to be automatically reflected in the other—then this level of integration is achievable only to a certain extent. Examples of hard-linking integration approaches are (Boubault et al., 2019; Pehl et al., 2017; Tokimatsu et al., 2016). These studies share a common focus on the systematic management of the life cycle inventory, including the modification of prospective background and foreground inventory data. The contribution of these studies initiates an important discussion on the role of prospective LCA, particularly regarding methodological alignment and the need for tools that facilitate its implementation.

As the primary goal of most integration approaches is to evaluate the energy transition, optimization models with a long-term horizon (e.g., for periods between 2020 to 2050) are the most common choice. For example, Reinert et al. (2021) employs a step-wise optimization model with a 5-year interval, spanning from 2016 to 2050. The model includes 192 time steps, eight typical periods, and a 24-hour resolution for each time step. Blanco et al. (2020) propose a multi-sectoral model with a time horizon covering 2010 to 2050. Although hourly resolution is possible, the model uses time slices of 24 hours for the power sector and twelve hours for other sectors. Long-term models are typically complex and require robust computing infrastructure. In contrast, short-term models are less computationally intensive and can also be used to assess future scenarios. They are particularly suitable for systems that demand high technological and temporal resolution, such as those incorporating variable renewable energy sources and storage systems. For example, Junne et al. (2021) introduce LCA indicators in a multi-objective optimization models with short-term horizon (i.e., target year and simulated year are the same, see Section 2.5).

Studies also vary regarding the type of LCA (i.e., attributional or consequential) integrated into their frameworks. Some authors (García-Gusano et al., 2017; Reinert et al., 2021) advocate for using indicators from consequential LCA (CLCA), as it aligns with the purpose of long-term models that make dynamic decisions. Arvesen et al. (2018) point out that CLCA is less frequently applied than attributional LCA. However, the use of attributional LCA within short-term horizon is adequate as these models focus on a specific target year (future) and higher technological representativeness. Regarding the acquisition of LCA inventory data, commercial databases like ecoinvent (Wernet et al., 2016) are often the primary source. However, most studies do not specify which ecoinvent system model (e.g., APOS or cut-ff, see Section 2.5) they use, with the exception of Reinert et al. (2021), who argue that APOS is a suitable option because it distributes the burdens along the value chain. In general, ecoinvent databases contain inventory data that primarily represent mature technologies in their current state. Technologies that are still at a low Technology Readiness Level (TRL) or are well-known but have not yet achieved significant market penetration are typically not included in ecoinvent databases. Therefore, in many cases external sources are needed because commercial databases lack data (e.g. for carbon capture and storage, or newer photovoltaic systems) (Arvesen et al., 2018; Blanco et al., 2020).

As mentioned in Section 3.1.1, most modelling frameworks primarily focus on climate change. However, LCA enables a broader range of environmental concerns through its impact categories. For instance, the impact method of Environmental Footprint contains impact categories with a at least 16 indicators (Damiani et al., 2022). Since a comprehensive evaluation involves several indicators, there is no consensus —apart from climate change— on which impact categories should be prioritized, as not all indicators have the same level of reliability and relevance (Baumgärtner et al., 2021). For instance, the authors suggest following the recommendations of the European Commission's Joint Research Centre, which classifies LCA indicators on quality levels such as quality I (e.g., climate change, ozone depletion and particulate matter), quality II (e.g., acidification, eutrophication, ionizing radiation, photochemical ozone formation) and quality III (human toxicity, ecotoxicity, land-use, water scarcity, resource depletion). Quality II and III cluster those indicators that require improvements and should be applied with caution (Joint Research Center-European Commission-Institute for Environment and Sustainability, 2010). Although most studies agree on assessing climate change, the selection of the Life Cycle Impact Assessment (LCIA) method varies, being the most cited LCIA ReCiPe (Huijbregts et al., 2016), ILCD, and Environmental Footprint (EF) (Jungbluth, 2025). LCIA methods are designed to cover the same areas of protection —such as human health, ecosystems, and resource use (Rosenbaum et al., 2018). While climate change impacts are typically modelled based on IPCC methodologies, other impact categories are implemented differently by various research groups, leading to variations in results across LCIA methods (Rosenbaum et al., 2018). Furthermore, LCIA based on the concept of Planetary Boundaries (see Section 2.5.2) developed by Ryberg et al. (2016) has been applied to study the sustainability of the electricity sector in the US (Algunaibet et al., 2019).

Finally, the results of these integration approaches indicate trends, as a direct quantitative comparison could be misleading due to differing assumptions. For instance, studies agree that emissions from upstream processes (e.g., materials and construction) become more significant than those from the operation phase, especially in systems with higher shares of low-carbon technologies (Baumgärtner et al., 2021; Blanco et al., 2020; Junne et al., 2021). Despite most indicators decrease as GHG emissions decrease, burden shifting effects[6] are observed. For instance, systems with a high share of photovoltaics and wind energy are good at mitigating GHGs but these systems tend to have higher impacts in toxicity-related and resource-related impacts (García-Gusano et al., 2017; Junne et al., 2021; Reinert et al., 2021), and land-use (Berrill et al., 2016). Additionally, Volkart et al. (2018) highlight that photochemical ozone formation (POF) is linked to the burning of fossil fuels, such as natural gas, POF is higher in systems with a higher share of natural gas. Freshwater eutrophication is also associated with an increased share of wind energy due to higher copper demand, which correlates with elevated phosphate concentrations during mining activities. A similar trend is observed in freshwater ecotoxicity. Moreover, Boubault et al. (2019) find that the construction of hydro, wind, and solar power plants is associated with a higher use of metallic and non-metallic resources, and even greater fossil fuel consumption. From the perspective of planetary boundaries, Algunaibet et al. (2019) demonstrate that a system with the lowest GHG emissions costs twice as much as a conventional one. Even under these optimal conditions, at least one planetary boundary is still transgressed. For instance, the boundary called biochemical flows, which is related to the nitrogen and phosphorus cycles (Rockström et al., 2009).

Although the integration approach allows for the identification of these important trends, it is crucial to acknowledge its limitations. For instance, the insufficient consideration of social aspects, which constitutes a drawback of optimization methods based on cost-optimal solutions. Additionally, LCA inventories for various technologies may exhibit varying levels of representation. For instance, in the case of wind energy, most LCA inventories provide detailed depictions of the construction phase, whereas other stages, such as operation, remain insufficiently characterized. Similarly, when assessing photovoltaic (PV) systems, existing inventories may fail to capture the full range of technological possibilities (Laurent et al., 2018).

Although integrating LCA into ESM/IAMs enhances the understanding of environmental implications within future energy scenarios, it is important to recognise that this integration alone does not inherently ensure sustainability (Moltensen & Bjørn, 2018).

3.2 Methodological challenges of integration LCA and ESM

Vandepaer and Gibon (2018) summarize the challenges of integrating LCA within ESM or IAM in two main points, including structural and data inconsistencies. The first challenge concerns differences in the technological representation between the two methodologies. The second challenge arises due to varying levels of data requirements, and it is discussed in section 3.2.1. Additionally, as the issue of double counting is mentioned frequently in the previous studies, it is examined in section 3.2.2.

[6] Burden-shifting refers to the decrease in GHG emissions but an increase in other impacts.

3.2.1 Technological, temporal and geographical representativeness

According to Vandepaer and Gibon (2018), structural and data inconsistencies reflect differences in technological, temporal and geographical representations of technologies when defined in ESM/IAM and LCA. Different levels of technological representation relate to the resolution at which a technology is depicted in these models. The authors identify three categories of technological mismatches: (1) the technological resolution in the ESM/IAM and LCA is equal, (2) ESM/IAM provides more detailed representation than LCA, and (3) the LCA model offers a higher technological resolution than ESM/IAM. The second and third cases require a certain level of aggregation, which might be conducted arbitrary, potentially compromising the level of detail in the final model or scenario.

Although LCA models are characterized by a high level of technological representation, their resolution can vary significantly. This means some technologies might be better represented than others. Furthermore, LCA inventories might not reflect all potential technological variabilities. For instance, LCI data from commercial databases may provide information on a specific technology or, in the best case, a market-based representative value depending on available data. The LCA inventory data represents then generic mixes of technologies and fuels (Astudillo et al., 2017). Additionally, technologies in ESM/IAMs present different levels of aggregation compared to LCA. For instance, technologies in ESM/IAMs are normally defined based on technology groups or energy carriers, without major technological detail and by a limited set of input parameters (e.g., capacity, efficiency, cost). Moreover, the underlying assumptions reflected by inputs parameters in both methods ESM/IAMs and LCA could vary significantly leading to data inconsistencies, such as different efficiency or lifetime values for the same technology. This disparity in technology resolution or technological coverage often forces modellers to select LCA data based on technological resemblance, at times without sufficient information or knowledge. Moreover, resolving data inconsistencies requires harmonised assumptions in both methods. For instance, technical features (i.e., efficiency, unit capacity, lifetime) in the ESM and LCA should be equivalent. This could be achieved by scaling up existing LCA inventories based on efficiencies or installed capacity, extrapolation or regression. Yet, this step could be roughly performed as LCA inventories are typically aggregated. For example, in the case of fossil-fired power plants, adjusting efficiency also requires adjusting the combustion products. Without the proper chemical equation, adjusting combustion products through linear extrapolation based solely on efficiency could lead to misleading results. The completeness of LCA inventory data is also a topic of concern. LCA requires a high level of detail, as it aims to cover all phases of a product's life cycle. However, inventories are often incomplete or directly do not exist. A common solution is the use of proxies to compensate for missing information, a decision that should be well documented (Astudillo et al., 2017).

Regarding temporal representativeness and mismatches, three main issues arise in this context. First, ESM/IAMs generate prospective scenarios that anticipate technological advancements and improvements in supply chains. Despite LCA also incorporates temporal description in its goal and scope definition, the temporal representation of technologies within LCA inventories generally reflects, at best, the current[7] state of the art. As a result, LCA data is missing for technologies that are still in the

[7] The term "current technology" is unclear because LCA data is generated based on statistical values and reports, which may reflect different years or outdated information (Astudillo et al., 2017)

development stage but are expected to become relevant in the future (e.g., direct air capture technologies). Second, conventional LCA allocates life cycle burdens without clear temporal distinctions. This limitation can be particularly problematic for technologies with long lifespans, as environmental impacts from different life cycle phases—especially decommissioning—occur far in the future. In this regard, dynamic LCA could offer a valuable approach for allocating environmental burdens more accurately over time (Reinert et al., 2021). The term dynamic LCA is not standardised. In Reinert's study, dynamic LCA is employed to account for temporal variation of the life cycle inventory (van der Giesen et al., 2020). The third aspect relates to the evolution (technical development) of the supply chain, which is not accounted for in LCA databases due to their static nature.

The structural inconsistencies also concern the geographical coverage or representation of technology input data in both methods. In this regard, mismatches occur because ESM/IAM can vary significantly in geographical scope (e.g., national, regional, or global levels). ESM/IAM with a global scope may include countries that lack region-specific LCA databases, requiring the selection of proxy data. For example, LCA data on hydropower plants in Brazil might rely on LCA data from hydropower plants in Switzerland as a proxy, even though the technologies differ substantially. Similarly, LCA data, particularly those available in commercial databases, offer limited options regarding regional coverage. While ecoinvent (Wernet et al., 2016) aims to cover the most relevant locations, it often uses the geographical location global (GLO) or Rest-of-the-World (RoW) to represent average global production of a process within the datasets (Mutel, 2023). Differences in geographical resolution occur among IAMs, which divide the world into regions rather than countries, with varying levels of regional detail. This issue is particularly relevant for integration approaches with a global scope, as LCA data for regions outside Europe and the United States are often underrepresented or entirely absent (e.g., Africa) (Astudillo et al., 2017).

Additionally, time and geography play a crucial role in renewable energy and electricity mixes in general, as they exhibit seasonal variations. While this seasonality is captured in most ESM/IAM models through time series, which provide a more accurate representation of the availability of wind and solar resources and electricity demand across different locations and time periods, this dynamism is omitted in LCA models, where values are estimated based on annual averages. LCA databases rely on average full-load hours to approximate electricity generation over a technology's lifetime, with regional differences defined solely by full-load hours. For example, commercial LCA data on offshore wind rarely represent wind turbines with monopile foundations, which are suitable for wind farms located in the southern part of the North Sea (e.g., Germany, the Netherlands). However, in other regions, particularly in Asia, different foundation types (e.g., jacket piles) are more representative, yet they are not included in commercial databases.

After gaining a clearer understanding of the challenges, it is important to explore potential solutions. The selection of an appropriate model for integrating LCA should also be carefully considered. Long-term models are useful for evaluating transition pathways but often lack the time resolution needed to accurately capture the variability of electricity production from renewable sources. In such cases, short-term horizon models may be a more suitable option.

According to Vandepaer and Gibon (2018), to mitigate technological coverage mismatches, modelers should establish a consensus on the appropriate level of aggregation when representing technologies. Well-documented and transparent data sharing is crucial. To address data gaps (e.g., for current or future technologies), expert interviews and workshops can be valuable, along with utilizing statistical tools (e.g., regression, extrapolation) when data is available, and employing proxies where necessary. Overall, agreement on conducting future-oriented LCA studies is essential, (see Section 3.4). Moreover, structural changes are needed for flexible, parametrized and adjustable LCA inventories, which require the development of dedicated tools. Over the years, several attempts have emerged, such as THEMIS (Gibon et al., 2015), Wurst (Mutel, 2017b), and more recently Premise (Sacchi et al., 2022).

3.2.2 Double counting

Several authors have highlighted the issue of double counting, which is related to the definition of system boundaries. However, the occurrence and nature of double counting can vary depending on the modelling framework, the sectors involved, and the specific technologies considered. For instance, in multi-sector models double counting occurs when material demand of one sector and material consumption in the construction phase overlap (Blanco et al., 2020). Double counting also occurs when the life cycle inventory for a technology includes energy flows that are already within the system boundaries, such as battery storage, pumped hydro storage, or electrolysis that utilizes surplus electricity to operate the plant (Blanco et al., 2020). In the power sector, combined heat and power (CHP) systems are multi-output processes, meaning that environmental burdens must be appropriately allocated between electricity and heat (Baumgärtner et al., 2021). This is particularly relevant for systems that consider both commodities within their scope. In the context of the integration of LCA into ESMs, double counting occurs when the environmental impacts of infrastructure are accounted for within the inventories of operational activities (Astudillo et al., 2018; García-Gusano et al., 2017; Volkart et al., 2018).

To overcome double counting, several approaches are proposed, including endogenous modelling of material, fuel, as well as separate dismantling from upstream processes (Volkart et al., 2018). The disaggregation of LCA inventory into phases is recommended by several authors, yet there is a slight difference in the number of LCA phases (Arvesen et al., 2018; Junne et al., 2021; Reinert et al., 2021; Volkart et al., 2018), and it is achieved by eliminating operation related flows (e.g., fuel consumption) from the infrastructure. García-Gusano et al. (2017) recommend the use of LCA inventory per KW of installed capacity to separate impacts from infrastructure and operation. In those integration approaches, where electricity is used in other sectors (e.g., heat and transport), a way to omit double counting is by allocating all the impacts to the electricity supply (Baumgärtner et al., 2021). Additionally, it should be kept in mind that a fossil-based power plant produces heat and power. From the LCA perspective, this is a multifunctional process, which can be address in several ways. For instance, allocating all the burdens to the electricity produced and assume the heat as waste (Baumgärtner et al., 2021). Yet, other allocation methods exist based on cost or energy.

To avoid system boundary overlap, it is essential to address double counting in this thesis. Without careful harmonisation of system boundaries, the same process emissions could be counted multiple times.

3.3 The role of prospective LCA

The preceding section concentrated on the methodological challenges associated with integrating LCA into ESMs. The identified challenges can be primarily attributed to methodological discrepancies. LCA is often viewed as static, providing a snapshot of environmental impacts at a specific point in time. In contrast, ESMs are dynamic models that capture the temporal evolution of energy systems (García Gusano et al., 2016). This section discusses the role of prospective LCA (pLCA) as a potential methodological solution in addressing these issues.

In the integration of LCA with ESM/IAMs, pLCA plays a crucial role in aligning LCA data with the target year of ESM/IAM projections, thereby minimising data inconsistencies between both models. In addition to the challenges discussed in the previous sections, a key consideration is the technological development over time. This evolution is often captured from an economic perspective using the concept of learning rates (Rubin et al., 2015). For instance, with increasing production volumes, it is anticipated that technologies will become more cost-effective due to efficiency improvements and manufacturing optimizations. A similar approach can be observed in environmental aspects, as technological advancements may lead to changes in environmental performance, either positive or negative (Luderer et al., 2019). Given the need to harmonise input data across methodologies, pLCA provides a structured framework for integrating these changes within coherent narratives. This not only facilitates the alignment of technological parameters but also ensures the synchronization of economic assumptions. As a result, pLCA helps to address challenges related to data inconsistencies in temporal, technological, and even geographical representativeness by enabling parameter adjustments tailored to specific contexts.

Although ESM/IAMs mostly consider technologies that are well-known, or already achieve a mature stage, those technologies could still experience developments. For instance, for the electricity sector a significant increase in the share of renewables technologies is expected (see Section 2.2.2). A rapid deployment of renewable technologies is associated with more technological development in the sector. In the case of solar energy, new materials for photovoltaic cells are in continuous development, as well as new types of cell formats (e.g., thin film, perovskite solar cell, etc.) (Schwede, 2023). Even biogas power plants might experience changes in performance due to the introduction of new substrates (Verma, 2022). In the case of offshore wind turbines, advancements in new types of foundations (e.g., floating foundations) are expected in the coming years, along with a higher market penetration of new types of generators and larger components (Benitez et al., 2024). Similarly, carbon capture technologies that have currently reached a TRL between 7 and 9 (Bukar & Asif, 2024), but still have low manufacturing readiness level (MRL) and may see significant changes in the future supply chain. As these changes are rarely considered in commercial LCA databases, obtaining environmental performance data for technologies at different TRL and MRL is essential and can be achieved through the implementation of pLCA.

Conventionally, LCA evaluates the environmental performance of technologies that already exist or are currently in operation. Conducting an LCA at an early stage of development (i.e., emerging technologies) has gained attention (Cucurachi et al., 2018), as it allows for informed decision-making at a point in time (e.g., during the design phase), when changes are still possible and can have a significant impact . Moreover, pLCA enables fair comparisons between novel technologies and the existing technologies they aim to replace by positioning both at the same level of technological maturity and within the same timeframe. According to Arvidsson et al. (2023); Arvidsson et al. (2018), prospective LCAs incorporate two dimensions: temporal positionality and technological maturity. The first refers to the timeframe of the LCA study, whereas technological maturity signifies the development and advancement of the technology in question. For this reason, the pLCA approach provides LCA indicators that better align with the temporal and technological, and even geographical representation of technologies defined in ESM/IAMs.

However, in future-oriented LCAs, data scarcity and high uncertainty—already present in conventional LCAs—are further intensified. To address these challenges, Mendoza Beltran et al. (2020) discuss methods to enhance consistency between foreground and background systems, adjusting background system (i.e., electricity mixes) according to scenarios from IMAGE and highlight important impacts of the environmental performance of electric vehicles. Additionally, an increasing number of studies have emerged to provide methodological guidance on adapting the classical LCA framework—including goal and scope definition, inventory analysis, impact assessment, and results interpretation—for the assessment of emerging technologies (Arvidsson et al., 2018; Cucurachi et al., 2018; van der Giesen et al., 2020). These efforts aim to refine LCA methodologies to better capture the complexities and uncertainties associated with prospective analyses.

The challenges associated with modelling foreground systems in prospective LCA are higher with technological immaturity. Defining the functional unit within the goal and scope phase presents difficulties at early development stages, as the final application of the technology or product remains uncertain (Cucurachi et al., 2018). Arvidsson et al. (2018) conducted a comprehensive review of pLCA studies, providing valuable guidance for modelling foreground and background systems. In cases where the future application of a technology is unclear, the authors suggest focusing on a single application while also considering analogous products. Additionally, cradle-to-gate assessments are recommended, as they allow for a more controlled evaluation of environmental impacts without requiring assumptions about the technology's entire life cycle. Modelling the foreground system should incorporate scenarios, including a predictive scenario reflecting the most likely trends of inventory parameters or, alternatively, a scenario representing the current state, both serving as references. Additionally, scenario ranges representing extreme cases (e.g., best and worst cases) should be included to account for uncertainties, which are inherently high and difficult to quantify. Then, after identifying the most relevant processes and parameters of the process, projections of key input parameters (e.g., materials and energy inputs and outputs) reflecting technological development can be estimated using learning curves, up scaling of processes could follow engineering laws, or simulation software, while data gaps can be addressed through expert interviews, patents, scientific literature, and unpublished lab results. Learning curves describe the relationship between technological performance improvement per unit and the increase in cumulative production, an example of the implementation of learning curves supporting pLCA for carbon capture technology is provided by Faber et al. (2022). Additionally, the use of engineering laws to estimate materials and energy inputs when scaling up wind turbines is done by (Caduff et al., 2012).

Learning curves, and technology learning rates are used often in techno-economic assessment to estimate expected cost improvements (McDonald & Schrattenholzer, 2001). Learning curves are graphical representations used to illustrate the enhancement of a specific metric (i.e., cost or performance) of a technology with increasing production or deployment. The technology learning rate is defined as the percentage that quantifies the decrease in the cost of a technology with each doubling of cumulative production (Rubin et al., 2015). When these concepts are combined with coherent scenario narratives, they can support to harmonise assumptions (input parameters) in integration approaches combining ESM/IAMs and LCA. This thesis uses this approach to harmonise technical, economic and environmental input data (see Chapter 4).

Similar strategies adopted for modelling foreground systems should be applied to background systems (e.g., scenarios, upscaling background input parameters) to minimize technical, temporal and geographical mismatches. In this regard, prospective environmental data necessitates scenarios that reflect future projections. Arvidsson et al. (2018) recommend considering a predictive scenario along with a set of extreme scenario cases (e.g., best and worst case), as is done for foreground systems. For example, projections of electricity mix can be obtained from the International Energy Agency or, depending on the country or region, from reports that are frequently published. In particular, normative scenarios illustrate a desirable future and can be used to describe the best possible case. While most changes in the background system focus on electricity mixes, the entire supply chain (e.g., critical materials, transport) will evolve over time. Therefore, it is essential to identify processes that are most likely to change. Conversely, processes expected to remain like current conditions can be left unchanged. For example, unless a novel method for copper production is introduced, it can be assumed that future copper production will resemble current practices.

This thesis implements pLCA to derive LCA indicators for offshore wind turbines (Benitez et al., 2024). For instance, existing inventories represent offshore wind turbines based on 2012 technology with a nominal capacity of approximately 3 MW. In contrast, by 2030, wind turbines with an average capacity of 10 MW are expected to be installed (see, Section 2.3). Therefore, the recommendations outlined above serve to adjust the foreground system of an existing LCA model for offshore wind turbines to meet the requirements of the energy system model. For example, engineering laws are used for scaling up wind turbine components (Caduff et al., 2012), material efficiency rates are estimated based on technology learning curves, and data gaps (e.g., for the operation phase) are addressed through expert consultations and scientific literature. Additionally, the Scenario-based inventory Modelling for Prospective LCA (SIMPL) approach (Langkau et al., 2023) is used to systematically assess future environmental impacts of offshore wind turbines, ensuring that data assumptions are clearly and transparently documented (Benitez et al., 2024). The SIMPL is an approach for modelling prospective life cycle inventories. The primary focus of SIMPL is the incorporation of technological developments in the foreground systems of an LCA, with the utilisation of existing scenarios to delineate future advancements in the background systems (Langkau et al., 2023).

Despite existing guidelines on conducting pLCA and handling foreground and background systems in an LCA model, additional methodological support is required to facilitate the generation of coherent scenarios that consider both internal and external aspects of LCA. While existing recommendations provide a broad framework, applying them within a system that combines multiple technologies requires numerous assumptions, leading to a vast array of parameters that must be carefully managed. Therefore, beyond general guidelines, more specific methodological approaches—such as SIMPL (Langkau et al., 2023)—are necessary to support scenario development and integration efforts.

The SIMPL method summarizes previously discussed lessons and integrates knowledge from other disciplines (e.g., future studies, scenario generation), as pLCA inherently relies on assumptions. Essentially, SIMPL provides a structured approach to adapting the classical LCA methodological framework to meet the needs of prospective studies. It helps align internal model assumptions with external trends, such as those expressed in scenarios—for example, projections provided by the IPCC and IEA (discussed in Section 2.2). This ensures that assumptions are developed in connection with broader expectations about future developments rather than in isolation.

The SIMPL method follows the standard LCA methodology while introducing specific adjustments (see Figure 3.1). For instance, in the goal and scope definition phase, it recommends formulating a research question aligned with predefined scenarios (e.g., predictive, explorative, or normative; see Section 2.1.2). The life cycle inventory phase requires the most effort, as it considers both internal and external aspects of the LCA model. This phase consists of three steps: a) Identifying relevant inventory parameters and key factors that influence future projections, b) Defining assumptions to estimate the future evolution of these parameters based on expected technological and market developments, and c) Integrating these parameters in a way that ensures coherence within a structured narrative. By following this approach, the SIMPL method ensures that both components of the LCA model—foreground (FG) and background (BG) systems—are aligned within a common and consistent scenario narrative. This structured alignment enhances the reliability and applicability of pLCA results in future-oriented environmental assessments.

Additionally, to support the identification of key factors (Step A), Langkau et al. (2023) recommend following a checklist aligned with the PEST approach, which stands for political, economic, social and technological factors, or the PESTEL approach which includes environmental and legals factors (Langkau et al., 2023). However, an important distinction exists between key factors and inventory parameters. Key factors influence the inventory analysis indirectly, as they are not necessary part of the inventory model (e.g., political decision, investment). In contrast, inventory parameters quantify elementary and intermediate flows (e.g., material, energy inputs) and are incorporated into the foreground and background systems of the LCA model. For example, a key factor might be the decision to invest in research and development, whereas an inventory parameter could be the kilograms of steel required to construct a wind turbine tower.

To evaluate the relationships between factors and inventory parameters, the SIMPL approach proposes causal loop diagrams to identify similar or opposing trends between different parameters (STEP A, see Figure 3.1), which are subsequently quantified. Overall, inventory analysis involves collecting inventory data, meaning that values or value ranges must be assigned to each parameter. However, depending on the complexity of the LCA model and the number of parameters involved, this step can be too laborious and confusing. Therefore, during Step B in Figure 3.1 , Langkau et al. (2023) propose using structured tables to display relevant parameters and key factors, facilitating their quantification. Parameters are then sorted in a way that aligns with assumptions needed for scenario generation. In Step C (scenario generation), parameters are combined to follow a coherent narrative, ensuring consistency with the study’s assumptions and research question. At this stage, multiple scenarios are generated, and the most relevant ones can be selected—such as those representing best- and worst-case scenarios. All the information generated then can be transfer to LCA software to proceed with the calculation of the scenarios and LCA values.

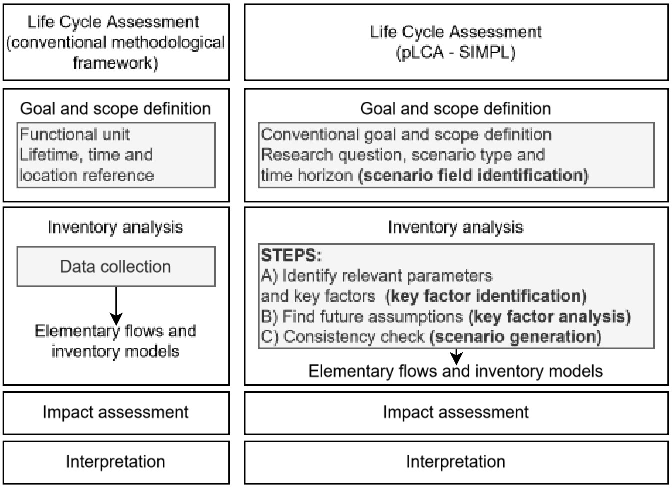


Figure 3.1 SIMPL methodological framework for prospective LCA

Source: Based on Langkau et al. (2023)

In this way, LCA indicators can be derived to be used within ESM/IAMs. During data collection for foreground systems, inventories can be adjusted to address data inconsistencies by following clear and consistent narratives. The data collection process is conducted in a systematic and well-documented manner, ensuring transparency.

3.3.1 Challenges in Integration: The need for advanced tools

The structure of LCA models requires simultaneous adjustment of foreground and background life cycle inventory data. Therefore, deriving pLCA indicators necessitates the development of tools that facilitate the adjustment of Life Cycle Inventory (LCI) data to reflect future conditions. According to Vandepaer and Gibon (2018), software capable of modifying LCI databases based on external scenarios should be flexible and allow for data programming on demand. For instance, Brightway (Mutel, 2017a), an open-source, Python-based framework for LCA calculations, provides the flexibility required by most modellers. Furthermore, Brightway allows for the development of other software, such as the Activity Browser (Steubing et al., 2020), which offers a visual interface and facilitates scenario-based LCA calculations, as well as more possibilities for uncertainty analysis.

Improving pLCA practices requires not only more flexible LCA software but also the development of tools that enhance inventory management by allowing the adjustment and manipulation of life cycle inventories. Over the years, several initiatives emerge as shown in Figure 3.2. The tags in blue correspond to studies with the focus on methods and integration approaches, some of them already discussed in Section 3.1.2 and 3.4, while the grey tags correspond to the development of tools. Gibon et al. (2015) introduced THEMIS (Technology Hybridized Environmental-economic), which is a multi-regional and prospective LCA modelling framework and derives prospective LCA data for its integration in IAMs (Arvesen et al., 2018). THEMIS can adjust LCA databases (e.g., ecoinvent) based on projection of scenarios provided by the IEA, yet it focusses on electricity mixes and key industrial processes such as aluminium, copper, nickel, iron, and steel, metallurgical grade silicon, flat glass, zinc, and clinker. Another initiative is the Python package *wurst* (https://github.com/IndEcol/wurst), which utilizes Brightway2 as its data backend[8]. *Wurst* enables dataset modifications at the database level, incorporating technological advancements over time. For instance, *wurst* allows a modification of technology market shares (e.g., supply markets, efficiency, emissions) as well as disaggregate datasets to provide regional-wide inventory data. Yet, wurst works as a package compatible with Brightway. *Futura* (Joyce & Björklund, 2021) is another Python package (built on Brightway and *wurst*) that provides visual support for adjusting commercial databases based on user-defined scenarios. Its primary objective is to offer a framework for adjusting and sharing prospective scenario data, promoting data exchange and reproducibility. Since a main limitation for sharing prospective data lies in the licensing restrictions of commercial databases, Futura facilitates practitioners with access to ecoinvent database to reconstruct LCA inventories based on predefined scenarios. Futura uses the concept of recipes (i.e., scenarios) and ingredients (i.e., databases) to overcome the challenge of directly sharing licensed databases. Instead of distributing datasets, Futura shares "recipe files" in YAML format, which contain all the necessary information to reproduce scenarios with prospective data. These files can be read in most programming languages using appropriate libraries. Recognizing that many LCA practitioners prefer a more intuitive approach, Futura offers a user-friendly interface that enables sharing prospective data and making reproduction more accessible. Its outputs are compatible with both Brightway and the Activity Browser. A notable drawback, however, is that scenarios are freely defined by users and do not necessarily align with global trends (e.g., IPCC scenarios).

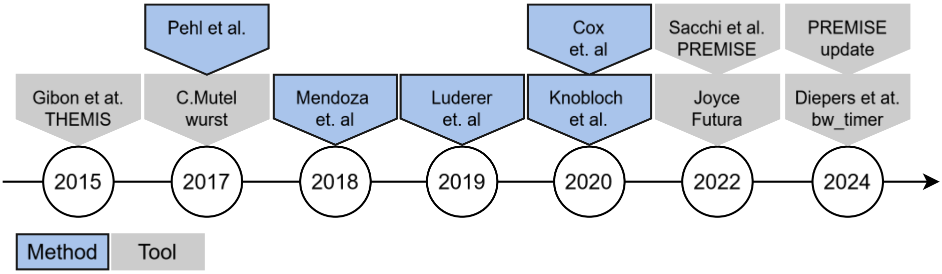


Figure 3.2 The history of scenario-based prospective LCA

Source: Based on Sacchi (2025)

Later, *wurst* contributed to the development of the PREMISE framework (see Section 3.4.1)(Sacchi et al., 2022), which makes possible the generation of complete databases based on scenarios derived from IAMs and allows their export to either Brightway or the Activity Browser. More recent advancements include the Python tool *bw_timex* (https://github.com/brightway-lca/bw_timex), which focuses on dynamic LCA.

Despite ongoing efforts, sharing models across different LCA software tools remains challenging due to variations in interfaces and model structures (Ciroth & Schulz, 2017). As recent advancements in prospective LCA tools are largely built on Brightway, prospective data derived from these Python-based tools cannot be directly imported into commercial LCA software, restricting compatibility to Brightway, Activity Browser, SimaPro (SimaPro, 2018), and openLCA (https://www.openlca.org/). The

[8] It refers to the part of a system or application that operates behind the scenes and is not directly visible to users.

development and expansion of open-source tools for prospective LCA needs long-term support and maintenance. Many of these tools are initially developed as part of doctoral theses or specific research projects, which often means that once the project is completed, funding and institutional backing for further development cease. As a result, critical updates, bug fixes, and improvements may not be implemented, limiting the usability and adoption of these tools by the broader LCA community. Ensuring the sustainability of open-source prospective LCA tools requires dedicated funding, institutional commitment, and community-driven efforts to maintain and expand their capabilities over time.

3.3.2 Premise

PREMISE is an open-source framework that derives prospective LCA data, with the unique capability of exporting complete databases based on predefined scenarios, most of which are integrated into its framework (Sacchi et al., 2022). As deriving prospective data requires making future assumptions, PREMISE aligns ecoinvent (Wernet et al., 2016) datasets to the existing and well-defined future scenarios obtained from different IAMs such as IMAGE and REMIND (see Section 2.4.1) (Luderer G, 2020; Stehfest et al., 2014). This ensures that assumptions are not arbitrary and are in line with global trends.

Despite the possibility for user-defined scenarios (Sacchi, 2023), PREMISE by default incorporates a predefined set of scenarios that describes two aspects. The first refers to the level of societal commitment for climate mitigation challenges, as outlined in the Shared Socioeconomic Pathways (SSPs). The second reflects the degree of tolerable adaptation challenges, linked to greenhouse gas (GHG) concentrations and potential global temperature variations, as described by the Representative Concentration Pathways (RCPs) (see Section 2.2.1). GHG concentrations express the amount of gases in a certain volume of air and are commonly expressed in parts per million (ppm) (Copernicus Climate Change Service, 2024). SSP scenarios define key macroeconomic indicators—such as population growth, economic development, and technological progress—to construct different future narratives. PREMISE considers three SSP narratives: SSP1, SSP2, and SSP5 (Sacchi, 2023). For example, SSP1 envisions a world pursuing sustainable development while respecting environmental boundaries, with an emphasis on economic growth (i.e., higher gross domestic product) and a transition in population dynamics (i.e., declining population growth). Consequently, lower adaptation challenges are expected, as GHG concentrations remain within levels that are compatible with global temperatures stabilizing between 1.5 °C and 1.9 °C by the end of the century. These global temperatures are linked to GHG concentrations, which drive an increase in radiative forcing. For example, RCP2.6 scenario represents global temperatures rising between 1.3 °C and 1.8 °C, while RCPBASE or RCP6.5 scenario corresponds to a temperature increase of approximately 3.5 °C (Sacchi, 2023). These scenarios are generated by various IAMs, which differ in their methodological approaches. Thus, projected outcomes can vary.

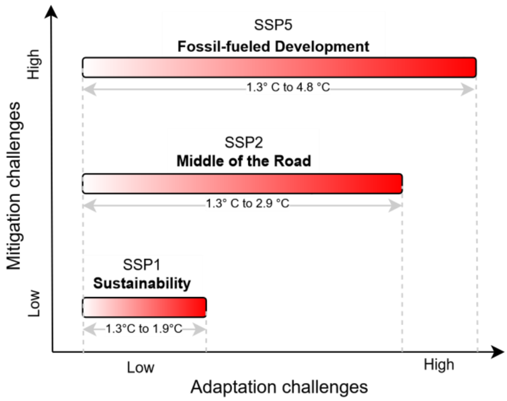


Figure 3.3 Shared Socioeconomic Pathways (SSPs) pathways

Source: Based on Langkau et al. (2023); Sacchi (2023)

PREMISE aligns existing LCA inventories with its default scenarios by addressing three key challenges: temporal, technological, and geographical representativeness, as previously discussed. These adjustments primarily focus on the energy sector, fuels, transport, and industrial processes such as cement and steel production, modifying production volumes and efficiency levels accordingly. Depending on the selected IAMs, PREMISE also incorporates additional LCA inventories for technologies and locations not covered in the original LCA databases. For instance, to address inconsistencies in geographical resolution, PREMISE maps IAMs to LCA dataset locations while simultaneously regionalizing datasets to represent regions within the IAMs (Sacchi, 2023). Similarly, PREMISE aligns technologies present in the IAMs with LCA inventories and incorporates new inventories as needed. However, this process relies on external datasets collected from various studies, and the technological and geographical resolution of the IAMs. For instance, PREMISE includes LCA inventories for technologies such as photovoltaic panels gathered from (Frischknecht et al., 2020), carbon capture, and hydrogen production (Sacchi, 2023). Therefore, although prospective databases include new regions, it is important to assess their coverage, as regional LCA data may not fully reflect the latest energy policies of a specific country. Similarly, to address data gaps, regional inventories are often created using generic datasets from the original database with minimal adjustments. For example, changes in steel and concrete production may primarily reflect updated production shares based on new volumes but may not account for technological advancements such as hydrogen-based steel production, which is not yet available (Benitez et al., 2024; Sacchi, 2023).

Regarding environmental impacts, prospective databases provide a more accurate representation of climate change indicators. However, PREMISE also incorporates projections for air pollution and land-use transformation (Sacchi, 2023). This means that not all environmental impact categories will fully reflect changes accounted for in future scenarios. Therefore, the selection of LCA indicators should be done carefully.

The output of PREMISE is a complete prospective database that can be imported into LCA software such as Brightway and the Activity Browser, enabling the development of new LCA models based on prospective data. Additionally, PREMISE is compatible with the Superstructure approach, which was developed for conducting prospective LCA in the Activity Browser (Steubing & de Koning, 2021).

3.3.3 The superstructure approach

The superstructure approach has been development in order to facilitate scenario-based LCA (Steubing & de Koning, 2021). It is a feature within the Activity Browser (Steubing et al., 2020), which makes possible the implementation of the SIMPL method (see Section 3.3). The approach structures LCA models in a modular and scalable way, allowing for the systematic incorporation of evolving technologies, dynamic supply chains, and projected environmental changes. By organizing the LCA model into interconnected building blocks, the Superstructure approach enables the assessment of multiple technological pathways and alternative future developments within a single modelling framework.

One of the key advantages of the Superstructure approach is its ability to handle large-scale, scenario-based assessments efficiently in a user-friendly manner. As it relies on excel files, also called scenario difference files (SDF) that can be created by the Activity Browser, or it can be derived from PREMISE. Thus, instead of modifying individual LCA inventories manually, this method allows for automated updates based on predefined future scenarios, such as those generated by IAMs or user-defined scenarios.

In the context of this thesis, PREMISE and the superstructure approach are used to obtain prospective and regional data for all the technologies considered in the integration framework. Additionally, SDFs are used to disaggregate LCA datasets and obtain inventories of the technology infrastructure and operation, adjusted to the time frame of the study (e.g., 2030 and 2050). Moreover, SDFs incorporate homogenized technological parameters, which are in line with the assumption adopted in the integration framework.

3.4 Model selection and justification

The aim of this section is to justify the selection of the energy system model used in the context of this thesis. Building on the previous discussion—Section 2.4.2, which presents the general characteristics of modelling frameworks, and Section 3.1.2, which outlines the features of energy system models in the context of the integration with LCA—this thesis adopts the Calliope modelling framework (Pfenninger & Pickering, 2018) to develop an electricity system model that integrates LCA.

One of the primary reasons for selecting Calliope is its flexibility to build bottom-up energy system models from scratch. Given that this thesis focuses on offshore wind integration within an electricity system model, it is essential that the chosen modelling framework allows for a detailed representation of technologies and can accommodate high shares of variable renewable energy sources. Calliope fulfills both requirements. Although most integration approaches reviewed in Section 3.1.2 employ models with a long-term time horizon, these often trade off temporal resolution due to computational constraints (see Section 2.4.2). In contrast, Calliope operates over a shorter time horizon while offering high temporal granularity, making it more suitable for analysing energy systems dominated by intermittent renewable energy sources such as wind and solar (Calliope contributors, 2020). Additionally, Calliope’s Python-based architecture supports seamless integration and harmonisation of datasets, facilitating the automation of input parameters and the incorporation of literature-based data. This feature is particularly valuable for aligning life cycle inventory data with the energy system model, as well as for generating scenarios in a structured and consistent manner.

Another strength of Calliope is its ability to integrate LCA indicators directly into the model formulation. For instance, the Calliope framework enables the definition of environmental indicators—such as LCA impact categories—as part of the objective function through its "cost class" functionality. This means, the target function of the model could be defined to minimise total system costs or to minimise any LCA impact categories (e.g., total greenhouse gas emissions) (see Figure 3.4). The mathematical formulation is shown in Equation 3.1, which describe the target function (z) in terms of costs (e.g., fixed and variable) per technology (tech) and location (loc). The parameter $weight_k$ sets the cost class target. The target function minimises total system cost for specified cost class or a set of cost classes.

$$\begin{aligned} min: z = & \sum_{loc::techcost,k} (cost(loc :: tech, cost = costk) \times weight_k) \\ & + \sum_{loc::carrier,timestep} (unmet\ demand(loc :: carrier, timestep) xbigM) \end{aligned} \tag{3.1}$$

According to Calliope documentation:

“The cost_class is a string or dictionary. If a string, it is automatically converted to a dictionary with a single key:value pair where value == 1. The dictionary provides a weight for each cost class of interest: cost_1: weight_1, cost_2: weight_2, etc. If unmet_demand is in use, then the calculated cost of unmet_demand is added or subtracted from the total cost in the opposite sense to the objective.” (Calliope contributors, 2013). Strings and dictionaries are data structures in Python used to store and manage information.

This thesis defines a set of cost classes as a dictionary (see Figure 3.4), where each element represents an LCA indicator with an assigned weight (e.g., 0 or 1). If the optimization is based on monetary values (Euros), the weight for monetary is set to 1. If the optimization is based on global warming potential (GWP), the weight is set to 1, while all others are set to 0. For instance, in this thesis, the string has the structure shown in Figure 3.4. This capability supports the thesis's aim of embedding comprehensive environmental impacts into energy system analysis, to assess trade-offs between cost and environmental impacts.

```
model:
    name: ESM-LCA (EU)
    calliope_version: 0.6.10
    timeseries_data_path: 'timeseries_data'
    subset_time: '2030'

                                                    LCA impact categories
run:
    objective_options.cost_class: {'monetary': 1,'Global warming potential':0, ..., 'Human toxicity':0}
```

Figure 3.4 Example of the model definition when setting cost classes in the Calliope framework

Source: Based on Calliope contributors (2013)

Moreover, the Calliope framework offers flexibility in defining technologies and the spatial configuration of the system. For instance, countries can be disaggregated into regions, improving geographical resolution—an important consideration for this thesis, as the technical, economic, and environmental inputs in the energy system model must be aligned with the system boundaries defined in the LCA.

3.5 Summary

Energy system models (ESMs) can evaluate climate change mitigation strategies, yet their treatment of emissions is characterized by notable limitations. First, emissions are typically assessed using emission factors that do not account for the full life-cycle emissions of technologies. Second, most ESMs focus predominantly on carbon dioxide (CO_2), while other greenhouse gases are often omitted or only marginally represented. Even in cases where models include a broader range of greenhouse gases, the primary emphasis remains on climate change. In contrast, Life Cycle Assessment (LCA) offers a more comprehensive environmental perspective by evaluating multiple impact categories across a product's entire life cycle. However, LCA lacks techno-economic parameters and does not reflect the system-level dynamics modelled in ESMs.

The analysis of existing integration approaches reveals that modelling frameworks used to combine LCA, and ESMs vary significantly in structure, scope, and methodological features. Despite their diversity, these approaches share a common objective: supporting the assessment of the energy transition. Integration approaches cover a wide range of models and sectors. For instance, a significant number of studies adopt optimization-based models at national, regional, or global scales.

In terms of model types, bottom-up models are more frequently used due to their ability to provide detailed technological resolution, which is crucial for linking with LCA inventories. Furthermore, multi-sector energy system models have become the preferable option to evaluate the electrification of the sectors. These models allow for a more comprehensive assessment of cross-sectoral interactions and emissions. Time horizon and temporal resolution are critical factors in model selection. Long-term models are essential for exploring decarbonization pathways and infrastructure developments over decades. However, they often compromise on temporal resolution due to computational constraints. As the share of renewable energy increases, the importance of capturing short-term system dynamics grows—especially to assess the integration and variability of technologies such as wind and solar power. Thus, short-term models with higher temporal granularity can complement long-term assessments by providing insights into operational feasibility and technology performance under fluctuating conditions. Another relevant criterion in model selection is the flexibility to incorporate environmental indicators. In some frameworks, LCA results are added in a post-processing stage, whereas others allow for the integration of environmental impacts as endogenous elements of the model. The latter is preferable as it enables direct trade-offs between economic and environmental objectives. Effective integration demands future-oriented LCA inventory data.

Considering these factors, the selected model in this thesis strikes a balance between technological detail, temporal resolution, and flexibility in incorporating LCA indicators. This ensures a meaningful integration of life cycle-based environmental impacts into energy system modelling, supporting more informed decisions for the energy transition.

Despite the diversity of models and methods, certain trends emerge. For instance, the inclusion of renewables tends to reduce CO_2 emissions but may introduce burden-shifting to other impact categories (e.g., resource use, land use). Social aspects are typically absent, and techno-economic models often fail to capture end-user behaviour, which is crucial in demand-side management strategies. The integration of LCA into ESMs represents a promising pathway for enhancing the environmental robustness of energy transition analyses. While this interdisciplinary effort has already yielded valuable tools and methodological frameworks, substantial challenges remain.

4 Implementation of the integration approach for offshore wind

This chapter describes the implementation of the modelling approach to create a coherent integration of an energy system model and life cycle assessment (ESM-LCA). As the objective of this thesis is to demonstrate the integration of LCA into ESMs and provide an example of how to address integration challenges, this chapter clarifies the key considerations in defining, selecting, and combining input data relevant to the methodological approach. The Calliope framework (see Section 3.5) provides the basis for constructing energy systems utilizing building blocks that contain technical, environmental and economic input data. These data are defined to ensure consistent scenarios. The purpose of this thesis is to develop an exemplary case study that demonstrates the integration of an ESM with LCA. The resulting integrated model constitutes a simplified representation of the European electricity system, which in this thesis is referred as the ESM-LCA model, and it is designed to illustrate the methodological and analytical implications of such integration. While the approach is adaptable to a broader regional context, the present thesis focuses specifically on Germany. In particular, it explores how potential developments in the offshore wind sector can be incorporated into the integrated ESM-LCA model to assess their environmental implications within future energy scenarios. Overall, this chapter aims to answer the question:

- How can future input parameters, particularly those related to offshore wind, be derived and applied within an integrated ESM-LCA modelling approach?

This chapter is organized as follows: Section 4.1 outlines the integration approach, providing an overview of the approach used in this thesis. Section 4.2 introduces the consideration regarding offshore wind in the context of this thesis. Section 4.3 discusses the model's system boundaries. Section 4.4 presents relevant input parameters (i.e., electricity demand, wind and solar resources, technical, economic and environmental parameters). Section 4.5 outlines the scenarios narratives, and the last section addresses the limitation of the study.

4.1 Description of the integration approach

Informed by the findings of the previous chapters, the modelling framework used in this thesis is selected. Accordingly, this section presents two key aspects of the present thesis. First, essential features of the model selected, which are presented in Section 4.1.1. Second, the description of the systematic process to compile and harmonise input data, which is outlined in Section 4.1.2. The clarification of these two aspects is essential to achieve the objectives of this thesis.

4.1.1 Essential features of the modelling framework

Despite the existence of several integration approaches for linking LCA with modelling frameworks, the complexity of assessing future pathways means that no single model can yet comprehensively address all related challenges (IPCC, 2022b). As a result, different modelling frameworks are needed depending on the research scope, data availability, and specific methodological requirements. Ideally, models should be selected based on a well-defined research question (Boyd, 2016b). However, in practice, LCA practitioners and energy system modellers can face constraints that limit their choices. Some may be inclined to develop their own models to meet specific needs, while others are restricted to using only open-source tools. Developing a model from scratch typically requires collaboration within a research team, making it resource intensive. Accordingly, already existing frameworks for building ESMs provide a structured and flexible approach to building energy system models that are sufficiently robust to address specific research questions effectively within the energy sector.

This thesis focuses on integrating LCA into an ESM built on the Calliope framework version 6.10 (Pfenninger & Pickering, 2018) (see Section 3.5) and employs the solver Gurobi version 11.0.12. The model is based on the ESM Stella developed by Jesse et al. (2020), which is extended to simulates the conditions of two target years, 2030 and 2050, with a time resolution of 1 h. The ESM contains 29 interconnected regions and outer regions belonging to the European electricity system (Jesse et al., 2020). Table 4.1 presents the technical characteristics of the modelling framework, including a description of the computational resources used to perform the calculations.

Calliope's mathematical formulation (see, Equation 3.1) defines the objective function based on the minimisation or maximisation of the total costs associated with a specific cost class or a combination of cost classes[9] (Pfenninger & Pickering, 2018). The cost classes in question comprise the monetary values of various cost components, defined as costs per energy capacity (€/kW), as well as costs per carrier (€/kWh), where a carrier (energy carrier) refers to a substance that stores energy and can be converted into usable energy. Furthermore, cost classes can also represent emissions or LCA indicators.

Table 4.1 Technical characteristics of resources utilized in the context of this thesis

Models	Technical characteristics
ESM	Calliope version 6.10. Solver: Gurobi Optimizer version 11.0.12 build v11.0 2rc (linux64) CPU model: Intel (R) Xenon (R) Gold 6154, 36 physical cores and 72 processors, using up to 8 threads.
LCA software	Activity browser version 2.10 Prospective databases based ecoinvent 3.7.1 derived by Premise version 2.1.0. LCIA EF 3.0 (all categories included)

This thesis employs PREMISE (see Section 3.4.1) to derive prospective LCA impact categories belonging to the impact assessment method EF 3.0 (see section 4.4.5 and Table 4.2). These categories are integrated into the ESM as cost classes. For instance, the cost class "GWP" is indicative of the impact category climate, through the LCA indicator of Global Warming Potential. Thus, kg CO_2-eq/KW represents GWP coming from the technology's infrastructure and kg CO_2-eq/kWh represents GWP coming from the technology's operation. Calliope employs linear programming (LP) or mixed-integer linear programming (MILP) approaches, depending on the level of detail and constraints defined within the system. While certain constraints (e.g., unit capacity) enable the definition of technologies with more specific features, they convert the problem into a MILP[10] formulation. This approach, however, comes at the expense of increased computational complexity and longer resolution times.

The Calliope framework provides pre-defined building blocks to represent elements of an ESM (Calliope contributors, 2020; Pfenninger & Pickering, 2018). These elements include carriers, resources,

[9] https://calliope.readthedocs.io/en/stable/user/ref_formulation.html

[10] https://calliope.readthedocs.io/en/stable/user/advanced_constraints.html#binary-and-mixed-integer-constraints

technologies that contain technical, economic, and environmental input parameters, decision variables, constraints, and sets or indexes that interact with the model's mathematical formulation. For instance, *carriers* cluster technologies within the same commodity network (e.g., heat or electricity). The *resources* are sources or sinks of energy, defined exogenously through time-series files or static values. They represent the available energy (kWh), energy per area (kWh/m^2), or energy per power capacity (kWh/kW) that a supply technology can introduce to the system at a given time. Table 4.2 shows predefined building blocks that can be used to define *technologies* to produce, consume, convert or transport energy. A supply technology extracts energy from a resource and provides it to an energy carrier. Conversion technologies convert the energy carrier into other forms such as heat and electricity, which can be transmitted, stored, or consumed. The model defines technology with arbitrary characteristics, which requires three types of inputs: essentials, technical constraints, and costs. Finally, *location* contains the technologies and supplies for a given area (e.g., country, region, etc.).

Table 4.2 Terminology in the Calliope python framework

Carriers	Resources	Technologies	Locations
Electricity, heat, fuels.	Static Dynamic (timeseries files)	*Predefined technologies:* Supply Supply plus Demand Storage Transmission Conversion Conversion plus	List of technologies, resources, carriers within a site (country, region, sector, etc) and their links to other locations.

Source: Based on Calliope contributors (2020)

Figure 4.1 summarizes the ESM-LCA integration framework. First, the demand and energy carriers are defined. In this thesis, the demand refers to the hourly electricity demand in each country within the ESM. The demand is represented as a time series, thereby defining the temporal scope of the ESM and consequently determining the target year (see Section 4.3.1). Regarding resources, energy carriers refer to the fuels (e.g., hard coal, lignite, natural gas, hydrogen, etc.), which are employed by technologies to generate electricity. In contrast, the availability of solar and wind resources at each location is represented through capacity factors (see Section 4.3.2). The definition of these resources is contingent upon key characteristics, including resource availability, lifetime, interest rate, and costs sourced from literature values. Interconnectors in the ESM serve as a simplified representation of transmission grids. In addition to monetary costs, their distances are estimated based on geographical references and transmission capacities based on (Jesse et al., 2020). It is acknowledged that such interconnector representations are inherently approximate, in view of the complexities inherent in real-world transmission networks.

Calliope facilitates the creation of different types of components within an ESM in technology groups that share common technical or economic characteristics. In this thesis, the technologies within the ESM are therefore categorised by fuel groups that share common characteristics such as efficiency, lifetime, and capacity. Due to variations in the level of detail, the majority of the technical characteristics of the technologies are adapted based on the descriptions provided in the LCA inventories documentation and literature sources (see Section 4.4.3). Although prospective databases are employed to calculate environmental impact indicators, the technical parameters of the input data in both the LCA and ESM are consistent. This is ensured through cross-referencing data from the inventory documentation with values sourced from the literature (see Section 4.4.5).

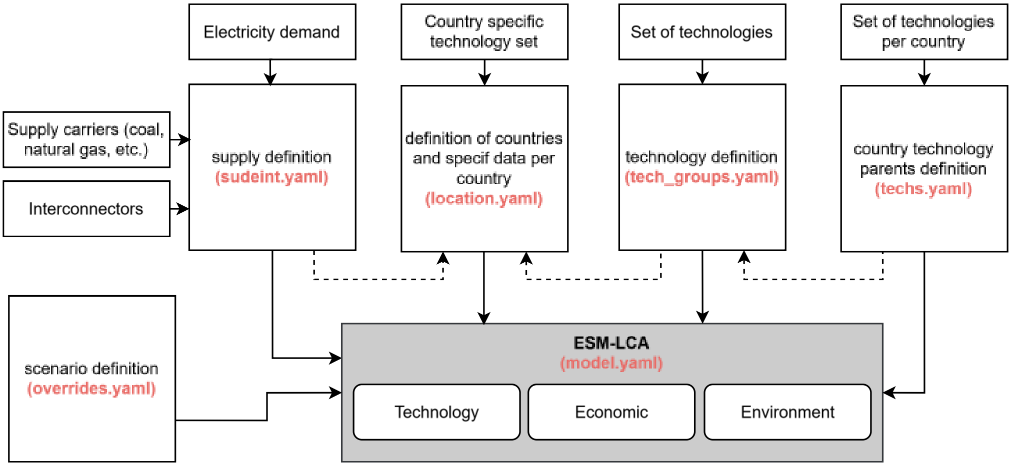


Figure 4.1 Calliope framework and building blocks
Input parameters are defined within yaml.files (in red colour)

Source: Own representation

The ESM employs a geographical coordinate system to represent each location as a node, with latitude and longitude corresponding to an arbitrary location within the country under consideration. These coordinates are then utilised by the model to estimate distances between interconnected transmission grids. Additionally, this thesis employs country-specific interest rates to standardize cost data across different timeframes, as the values are sourced from literature covering various periods. To maintain consistency with the technical assumptions, cost data are scaled up based on the nominal capacity of generation units (see Section 4.4.2).

The environmental burdens associated with the operation phase include fuels and maintenance activities. These values are calculated at the country level, as the LCA inventory provides datasets that reflect the operation of power plants in different locations. For instance, although the infrastructure for renewable and fossil-fired power plants remains consistent across countries, as they represent a standard technology at the European level, operational differences arise due to location-specific resources. This includes variations in solar and wind availability for renewable technologies, as well as differences in the chemical composition of fuels (e.g. water content) depending on their origin. Consequently, the environmental burdens associated with power plant operations are determined at the country level.

Scenario analyses are enabled through the use of override options (see Figure 4.1), which allow for the variation of input parameters in alignment with predefined scenario narratives. This functionality supports the exploration of alternative futures by modifying key assumptions such as technology performance, resource availability, or policy constraints. Finally, all input parameters are defined within YAML files (highlighted in red in Figure 4.1). This methodological approach guarantees that the construction and documentation of the model are carried out in a clear, transparent, and reproducible manner.

4.1.2 Systematic management of input parameters

The present thesis focuses on the management of input parameters that are relevant to LCA and ESM. Input data refers to the information used in a model to produce meaningful results, encompassing the environmental, economic, and technical parameters necessary for integrating LCA into the ESM. While the input data required by LCA and ESM may be similar, they can present variations in format and level of detail (see Section 3.2.1). Thus, a careful interpretation of the underlying assumption within economic, technical and environmental input parameters is necessary to ensure accurate representation. Accordingly, this involves addressing geographical, temporal and technological discrepancies within LCA and ESM input data by establishing consistent and harmonised assumptions when defining the model's environmental, economic, and technical aspects. The harmonisation of input data thus renders a consistent ESM-LCA framework, which represents a simplified version of the European electricity system.

The collection of input data relevant to the integration approach that combines the ESM and LCA involves analysing of the ESM requirements. For instance, the Calliope framework stores all the relevant information in YAML files (see Figure 4.1). Setting up these YAML file requires extensive data processing. Consequently, an important contribution of the present thesis is an extensive data collection and the development of a systematic process through Python scripts to organise, sort and harmonise data, which are compatible with the model facilitating the creation of YAML files. For instance, a vast number of data have been collected, this data for instance refers to installed capacity values from the year 2015 to 2023 of the 29 countries belonging to the ESM per production technology. As well as time series data representing load at 1 h resolution from the year 2015 to 2023 of the electricity demand of 29 countries. The collection and evaluation of these data is fundamental to assess the current situation of the European electricity sector and to define the technologies that are included per location in the ESM. Accordingly, in this thesis, the term technology set is employed to denote the technologies that are available per country.

As the ESM incorporates renewable energy resources, time series data representing capacity factors for offshore wind, onshore wind and solar are sourced from the existing literature. However, the time series are processed in order to adjust their timeframe to the target years and scenarios. Furthermore, given the focus of this thesis on offshore wind, Python scripts have been developed to estimate the annual production of electricity per offshore wind turbine nominal capacity at a given location. This denotes the processing of wind speeds over time, in conjunction with the calculation of power output according to power curves.

A comprehensive set of economic data, including inflation and interest rates, has been collected for the countries within the ESM-LCA model over the past nine years. The data has then been processed to obtain their average values per country. Furthermore, capital expenditure and operational expenditure on the technologies are collected. In the context of offshore wind energy, these values are subjected to scaling up. The cost reduction that is attributable to learning effects is estimated on the basis of expected global offshore wind deployment and inflation.

The management of life cycle inventory data corresponding to the technologies included in the ESM-LCA model is achieved through the utilisation of Excel files. These files contain prospective life cycle inventory data for each process, year and scenario. The Excel files under discussion are known as the 'scenario difference files' (SDFs), which belong to the superstructure approach (Steubing & de Koning,

2021) and are obtained via PREMISE (Sacchi, 2023). Subsequently, Python scripts are developed to process and incorporate LCA indicators into the ESM-LCA model.

4.2 Offshore wind energy within the ESM-LCA model

Section 2.3 describes offshore wind as a one key low-carbon technology and highlights the promising technological advancements that have enabled substantial growth in its components. Nevertheless, despite the ongoing efforts to derive prospective life cycle inventories using tools such as PREMISE (see Section 3.4.1), these prospective inventories may not fully capture all expected technological changes. A clear example of this limitation is provided by the case of offshore wind. While commercial databases such as ecoinvent (Wernet et al., 2016) provide offshore wind turbine inventories, these are often based on older technologies. As PREMISE relies on the existing ecoinvent database, and unless new or external inventories are integrated, it will use by default the current available ecoinvent data as proxies. For instance, at the time of developing this thesis, the prospective inventory for offshore wind turbines generated using PREMISE primarily relies on the 2 MW offshore wind turbine model. The adjustments made are largely limited to updates in background processes—such as revised energy mixes for steel production—while no new or updated foreground inventory reflecting recent offshore wind turbine technologies is included.

Table 4.3 Offshore wind turbines technical features considered in different frameworks

	Offshore wind						
Parameters	**LCA (ecoinvent 3.7.1)**	**Capacity factors (Ninjas)**	**CAPEX**	**Added (ESM-LCA model)**			
Capacity, MW	2	3.6	3 to 6	7	9.5	11	15
hub height, m	78	87	-	77	100	100	118
rotor diameter, m	80	107	117 to 154	154	164	200	236
cut-in wind speed, m/s	4	4	-	3	3	4	3
nominal wind speed, m/s	16	13.5	-	13	12	14	11
cut-of wind speed, m/s	25	25	-	25	25	32	30

CAPEX represents offshore wind turbines with annual full load values between 3,200 and 4,500 hours. Technical features retrieved from https://en.wind-turbine-models.com/

Source: based on Dones et al. (2007); Müller (2021); Tröndle and Pfenninger (2020)

In a similar manner, the estimation of time series data reflecting wind resource availability is contingent on assumptions regarding offshore wind turbine specifications. For instance, capacity factor datasets derived from Tröndle and Pfenninger (2020) are based on simulations using a representative offshore wind turbine from 2018, specifically a 3.6 MW model. Depending on the location, these time series represent capacity factors between 30 % and 40 %, while as offshore wind technology matures, capacity factors of up to 50 % can be achieved (Wiser et al., 2021).

From an economic perspective, capital expenditure (CAPEX) represents a significant proportion of the overall cost structure of offshore wind projects (see, section 2.3.3). According to Fingersh et al. (2006), CAPEX can be estimated based on key turbine design parameters, including rotor diameter, nominal capacity, and hub height. These physical characteristics directly influence material requirements, engineering complexity, and installation logistics. For instance, CAPEX values provided by literature represents a wind turbine rating 3 to 6 MW, which features rotor diameters between 117 m and 154 m (Fraunhofer, 2021). This underscores the necessity for capacity factor estimations, costs and prospective LCA indicators to be aligned with contemporary technological advancements in the field of offshore wind energy. As illustrated in Section 2.3, the nominal capacity of offshore wind turbines has increased significantly, and future representative units are expected to average around 10 MW, with a range spanning from 7 MW to 15 MW (see Table 4.3).

For this reason, the present thesis places particular emphasis on the offshore wind sector. Consequently, prospective life cycle inventories incorporating adjustments to both the foreground and background systems for offshore wind turbines have been developed. The prospective inventories include offshore wind turbines with nominal capacities of 7 MW, 9.5 MW, 11 MW, and 15 MW (Benitez et al., 2024).

Overall, the integration of offshore wind in the ESM-LCA model involves generating new inventory data that reflects anticipated technological advancements in the offshore wind sector, while simultaneously adapting technical and economic parameters to enable the integration of these offshore wind turbines within the energy system model.

4.3 System boundaries

This section provides an overview of the system boundaries of the integration approach, encompassing its geographical, temporal, and technological coverage. The purpose is to clarify the assumptions regarding the countries included in the model, the target years of the modelling framework, and the key technologies considered.

4.3.1 Geographical coverage

As mentioned above the ESM-LCA model represents 29 core regions and eleven outer regions (Jesse et al., 2020). The core regions consist of European countries, plus Norway and Switzerland, excluding Malta and Cyprus. Despite the Brexit, the United Kingdom is part of the model because it remains interconnected with the European electricity system through the transmission grid (GOV.UK, 2013). The outer regions include Albania, Bosnia, Belarus, Cyprus, Montenegro, North Macedonia, Serbia, Ukraine, Morocco and Russia. However, countries in the outer regions are only roughly represented by a single technology that supplies electricity (Jesse et al., 2020). Regarding the geographical resolution, each country is represented by a node, with individual nodes interconnected through transmission grids. Figure 4.2a shows the regions considered in the ESM. The latter is flexible regarding the definition of geographical coverage and resolution; the ESM-LCA model can add infinitely nodes for defining locations. However, the geographical resolution is constrained by the input data. For example, capacity factors for solar and wind can be derived from separate atlases, each with its own spatial resolution (e.g., 2.5 km x 2.5 km, or 27 km x 9 km x 3 km). To reduce computational effort, the model uses timeseries data such as capacity factors, electricity demand that represents average values per hour of each country. For instance, time series representing capacity factors for solar and wind resources are based on a 50 km^2 grid in Europe (Tröndle et al., 2019).

From an LCA perspective, the geographical coverage depends on the regions included in the prospective inventory data (Sacchi, 2023). Although these databases provide data for multiple regions, an exact representation is not always possible (see Section 3.2.1 and Section 3.4.1). For instance, most infrastructure inventories consider generic power plants that are representative of the European region (see Table 4.6). Consequently, LCA data for infrastructure include representative technologies for the region of Europe (RER) when available or datasets representing average global production (GLO) (see Figure 4.2b). However, LCA data for operation are available for several individual countries. To address geographical mismatches, prospective and region-specific inventories for the operation are used whenever available, ensuring alignment with the countries represented in the ESM (see Figure 4.2c).

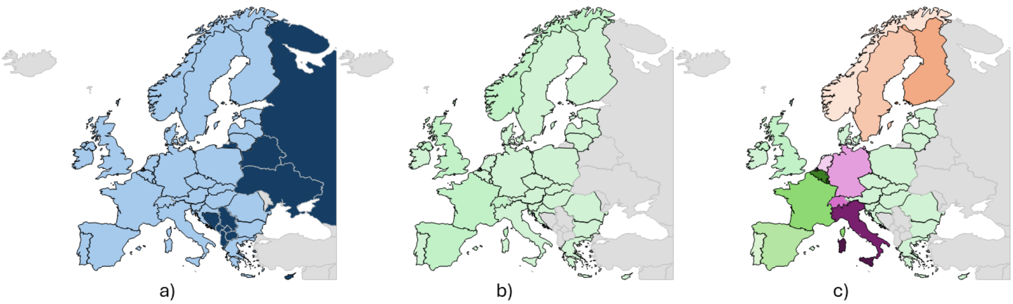


Figure 4.2 Geographical coverage assumed in this thesis
a) Geographical coverage in the ESM representing core regions (light blue) and outer regions (dark blue); b) Geographical considerations of LCA data representing infrastructure as considered in the ESM (light green), which represents a generic location depending on the technologies common for all the countries; c) The geographical coverage of the LCA indicators for the operation phase is defined at the country level, aligning with the geographical scope of the core regions in the ESM

Source: Based on Jesse et al. (2020)

4.3.2 Temporal coverage

This section discusses the consideration regarding the temporal scope of the study. The ESM-LCA model evaluates three target years—representing the European electricity system under current conditions, as well as in 2030 and 2050, with 1 h resolution. Data is collected from different sources (ENTSO-E, 2024a; OPSD, 2020). However, due to disruptions caused by the COVID-19 pandemic and the war in Ukraine—followed by economic deceleration affecting multiple countries in the region, including Germany—unusual variations are observed in key parameters such as inflation, interest rates, and electricity demand. Therefore, this thesis employs average values from recent years to account for these fluctuations (see Table 4.4). Additionally, compromises are necessary when compiling data from various sources, as they often originate from different time periods. Consequently, the term *current* does not refer to a specific year but rather represents the prevailing conditions in the countries included in the ESM. The year 2019 is used as a reference for timeseries representing current electricity demand, installed capacities and capacity factors, while costs are adjusted to present values (e.g., 2024). Electricity demand dropped in the years following the COVID-19 pandemic due to the resulting economic recession. For instance, annual electricity generation in Germany after 2019 did not recover to pre-pandemic values by 2023 (see Figure 4.3). As a result, the year 2019 is selected as a proxy for typical electricity demand, as it reflects pre-pandemic conditions and avoids distortions caused by the temporary downturn.

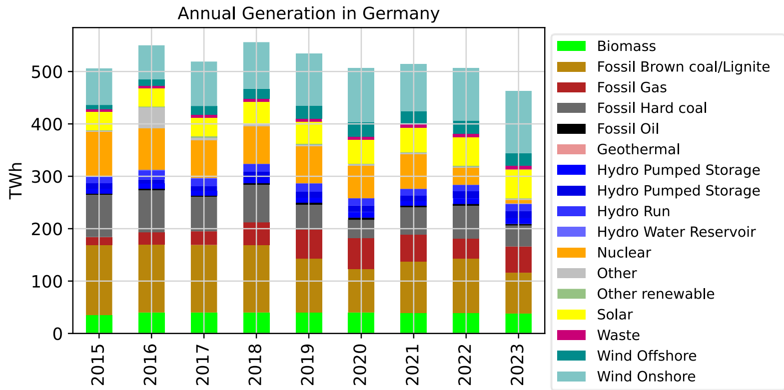


Figure 4.3 Historical annual generation in Germany.

Source: Based on ENTSO-E (2015)

The ESM-LCA model reflects the future conditions of the European electricity system in 2030 and 2050. For which, relevant input data are projected to represent future conditions. For instance, LCA indicators of technologies within the ESM-LCA model represents future environmental burdens for each target year (see, Section 4.5). The input parameters used to describe the economic aspects of the ESM-LCA model are sourced from the literature. To ensure consistency with the temporal framework of the ESM-LCA model, average interest rates and inflation rates are applied to adjust the monetary values to the target years considered in the model (see Section 4.4).

Table 4.4 Input data time coverage

Input parameter	**Time range**	**Assumption**	**Source**
Interest rate	2014 to 2023	Average per country	(EUROSTAT, 2025b)
Inflation rate	2014 to 2023	Average per country	(EUROSTAT, 2025a)
Installed capacities per country	2015 to 2023	Average installed capacity per technology per country	(ENTSO-E, 2024a)
Electricity demand	2019	Hourly average	https://transparency.entsoe.eu/load-domain/r2/totalLoadR2/show
Capacity factors (wind and solar)	2019	2019	www.renewables.ninja (Pfenninger & Staffell, 2016; Staffell & Pfenninger, 2016; Tröndle et al., 2019)

4.3.3 Technological coverage

As the energy system model employed in this thesis is based on the pre-existing Stella model (Jesse et al., 2020), the technologies defined in Stella are retained. Additionally, new technology sets, including different sizes of offshore wind turbines, are incorporated. Overall, this thesis assumes that currently existing technologies within the European electricity system will remain available in the target years. The installed capacity (GW) for each production technology and country is determined based on historical data (ENTSO-E, 2024a). For instance, Figure 4.4 shows the evolution of installed capacity by energy carrier for Germany, France and Italy, showing each country's electricity mixes. Future power plant mixes are aligned with national energy policies, such as the phase-out of hard coal, lignite, and nuclear power plants (see Table 4.5). While the technology set (see Table 4.6) remains unchanged for 2030 and 2050, key parameters such as efficiency, cost, and environmental indicators evolve depending on the year and scenario.

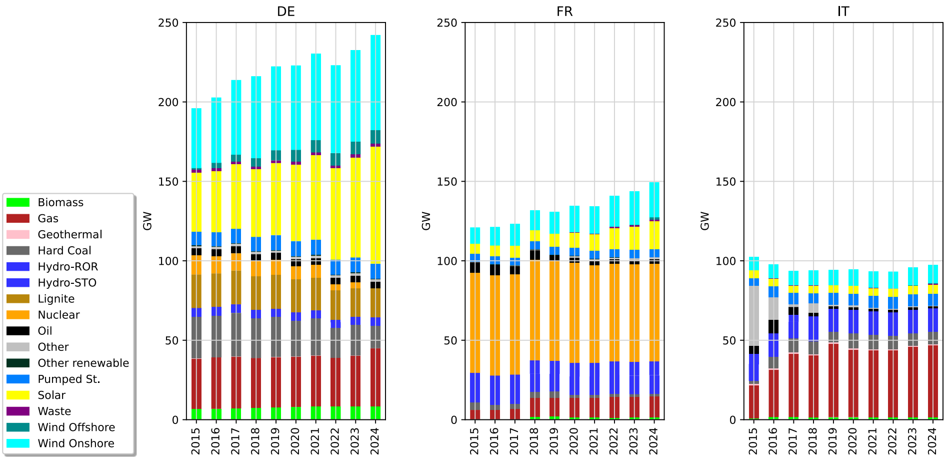


Figure 4.4 Production technologies per country from 2015 to 2024
Germany (DE), France (FR) and Italy (IT). ROR refers to run-of-river, STO refers to reservoir with storage hydropower plants.

Source: Based on ENTSO-E (2024a)

Technological improvements are accounted for through cost reductions driven by learning effects, particularly for solar and wind energy. Improvements over time are reflected in the LCA databases through efficiency improvements, regionalized inventories for fuels and electricity mixes that align with the conditions of the target years. Moreover, the model incorporates offshore wind turbines with capacities ranging from 7 MW to 15 MW. However, the infrastructure for offshore wind turbines is primarily representative of wind turbines with monopile foundations (see Section 2.3). The ESM optimizes and selects the most suitable technology mix for each target. While emerging technologies are not included, they can be incorporated into the model. This thesis omits carbon capture technologies for two primary reasons. First, in Germany, carbon capture is expected to be deployed primarily in sectors with unavoidable emissions, such as heavy industry, rather than in the electricity sector (Prognos et al., 2021). Second, this thesis assumes that most countries will phase out fossil fuel-based power generation in the coming decades, as announced by Beyond Fossil Fuels (2025). Given these considerations, the integration framework focuses on technologies aligned with decarbonization pathways that emphasize renewable energy expansion and fossil fuel phase-out. Additionally, hydrogen from electrolysis is considered as energy carrier as potential replacement of natural gas in gas power plants.

Table 4.5 Targets for coal and nuclear phase-out and the share of renewables in electricity generation

Country	Code	nuclear-free 2030	nuclear-free 2050	coal-free 2030	coal-free 2050	Share renewables 2030	Share renewables 2050
Austria	AT	-	-	yes	yes	100 %	100 %
Belgium	BE	no	yes	yes	yes	18.00 %	?
Bulgaria	BG	no	yes	no	yes	35 %	?
Switzerland	CH	no	yes	yes	yes	50 %	?
Czechia	CZ	no	no	no	yes	30 %	?
Germany	DE	yes	yes	no	yes	70 %	90%
Denmark	DK	-	-	yes	yes	100 %	100%
Estonia	EE	-	?	yes	yes	100 %	100%
Spain	ES	no	yes	yes	yes	80 %	?
Finland	FI	no		yes	yes	53 %	?
France	FR	no	no	yes	yes	42.50 %	?
United Kingdom	UK	no	no	yes	yes	40 %	?
Greece	GR	-	-	yes	yes	82 %	?
Croatia	HR	-	?	no	yes	42.50 %	?
Hungary	HU	no		yes	yes	30 %	?
Ireland	IE	-	-	yes	yes	70 %	?
Italy	IT	-	-	yes	yes	72 %	?
Lithuania	LT	-	-	yes	yes	100 %	?
Luxembourg	LU	-	-	yes	yes	25 %	?
Latvia	LV	-	-	yes	yes	50 %	?
Netherlands	NL	no	?	yes	yes	39 %	?
Norway	NO	-	-	yes	yes	98 %	?
Poland	PL	no	no	no	yes	53 %	?
Portugal	PT	-	-	yes	yes	85 %	?
Romania	RO	no	no	no	yes	34 %	?
Sweden	SE	no	no	yes	yes	65 %	?
Slovenia	SI	no	no	no	yes	27 %	?
Slovakia	SK	no	no	yes	yes	27 %	?
Europe	EU	no	no	no	yes	42.50%	100%

(?) indicates no clear targets; (-) countries without nuclear power plants

Source: Based on Beyond Fossil Fuels (2025); Friedrich-Ebert-Stiftung e.V. (2024)

As discussed in Section 3.2.1, the level of technological detail differs between the ESM and LCA. Since the ESM represents the European electricity system, representative generation units are defined for each energy carrier, such as combined heat and power (CHP) plants and power-only plants (PP) (Jesse et al., 2020). Table 4.6 illustrates the correspondence with the respective LCA inventories. This thesis considers hard-coal power plants with three nominal capacities: 100 MW, 500 MW, and 388 MW, covering CHP and PP plants. Hydropower plants include three technology types: run-of-river (ROR), reservoir storage (STO), and pumped storage. Reservoir storage comprises facilities in alpine regions (e.g., France, Switzerland, Italy, Germany, Austria, and Slovenia) and non-alpine regions (e.g., Norway). Natural gas technologies comprise three types: open-cycle gas turbines (OCGT), steam turbines (boiler-based systems using natural gas), and combined-cycle gas turbines (CCGT). Biogas power plants implement co-generation (CHP) units. Regarding nuclear energy, the models assume both pressurized water reactors (PWR) and boiling water reactors (BWR) while omitting small modular reactors also known as SMRs. The category "other fuels" includes a mix of technologies with a minor share, which are challenging to classify. This thesis assumes that the infrastructure for these technologies is similar to that of oil power plants. Ground-mounted photovoltaic (PV) plants (i.e., utility-scale), rooftop solar panels, and concentrated solar power (CSP) represent solar power technologies. Finally, wind power includes both onshore and offshore wind turbines, considering current models and those expected to be operational by 2030.

Table 4.6 Technology set considered in this thesis with the availability installed capacity units

Fuel group	**ESM**	**LCA (infrastructure)**	**MW**
Hard coal	CHP and PP	hard coal power plant construction (GLO)	100
		hard coal power plant construction (GLO)	500
		market for hard coal power plant (GLO)	380
Lignite	CHP and PP	lignite power plant construction (RER)	380
Natural Gas	CHP and PP		
	Open cycle gas turbine	gas turbine construction, electrical (RER)	10
	Steam turbine	gas power plant construction, electrical (RER)	100
	Combined cycle gas turbines	gas power plant construction, combined cycle, electrical (RER)	400
Biogas	CHP and PP	heat and power co-generation unit construction, electrical (RER)	0.16
Biomass	CHP and PP	heat and power co-generation, biomass wood chips power plant (GLO)	1
Oil	CHP and PP	oil power plant construction (RER)	500
Nuclear	PP	market for nuclear power plant, pressure water reactor (GLO)	1000
		market for nuclear power plant, boiling water reactor (GLO)	1000
Hydro	PP		
	Run-of-River	hydropower plant construction, run-of-river (EUR)	175
	Reservoir storage	hydropower plant construction, reservoir (RER)	237
	Pumped storage	hydropower plant construction, reservoir (RER)	237
Waste	CHP and PP	oil power plant construction (RER)	500
		oil power plant construction (RER)	500

Others	CHP and PP	oil power plant construction (RER)	500
		oil power plant construction (RER)	500
Solar	PP		
	Open ground	market for photovoltaic plant, multi-Si, on open ground (GLO)	0.57
	Rooftop	market for photovoltaic slanted-roof installation (GLO)	0.003
	CSP	market for concentrated solar power plant, solar thermal parabolic trough, (GLO)	50
Offshore wind	PP	Offshore wind turbine 7MW (DE)	7
		Offshore wind turbine 9.5MW (DE)	9.5
		Offshore wind turbine 11MW (DE)	11
		Offshore wind turbine 15MW (DE)	15
Onshore wind	PP	market for wind turbine, 4.5MW, onshore (GLO)	4.5
Hydrogen	PP	gas power plant construction, combined cycle (GLO)	400
Geothermal	PP and CHP	market for geothermal power plant (GLO)	5.5

GLO (global) and Region of Europe (RER) express regional aspects of LCA inventory data. Combined heat and power (CHP); power-only plants (PP)

Source: Based on Wernet et al. (2016)

4.4 Derivation of inputs parameters

Establishing a consistent integration framework for the ESM-LCA model begins with identifying key input parameters. This section outlines the approach used to derive electricity demand and details the assumptions made for projecting input parameters into the future.

4.4.1 Current and future electricity demand

This section explains how current and future electricity demand is determined, as it is a user-defined input in the ESM-LCA model. Time series representing historical electricity demand can be sourced from platforms like the Open Power System Data Source (OPSD) (OPSD, 2020), and the online platform European Network of Transmission System Operators for Electricity (ENTSO-E). The first provides datasets already prepared for being used in ESM (e.g., electricity demand, capacity factors, prices, etc.). The second provides yearly updated time series for all the countries belonging to the European electricity system. For instance, ENTSO-E provides actual load demand time series with hourly resolution. In the context of this thesis, hourly electricity demand of each country within the ESM-LCA is obtained from ENTSO-E. The year 2019 is chosen to represent the demand of the current year (see Section 4.2.2). Figure 4.5 illustrates the electricity demand for Germany, France and Italy with 1-hour resolution. Although Germany's annual average in Germany (500 TWh) is higher than in France (see Figure 4.5d), Figure 4.5b highlights that France experiences the highest peak-hour (80 GW). Additionally, the time series reveals that electricity demand in Germany and France is lower during summer than in winter, the opposite trend is observed in Italy. Overall, Figure 4.5c displays the annual electricity demand for the core regions considered in the ESM-LCA model.

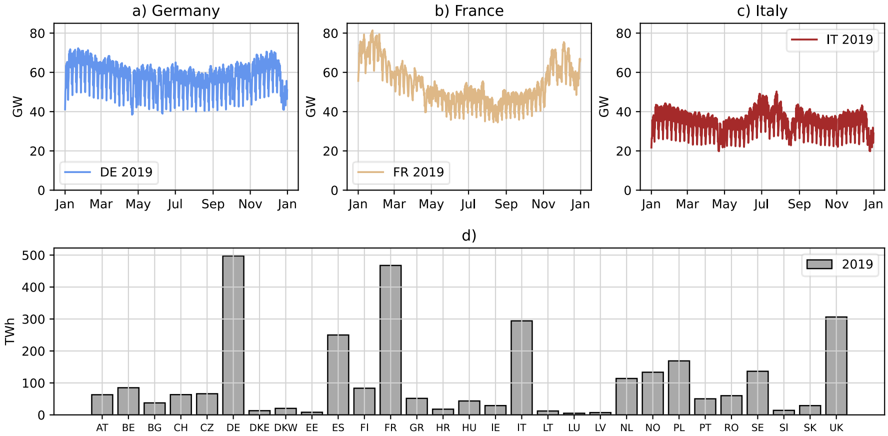


Figure 4.5 Electricity demand representing the current conditions
a) Profile electricity demand in Germany in 2019; b) Profile electricity demand in France in 2019; c) Profile electricity demand in Italy in 2019; d) Annual electricity demand (TWh) for core regions

Source: Own representation data retrieved from (ENTSO-E, 2015)

Section 2.4.3 outlines considerations for projecting future electricity demand, a task that is particularly challenging due to the increasing integration of weather-dependent renewable energy sources (Azeem et al., 2021; Steinborn, 2022). Therefore, future projection of electricity demand is beyond the scope of this thesis. In the context of this thesis, historical data retrieved from ENTSO-E are analysed. Except for Germany, future load demand is estimated using the highest hourly values observed between 2015 and 2023. Consequently, the electricity demand projections for 2030 and 2050 are represented by a time series incorporating these maximum hourly values. In this thesis, the impact of battery-electric vehicles (EVs) and heat pumps on electricity demand is analysed for Germany in a simplified manner. The impact of electric vehicles is estimated based on Hecht et al. (2023), which provides 1-year hourly resolution data for public charging stations. This thesis assumes that by 2030, the number of EVs and public charging stations will increase (see Table 4.7) while maintaining the charging behaviour observed in Hecht et al. (2023). The authors provide insights into charging patterns based on empirical data, which are used to develop an estimated demand profile due to EVs.

Table 4.7 Input parameters future electricity demand in Germany

Model input	**Parameters**	**Unit**	**Current**	**2030**	**2050**
Electricity demand profile	Electric vehicles, annual electricity demand (expected)	TWh	12	74	169
	N° of electric vehicles	million units	-	11.3 to 14.1	28.9 to 30.3
	Ratio PCS to electric vehicles	-	-	1/10	1/10
	Nominal capacity of PCS	KW	-	150,22,11,300	150,22,11,300

Share of PCS capacity	%	-	25,40,10,25	25,40,10,25
Heating, annual demand	TWh	0	120	216

Public charging stations (PCS)

Source: Based on Fraunhofer IWES/IBP (2017); Prognos et al. (2020)

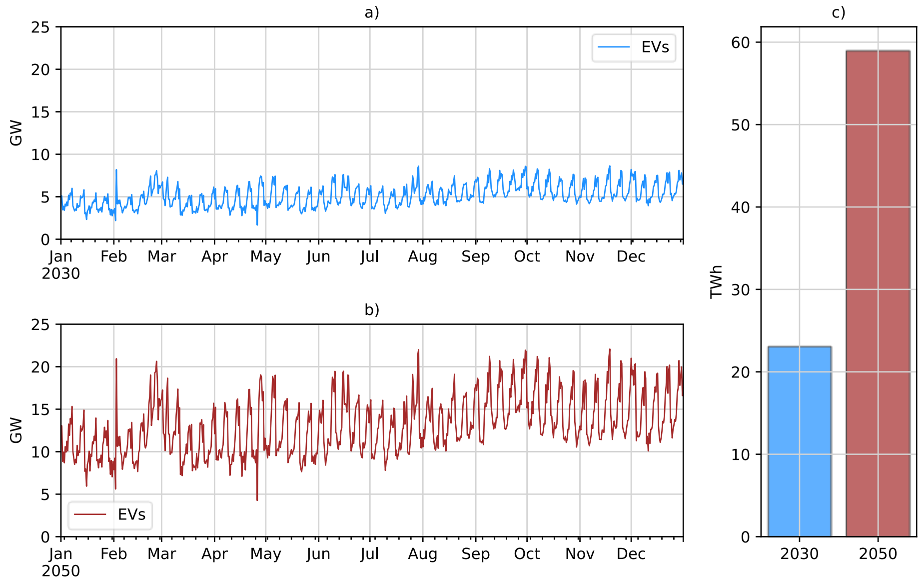


Figure 4.6 Electricity demand due to battery-electric vehicles (EVs) in Germany
a) Year 2030; b) Year 2050; c) Annual electricity demand (TWh)

Source: Own representation

The electricity demand for heat pumps is estimated using national time series that incorporate coefficient of performance (COP) values for different heating sources (e.g., water or space) and sinks (e.g., floor heating, radiators, water heating), heating demand across various building types (e.g., commercial, multi-family, single-family), and heating profiles from When2heat Heating Profiles (Ruhnau et al., 2019; Ruhnau & Muessel, 2019). The COP indicates the amount of heating or cooling delivered per kW of electricity consumed by the heat pump compressor. For example, if a heat pump has a COP of 2, it means that for every 1 kW of electricity consumed by the compressor, 2 kW of heating or cooling is provided. The normalized heat profiles correspond to an average annual demand of 1 TWh (Ruhnau et al., 2019). In the context of this thesis, the year 2019 is used as a proxy and scaled to align with the projected annual heat demand for 2030 and 2050 (e.g., 120 TWh and 216 TWh, respectively) (see Table 4.7). Then, an electricity demand profile is estimated (see Figure 4.7), representing an annual increase of approximately 35 TWh in 2030 and nearly 60 TWh in 2050.

Finally, the total electricity demand (in Germany) is obtained by adding the electricity demand from electric vehicles (Figure 4.6a and Figure 4.6b), heating (Figure 4.7a and Figure 4.7b) to a representative electricity profile, derived by averaging hourly load values corresponding from 2015 to 2023. As result, in 2030, the peak load could reach 87 GW, with an annual electricity demand of 560 TWh (see Figure

4.8b). By 2050, peak load could reach 106 GW, with an annual electricity demand of 618 TWh (see Figure 4.8c).

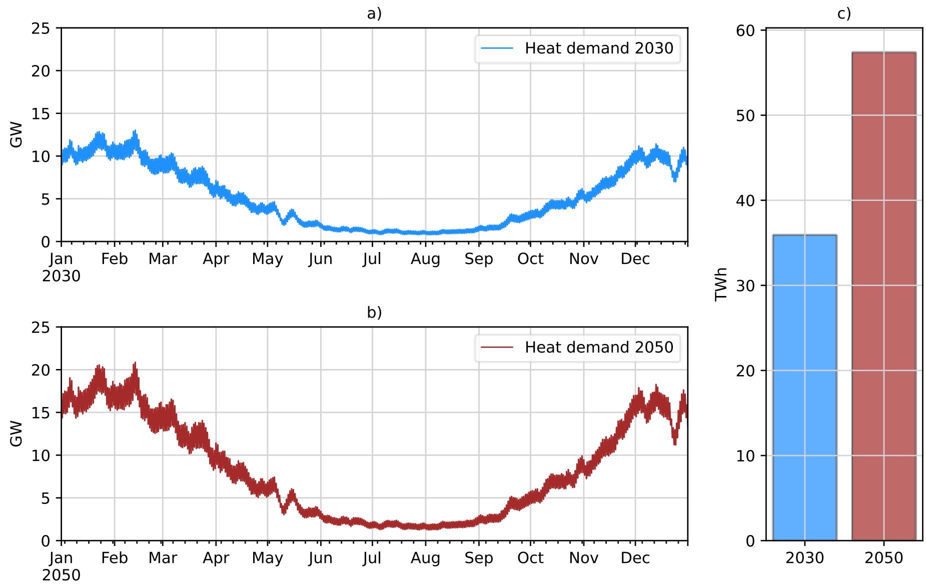


Figure 4.7 Electricity demand due to heating (heat pumps) in Germany
a) Year2030; b) Year 2050; c) Annual electricity demand (TWh)

Source: Own representation

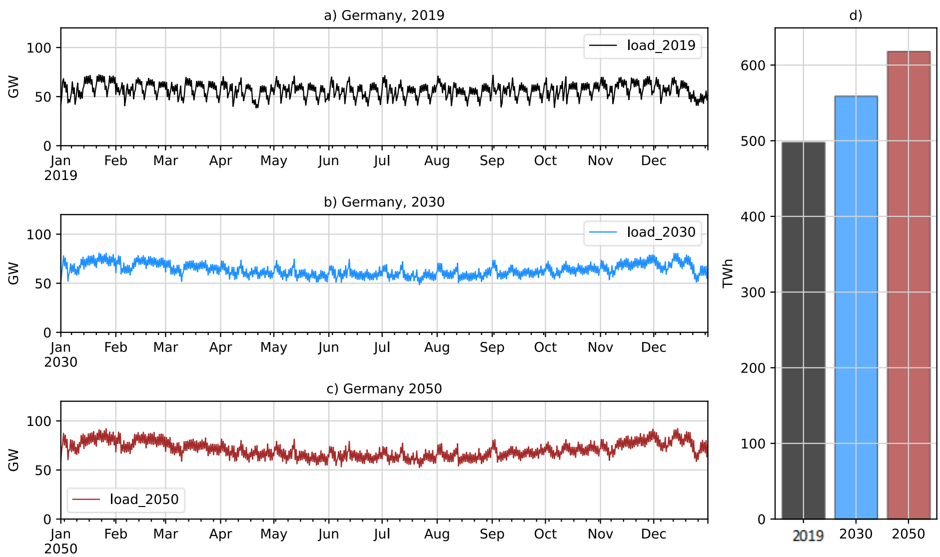


Figure 4.8 Electricity demand for Germany
a) Year 2019; b) Year 2030; c) Year 2050; d) Annual electricity demand (TWh)

Source: Own representation

4.4.2 Wind and solar resources

Time series representing wind and solar power generation capacities are sourced from www.renewables.ninja, which provides bias-corrected capacity factors (Pfenninger & Staffell, 2016; Staffell & Pfenninger, 2016). These datasets for wind power generation represent the simulated operation of wind farms. These simulated capacity factors undergo statistical corrections to ensure that the modelled renewable energy output aligns with observed data; for this reason, they are considered bias-corrected. Furthermore, the datasets reflect wind farms that were either in operation or under construction between 2016 and 2018 (Staffell & Pfenninger, 2016; Tröndle & Pfenninger, 2020). In this thesis, the capacity factors for solar and onshore wind in 2019 are used as a proxy to represent both current conditions and future generations in 2030 and 2050. Adjustments for future conditions (e.g., gradual change of climate) are beyond the scope of this thesis.

For the offshore wind turbines considered in this thesis (e.g., 7 MW, 9 MW, 11 MW and 15 MW; see Section 4.2), the hourly power output is calculated based on a generic power curve. The power output depends on the wind speed, air density, and the technical characteristics of these offshore wind turbines. Therefore, the hourly wind speed and density data for 21 offshore wind sites are obtained from www.renewables.ninja (Staffell & Pfenninger, 2016). The 21 sites shown in Table 4.8 correspond to existing offshore wind farms or designated offshore wind development areas in the 21 different countries considered in this thesis. The geographical coordinates are taken from online databases (The Wind Power, 2025). However, in this thesis, a single geographical coordinate is used to represent the wind distribution for each country. These sites are selected to provide wind speed data at hub heights corresponding to half of the rotor diameters listed in Table 4.3. The generic power curve, as described in Section 2.3.1, is used to estimate the annual energy production of the wind turbines. Specifically, Equation 2.10 is used when the wind speed at a given time falls below the rated operating threshold of the turbine (e.g., wind speed between 3 and 13 m/s depending on the wind turbine). Finally, hourly capacity factors are computed as the ratio of the actual hourly generation to nominal capacity of wind turbines to their nominal capacity.

Table 4.8 Locations of offshore wind farms considered in the ESM-LCA model

Country		Latitude	Longitude
Belgium	BE	51.59	2.94
Germany	DE	54.04	6.20
Denmark	DK	55.70	7.67
Finland	FI	63.79	21.82
France	FR	48.86	-2.54
United Kingdom	UK	53.91	1.55
Ireland	IE	52.79	-5.95
Italy	IT	37.46	11.73
Netherlands	NL	52.72	4.25
Norway	NO	61.33	2.70
Sweden	SE	58.79	19.60
Estonia	EE	58.19	21.26
Spain	ES	43.63	-8.32

Lithuania	LT	55.94	20.47
Latvia	LV	56.82	20.77
Poland	PL	55.52	17.26
Portugal	PT	32.95	-16.46
Bulgaria	BG	42.42	28.59
Greece	GR	40.24	24.92
Croatia	HR	44.83	14.09
Romania	RO	44.29	28.76

The geographic coordinates correspond to wind parks

Source: Based on The Wind Power (2025)

4.4.3 Technical parameters

This section outlines the assumptions regarding key technical parameters of power plants within the ESM-LCA integration approach. These parameters define power plant performance and are essential for modelling electricity generation, costs, and emissions. In this thesis, technologies are categorized based on their energy carriers. The Calliope framework has been developed to facilitate the definition of common technical features of power plants, such as efficiency, nominal capacity, or lifetime. These features are defined in a single file (in *techgroups.yaml*, see Section 4.1), while region- or country-specific variations can be adjusted separately (*location.yaml*, see Section 4.1). These technical parameters include efficiency, lifetime, resource availability, and installed capacity constraints. As LCA inventories that represent infrastructure are provided at the European level, implementing technology groups is consistent with LCA inventories. As result, technical parameters such as efficiency and lifetime match those used in LCA inventories. The fuel supply includes hard coal, lignite, natural gas, oil, biogas, solid biomass, uranium for nuclear energy, a mix of waste, and hydrogen from electrolysis. While the definition of fuels in the ESM requires minimal technical information, such as lifetime, and resource constraints, the LCA inventories demand a more detailed input data specification. This includes lower heating values (LHV) and information about the origin of the fuels, as LHV can vary based on the extraction location. These values are embedded in the databases, which allows the ESM-LCA model to adopt the assumptions provided by the LCA databases (see Table 4.9). Transmission grid capacities are based on Jesse et al. (2020).

Table 4.9 Low heating values (LHV) considered in the study

fuel	LHV (literature)[a)]	LHV in LCA[b)]	Units
Hard coal	23.9 to 25	27	MJ/kg
Lignite	10 to <17.4	11	MJ/kg
Natural gas	42 to 55	45	MJ/kg
Oil	42 to 47	43	MJ/kg
Biogas	30 to 45	23	MJ/kg
Solid biomass	16	19	MJ/kg
Waste	5.2 to 15.21	14	MJ/kg
Hydrogen	120 to 142	120	MJ/kg
Uranium		4,147,200	MJ/kg

Source: a) on own collection; b) based on (Sacchi, 2023)

At the country level, input parameters such as electricity demand (see Section 4.3.1), resources (see Section 4.3.2), and installed capacity constraints are defined. This thesis assumes that technologies such as hydropower, waste, biogas, and biomass power plants will not experience significant growth in the future but will maintain their status. As a result, historical installed capacity values are used as constraints to limit the maximum kW the system can build. Regarding fossil-fired power plants, lignite and oil power plants follow the phase-out trajectory of hard coal power plants, as outlined in Table 4.5. For 2050, this thesis applies targets at the European level. For example, a specific percentage of total electricity demand (e.g., 80 % to 100 %) must be met by renewable energy sources. As for the constrains on solar and wind power, energy potential per region, as well as installed capacity targets at country or global level, are considered to ensure the number and capacity of solar and wind facilities built by the system can remains reasonable.

Table 4.10 outlines the assumptions made in this thesis regarding the installed capacity per unit of the technologies considered. The unit capacity aligns with the assumptions in the LCA inventories and is consistent with the average unit capacity derived from the powerplantmatching database (Gotzens et al., 2019), which includes all existing plants in Europe. Additionally, Table 4.10 presents the values adopted in this thesis for efficiency and lifetime.

4.4.4 Economic parameters

This section outlines the data collected and the assumptions made to define the economic aspects of the ESM-LCA model. Key economic input parameters include capital expenditure (CAPEX), operating expenditure (OPEX), fixed and variable operation and maintenance (O&M) costs, and fuel costs for technologies within a country’s electricity mix, as well as interest rates and asset lifetimes. In this thesis, CAPEX represents the funds required to acquire, upgrade, and maintain assets, covering the investment of power plant infrastructure. Operational costs include OPEX (excluding fuel expenses), fixed and variable O&M costs, and fuel costs. Since cost data and other economic parameters are sourced from the literature, they reflect different time periods and are estimated based on reference technologies (see Table 4.10, columns in light grey). Consequently, these parameters may not always align with the assumptions of the ESM-LCA model and require adjustments to fit its temporal and technical framework, as explained below.

Table 4.10 Relevant economic input parameters for the ESM-LCA model

Tech	ESM-LCA, MW	CAPEX, €$_{2024}$/kW	MW	CAPEX	Currency	Learning rate	Life Time, years	Efficiency
Hard coal	100 to 500	1,035 ± 369	800	1500 to 2000	€$_{2021}$/kW	-	35 to 45	35 % to 46 %
Lignite	380	1,131 ± 39	1000	1600 to 2200	€$_{2021}$/kW	-	33 to 35	26 % to 38 %
Gas CCGT	10 to 100	748 ± 186	500	800 to 1100	€$_{2021}$/kW	-	25 to 30	40 % to 60 %
Gas turbine	400		200	400 to 600	€$_{2021}$/kW	-	25 to 30	35 % to 45 %
Biogas	0.16	3,800 ± 147	0.5	2500 to 5000	€$_{2021}$/kW	-	25	40%

Biomass	1	4,021 ± 192	-	3000 to 5000	€2021/kW	-	25 to 30	16 % to 42 %
Oil	500	929 ± 326	-	500 to 950	€2010/kW	-	40	37%
Nuclear	1000	5,000	-	5000	€2018/kW	-	40 to 60	-
Hydropower	175 to 237	929 ± 326	>100	951 to 3329	€2010/kW	-	80 to 100	-
Hydro pumped storage	237		-	400 to 1500	€2021/kW	-	80 to 200	-
Waste	500	5,743 ± 173	-	6000	€2021/kW	-	30	-
Others	500	5,815 ± 250	-	5500	€2021/kW		40	-
PV rooftop	3 kWp	987 ± 40	30 kWp	750-1400	€2021/kW	1.2 % to 5.6 %	25	-
PV openground	0.57	702 ± 28	>1	500 to 800	€2021/kW	2.5 % to 7 %	25	-
Solar CSP	50	7372	-	4270 to 10082	€2022/kW	12%	25	-
Offshore wind	7 to 15	5,482 ± 1737	3 to 6	3000 to 4000	€2021/kW	6 % to 11 %	20 to 25	-
Onshore wind	4.4	1,665 ± 66	2 to4	1400 to 2000	€2021/kW	14 % to 20 %	20 to 25	-
Geothermal	5.5	5,535 ± 222	-	5600	€2015/kW	10%	25 to 30	-

Assumption this thesis

Assumption in literature sources

CCGT: combined cycle gas turbines; PV: photovoltaics; CSP: concentrated solar power. Sources: own collection based on (Fraunhofer, 2021; IEA, 2021; McDonald & Schrattenholzer, 2001; NREL, 2024; Rubin et al., 2015; Schröder et al., 2013; World Nuclear Association, 2024)

Subsequent to the collection of data, cost estimation entails the harmonisation of all monetary values to ensure consistency across sources. Initially, currency conversions are performed using historical exchange rates, such as USD to Euros (Statista, 2018), based on the time reference of each dataset. To account for economic differences across regions, average interest rates and inflation values at both the European and country-specific levels are obtained from Eurostat (EUROSTAT, 2025a, 2025b). For instance, over the past ten years, the average interest rates across the countries included in this thesis ranged between 1.63 ± 1.11 % (EUROSTAT, 2025b). In the same period, average inflation rates reached 2.72 ± 1.03 % (EUROSTAT, 2025a) (see Figure 4.9). Subsequently, all monetary figures are adjusted to match the study's reference year (2024). This adjustment is carried out using the average national interest rates applying the Equation 4.1, which represents the time value of money. In the equation, F denotes the future cost, P the present cost, i the interest rates and n the number of periods (Geldermann, 2014; Sayyaadi, 2021a). This approach ensures that cost data reflect present-day values in a consistent and comparable manner.

$$F = P(1 + i)^n \qquad 4.1$$

To estimate fuel costs in a format compatible with the ESM, which requires input data in terms of cost per kilowatt-hour (€/kWh), fuel prices—typically reported per tonne or kilogram—are converted into energy-based units using LHV of each fuel (see Table 4.9). For instance, the price of coal in 2024 was reported as 99.51 €$_{2024}$/t (Statista, 2024a). In the case of lignite, the cost is estimated based on the average prices in producing countries such as the Czech Republic, Germany, Poland, Serbia, and Turkey, reaching approximately 12.22 €$_{2012}$/t, with LHVs ranging from 6 to 16 MJ/kg depending on the origin and composition (Booz & Company, 2012). For natural gas, country-specific prices for non-household consumers, excluding taxes, are utilised, as reported by Eurostat (EUROSTAT, 2024). Average European prices for oil in 2024 reached 722 €/t are derived from (European Commission, 2024; Statista, 2024b). The International Energy Agency (IEA) asserts that the mean cost of biogas in Europe is approximately 16 USD/MMBtu (approximately 0.051 €/kWh) (IEA, 2020a). However, the cost of biogas production is contingent on the type, availability, and price of feedstocks, which exhibit significant variation across countries. To address this variability, Birman et al. (2021) provide country-specific data on feedstock types and costs. The feedstocks considered include agricultural residues, biowaste, energy crops, and green waste. The lower heating values (LHVs) of these feedstocks were utilised to convert the costs into energy-based units, thereby facilitating the estimation of average biogas production costs per country in a format compatible with the ESM (€/kWh). Likewise, solid biomass includes a mix of forest residues, wood waste, agricultural residues, and feedstocks vary from country to country. This thesis assumes average cost of solid biomass 0.0264 €$_{2024}$/kWh (IRENA, 2012). Country specific costs for waste and green hydrogen are obtained from (Ruiz et al., 2015) and Hydrogen Europe (2022), respectively. The uranium price is assumed as in (Jesse et al., 2020). Finally, Table 4.11 illustrates fuel costs assumed in this thesis.

Table 4.11 Fuel cost considered in this thesis

Fuel	Cost literature	Cost ESM-LCA	Source
Hard coal	99.51 €$_{2024}$/t	0.01 €$_{2024}$/kWh	(Statista, 2024a)
Lignite	12.22 €$_{2012}$/t	0.01 ± 0.002 €$_{2024}$/kWh	(Booz & Company, 2012)
Natural gas	0.07 ± 0.021 €$_{2024}$/kWh	0.07 ± 0.021 €$_{2024}$/kWh	(EUROSTAT, 2024)
Oil	76.36 €$_{2024}$ per barrel	0.059 €$_{2024}$/kWh	(Statista, 2024b)
Biogas	0.05 €$_{2018}$/kWh	0.06 ± 0.005 €$_{2024}$/kWh	(IEA, 2020a)
Solid biomass	0.02 ± 0.04 €$_{2011}$/kWh	0.03 ± 0.005 €$_{2024}$/kWh	(IRENA, 2012)
Waste	47 ± 54 €$_{2010}$/kWh	0.08 ± 0.098 €$_{2024}$/kWh	(Ruiz et al., 2015)
Hydrogen	4.75 ± 1.76 €$_{2022}$/kg	0.31 ± 0.075 €$_{2024}$/kWh	(Hydrogen Europe, 2022)
Uranium	10 € /MWh	0.01 €$_{2024}$/kWh	(Jesse et al., 2020)

Additionally, because the ESM has a short-term horizon timeframe (i.e., target year is the simulated year see Section 2.3), input parameters, including costs, should align with the model's temporal consideration. The fuel costs adjusted to 2024 (see Table 4.11) are projected to 2030 and 2050 considering the average inflation rate over the last ten years for each country in consideration (see Figure 4.9). Variation of fuel cost depending on the country are considered, as some fuels are produced locally such as biomass, biogas and waste.

Literature values of CAPEX and OPEX are representative of technologies with unit installed capacity showing in Table 4.10. Therefore, the effect of size on CAPEX and OPEX is considered by scaling the literature values to match the nominal capacity used in the model based on (Bejan et al., 1996). For instance, this adjustment is necessary because the original CAPEX data reflect large-scale power plants with capacities ranging from 800 MW to 1000 MW (e.g., hard coal and lignite), whereas the nominal capacities represented in the ESM are below these values (see Table 4.10). Similarly, offshore wind turbines are scaled up based on nominal capacity.

Before considering learning effects of solar and wind power costs, they are adjusted to inflation (e.g., assumed 2 % equivalent with inflation in China) and scale (Faber et al., 2022) (Haas et al., 2023). For instance, in the case of offshore wind turbines, CAPEX values reported into the literature (e.g., 3 MW) are scaled based on nominal capacity of future wind turbines (e.g., 7 MW to 15 MW). Considering the future global deployment of solar and wind power (IRENA, 2024), and their learning rates (see Table 4.10), learning effects on investment for wind and solar technologies are estimated. Finally, future cost (e.g., CAPEX, OPEX) for the year 2030 and 2050 are estimated based on Equation 4.1 and country average inflation rates (EUROSTAT, 2025a).

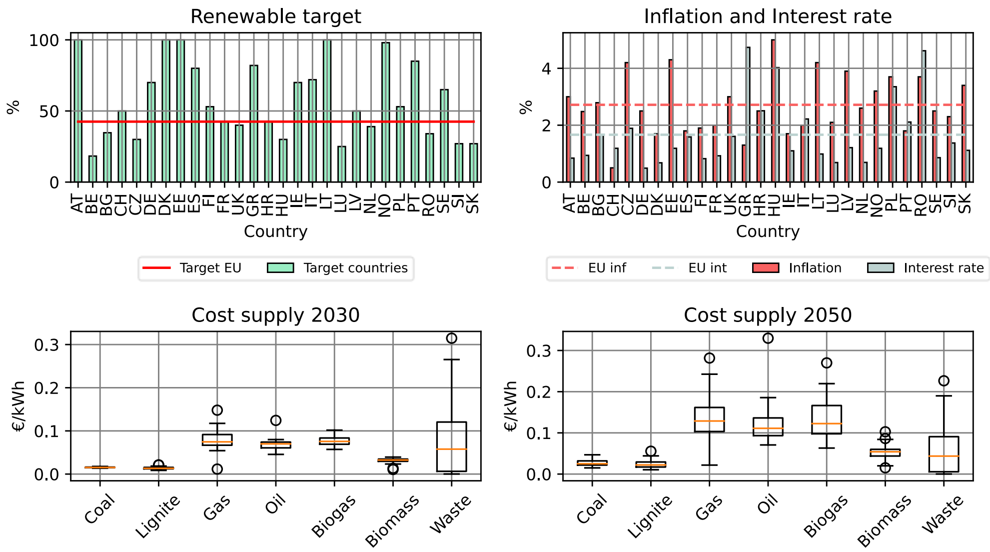


Figure 4.9 Economic parameters considered in the study

Source: Own representation

4.4.5 Environmental parameters

This section outlines the approach used to estimate the environmental input parameters that represent the environmental aspects of the ESM-LCA model. In this thesis, the environmental performance of the ESM is represented by LCA indicators. The calculation of the LCA indicators involves aligning the foreground and background life cycle inventory data representing each technology in the ESM-LCA model within its system boundaries. For this purpose, the present thesis uses the LCA software Activity Browser version 2.10 (Steubing et al., 2020), and the superstructure approach (see Section 3.4.2), which allows managing life cycle inventories with the support of Scenario Difference Files (SDFs). The SDF is an Excel file that facilitates the addition of activities and adjustments of values that can be read by the LCA software Activity Browser. A simplified version of the SDF is shown in Figure 4.10.

As modifying the foreground systems of an LCA model requires expertise in the technology to be upgraded and access to detailed and disaggregated data, this thesis relies primarily on existing inventory data from ecoinvent (Wernet et al., 2016). The exception is offshore wind turbines, for which the foreground life cycle inventory data is updated to represent monopile offshore wind turbines with a rated capacity between 7 MW and 15 MW based on Benitez et al. (2024). In addition, the present thesis uses PREMISE (see Section 3.4.1) to derive prospective databases with their respective SDFs, which contain inventory data for the technologies included in the ESM-LCA model. Two prospective databases based on ecoinvent version 3.7.1 cut-off are derived from PREMISE, following the scenario narratives SSP2-BASE (i.e., RCP65) and SSP2-RCP26 (see Section 3.4.1) generated by IMAGE (Sacchi, 2023) (see Section 3.4.1). The prospective databases contain inventory data for the years 2020 to 2060 in five-year intervals. Specific and regionalized prospective LCA indicators are estimated for the power plants within the ESM-LCA model (see Table 4.6). The prospective life cycle inventories are disaggregated into infrastructure and operation using the Superstructure approach. As such, LCA indicators representing infrastructure impacts are expressed in terms of LCA indicators per kW, while LCA indicators representing the operation of generation units are expressed in terms of LCA indicators per kWh.

Figure 4.10 presents a simplified example of the SDF used to calculate LCA indicators for infrastructure. The SDF outlines all modifications related to activities and exchanges. For example, in the inventory of a gas power plant, the activity representing electricity consumption—originally modelled as *"electricity, medium voltage, RER"*—is replaced by an alternative version, *"electricity, medium voltage, WEU."* The latter reflects a western European averaged electricity mix that incorporates (in each column) temporal and scenario-specific changes, thereby aligning the background data with the system boundaries of the ESM-LCA framework. The present thesis adopts the Environmental Footprint (EF) v3.0 EN15804 (European Commission, 2020) as the life cycle impact assessment method, and includes all LCA indicators shown in Table 4.12 in the ESM-LCA model.

The functional unit of the infrastructure captures the environmental impacts associated with the construction, installation and end-of-life of energy technologies. However, burdens coming from end-of-life, recycling materials and waste are not accounted for because this thesis considers the cut-off approach, meaning those burdens are allocated to the final user of recycled or waste material.

Table 4.12 Impact categories within LCIA EF 3.0

Impact category	Indicator	Abb	EF characterization model	Units	Model source	Description
Climate change, total	Global warming potential	GWP	Bern model - Global Warming Potentials over a 100-year time horizon	kg $CO_{2\text{-eq}}$	IPCC, 2013	Increase in average global temperature resulting from greenhouse gas emissions
Ozone depletion	Ozone depletion potential	ODP	EDIP model based on the ODPs of the WMO over an infinite time horizon	kg CFC-11 eq	WMO, 2014	Depletion of stratospheric ozone layer protecting from hazardous ultraviolet radiation
Humar toxicity, cancer	comparative toxic unit for human	CTUh	USEtox model	CTUh	based on USEtox2.1 model (Fantke et al. 2017), adapted as in Saouter et al., 2018	Impact on human health caused by absorbing substances through the air, water, and soil. Direct effects of products on humans are not measured
Humar toxicity, non-carcinogenic	comparative toxic unit for human	non-HTP	USEtox model	CTUh		
Particulate matter	particulate matter formation	PMFP	PM model	disease incidences	Fantke et al., 2016 in UNEP 2016	Impact on human health caused by particulate matter emissions and its precursors (e.g., sulphur and nitrogen oxides)
Ionising radiation, human health	human exposure efficiency relative to u235	IRP	Human health effect model	kBq U-235 eq	Frischknecht et al, 2000 (as developed by Dreicer et al. 1995)	Impact of exposure to ionising radiations on human health
Photochemical ozone formation, human health	tropospheric ozone concentration increase	POFP	LOTOS-EUROS model	kg NMVOC eq	Van Zelm et al., 2008, as applied in ReCiPe 2008	Potential of harmful tropospheric ozone formation ("summer smog") from air emissions
Acidification	accumulated exceedance (ae)	AP	Accumulated Exceedance model	mol H+ eq	Seppala et al., 2006; Posch et al., 2008	Acidification from air, water and soil emissions (primarily sulphur compounds) mainly due to combustion processes in electricity generation, heating and transport

Eutrophication, terrestrial	terrestrial, accumulated exceedance	TEP	Accumulated Exceedance model	mol N eq	Seppala et al., 2006; Posch et al., 2008	Eutrophication and potential impact on ecosystems caused by nitrogen and phosphorus emissions mainly due to fertilizers, combustion and sewage systems
Eutrophication, freshwater	fraction of nutrients reaching freshwater end compartment (P)	FEP	EUTREND model	kg P eq	Struijs et al., 2009 as applied in ReCiPe 2008	
Eutrophication, marine	fraction of nutrients reaching marine	MEP	EUTREND model	kg N eq	Struijs et al., 2009 as applied in ReCiPe 2008	
Land use	soil quality index	LQI	Soil quality index based on LANCA	pt (Regionalised CFs)	Soil quality index based on an updated LANCA model (De Laurentiis et al. 2019) and on the LANCA CF version 2.5 (Horn and Meier, 2018)	Transformation and use of land for agriculture, roads, housing, mining or other purposes. The impact can include loss of species, organic matter, soil, filtration capacity, permeability
Ecotoxicity, freshwater	comparative toxic unit for ecosystems	CTUe	USEtox model	CTUe	based on USEtox2.1 model (Fantke et al. 2017), adapted as in Saouter et al., 2018	Impact of toxic substances on freshwater ecosystems
Water use	user deprivation potential	WAU	AWARE model	m^3 water eq of deprived water (Regionalised CFs)	Boulay et al., 2018; UNEP 2016	Depletion of available water depending on local water scarcity and water needs for human activities and ecosystem integrity
Resource use, minerals and metals	Abiotic Depletion Potential	ADP	CML2002 model - Abiotic Depletion Potential (ADP) ultimate reserve	kg Sb eq	van Oers et al., 2002 as in CML 2002 method, v.4.8	Depletion of non-renewable resources and deprivation for future generations

Resource use, fossil	Non renewable Abiotic Depletion Potential	non-re ADP	CML 2002 model - Abiotic Depletion Potential (ADP) fossil	MJ	van Oers et al., 2002 as in CML 2002 method, v.4.8

World Meteorological Organization (WMO)

Source: Based on European Commission (2020)

Description derived from ecoinvent databases ↓ | Amount considered in each scenarios ↓

from activity name	from reference product	from location	to activity name	to reference product	to location	flow type	ecoinvent	SSP2-RCP65_2020	SSP2-RCP65_2030	…	Scenario n	
market group for electricity, low voltage	electricity, low voltage	WEU	gas power plant construction, 100MW electrical	gas power plant, 100MW electrical	RER	technosphere	0	236000	236000	…	n	← new background inventory
market group for electricity, medium voltage	electricity, medium voltage	RER	gas power plant construction, 100MW electrical	gas power plant, 100MW electrical	RER	technosphere	236000	0	0	…	n	← old background inventory
market group for electricity, low voltage	electricity, low voltage	WEU	market group for electricity, low voltage	electricity, low voltage	WEU	production	0	1	0.97446	…	0.974461714	← new inventory (from PREMISE)
market for sulfur hexafluoride, liquid	sulfur hexafluoride, liquid	RoW	market group for electricity, low voltage	electricity, low voltage	WEU	technosphere	0	0	3E-09	…	2.99E-09	←activities in the background
electricity production, solar tower power plant, 20 MW	electricity, high voltage	ES	market group for electricity, low voltage	electricity, low voltage	WEU	technosphere	0	0	8.7E-08	…	8.74E-08	←activities in the background
electricity production, solar thermal parabolic trough, 50 MW	electricity, high voltage	ES	market group for electricity, low voltage	electricity, low voltage	WEU	technosphere	0	0	4.1E-05	…	1.79197E-05	←activities in the background
…	…	…	market group for electricity, low voltage	…	…	…		…	…	…	…	←activities in the background

Figure 4.10 Simplified representation of a Scenario Difference File (SDF)

Source: Own representation based on Steubing and de Koning (2021)

The Figure 4.11 illustrates climate change indicators associated with infrastructure, including mainly the construction of power plants for three target years 2020 (current), 2030 and 2050. The y-axis represents GWP intensity in kg CO_2-eq/kW, while the x-axis categorizes the technologies by fuel type or energy carrier, with several technologies grouped under each fuel category. For instance, hard coal includes power plants ranging from 100 MW to 500 MW, while gas represent open cycle, combined cycle and conventional gas power plants. Additionally, each year includes LCA indicators calculated based on both scenario narratives (SSP2-BASE and SSP2-RCP26), which explain the variation in the results. Furthermore, the central line within each box represents the median emissions value. The upper and lower edges of the box indicate the interquartile range, covering the middle 50 % of the data. The whiskers extend to the minimum and maximum values, with any points beyond them representing extreme emission values. Among these technologies, natural gas power plants exhibit lower emissions per kW installed compared to conventional technologies. The GWP for conventional power plant infrastructure, including combined cycle gas turbine adapted for hydrogen (H2-CCGT), ranges from 100 to 600 kg CO_2-eq/kW. Additionally, GWP decreases over time, reflecting improvements considered within the prospective databases. Lower GWP is associated with enhanced inventories of steel production, concrete, and electricity mixes. Overall, renewable energy technologies have higher GWP per kW compared to conventional power plants. For instance, solar PV (representing technologies with capacities of 3 kWp and 1 MWp) and natural gas power plants (ranging from 10 MW to 400 MW) exhibit similar GWP per kW, with values between 40 and 160 kg CO_2-eq/kW. This outcome aligns with the energy-intensive manufacturing of photovoltaic panels, which requires materials obtained through an energy-intensive process involving mining, refining, and crystallization. For instance, solar panels contain silicon, silver, aluminium, and other rare materials that require extensive mining, transportation, and processing, leading to higher emissions per kW.

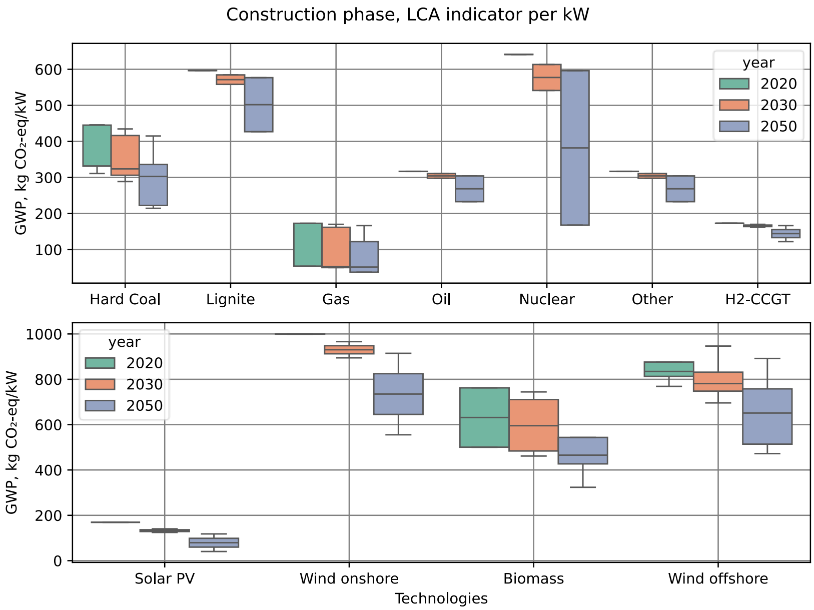


Figure 4.11 LCA indicator Global Warming Potential (GWP) per kW (infrastructure)

Source: Own representation

Inventories for the operational phase include fuel combustion for fuel-fired power plants and, to a lesser extent, other operational activities such as maintenance. However, the environmental contribution of maintenance is generally limited. For example, maintenance for solar technologies consists of cleaning the panels, while for onshore wind turbines it consists of changing lubricants. The environmental impacts of the operational phase are calculated using SDFs, which isolate operational activities by cancelling out infrastructure-related processes. Inventories for the operational phase include regionalised data, which means that fuel consumption in power plants depends on country-specific fuel mixes and, in the case of renewables, on locally available resources. The variation in the results shown in Figure 4.12 is therefore due to differences in the scenario narratives as well as to country-specific characteristics. For example, the starts represent average values for Germany. In general, GWP per kWh is low for renewable energy technologies, mainly because no fuel is burned during their operation. However, low GWP is also partly due to the limited representation of other operational activities such as maintenance.

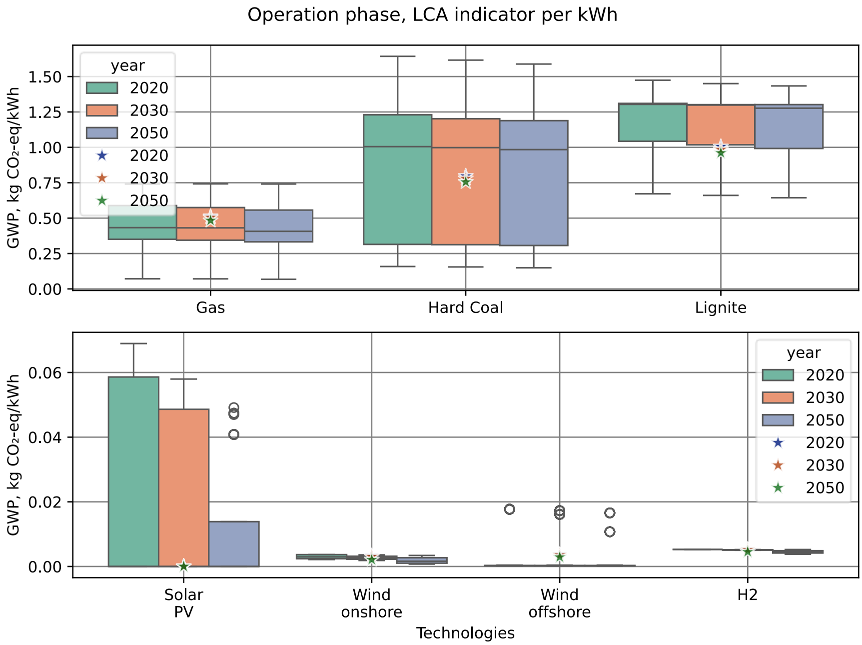


Figure 4.12 Global Warming Potential (GWP) from the operation phase
The starts represent annual average values for Germany

Source: Own representation

This thesis contributes with new inventory data for offshore wind turbines (see Table 4.3), for which foreground and background life cycle inventory data are updated using literature values, and scaling methods to adjust material demand based on the increasing size of wind turbines (Benitez et al., 2024). In addition, the use of prospective inventory data allows the incorporation of changes in the background data to reflect advances in the broader economy. Inventories for infrastructure are estimated for German conditions, assuming that components are assembled in Germany. However, the materials within the components represent global conditions (Mutel, 2023). For describing the construction and operation of offshore wind turbines in Germany, the LCA utilizes representative inventories shown in the Figure 4.13. Regarding the assembly phase, the LCA study assumes that energy requirements (e.g., electricity) are supplied by an electricity mix representative of Germany and in line with the temporal scope of the ESM.

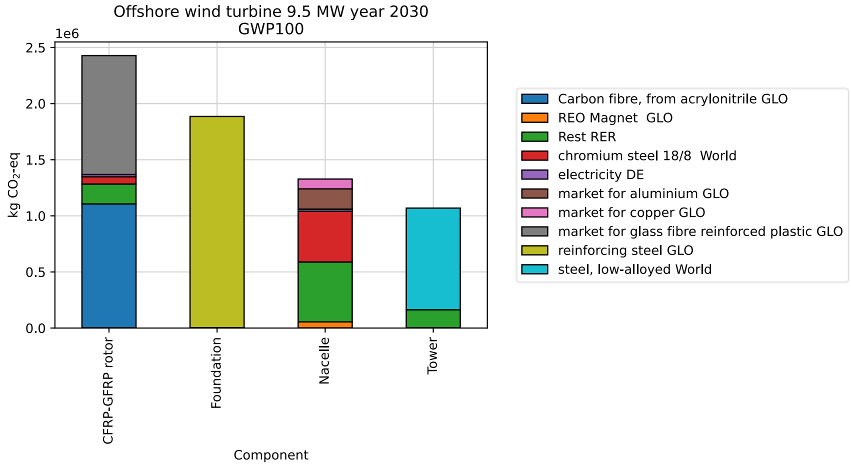


Figure 4.13 Geographical coverage of the components of a wind offshore turbine
CFRP-GFRP stands for carbon fibre reinforced polymer and glass fibre reinforced polymer within the rotor's blades for a 9.5 MW offshore wind turbine of 164 m or rotor diameter. GWP100 refers to the LCA indicator of global warming potential that assess impacts to climate change for the construction phase

Source: Based on Benitez et al. (2024)

The inventory of the operational phase is representative of the average conditions within the German territory, including wind potential and wind turbine characteristics (e.g., size, capacity, technology type) (Benitez et al., 2024). However, offshore wind turbines are present in 21 countries within the ESM-LCA model (see Table 4.8). For these countries, the inventories of offshore wind turbines are adjusted based on the available wind resources at specific locations, which are translated into an estimated annual electricity generation for the country as in Section 4.4.2.

4.5 Scenarios

This thesis proposes the evaluation of various scenarios for the current, and future years. As explained in Section 4.3.2, the term *current* does not refer to a specific year but rather represents the average conditions in the countries included in the ESM-LCA model over the last ten years. Accordingly, a reference scenario describes current conditions, and its purpose is to be used for comparison.

The present thesis employs explorative scenarios as part of an integrated approach. The scenarios are designed to fulfil two distinct purposes. Firstly, the development of scenario narratives provides a structured framework for combining diverse input data – economic, technical and environmental – collected from literature sources. This approach is adopted to ensure that data integration is executed in a consistent and coherent manner across the various components of the ESM-LCA model. Secondly, the scenarios facilitate the interpretation of ESM-LCA model outcomes. As outlined in Chapter 2, explorative scenarios are well-suited for long-term analyses in circumstances where future developments are uncertain. As such, these scenarios delineate a range of plausible futures rather than a single outcome. Therefore, exploratory scenarios provide results in ranges, which can illustrate extreme cases, such as best-case and worst-case outcomes.

In this thesis, *three explorative scenarios* such as optimistic, moderate and pessimistic are developed to assess potential outcomes for the years 2030 and 2050. The *optimistic scenario* anticipates a future in which substantial greenhouse gas emission reductions are accomplished through widespread electrification of sectors and the rapid adoption of low-carbon technologies in the electricity sector. The optimistic scenario is compatible with a narrative in which electricity demand is expected to increase due to the electrification of the transport and heating sectors. In the broader economy, the optimistic scenario assumes that the production of materials such as steel and cement is more efficient, and that the global electricity mix also reduces greenhouse gases. From the LCA perspective, these assumptions are embedded into the prospective life cycle inventories derived from Premise, which follows the narrative of the SSP2-RCP2.6 scenario (see Section 3.4.1). From an economic perspective, the optimistic scenario is predicated on the assumption that cost reductions for renewable energy sources – particularly offshore wind – are driven by their rapid deployment and learning effects. From a technology perspective, the rapid deployment of offshore wind implies advancements in offshore wind turbine design, materials, and control systems that increase efficiency, reliability, and energy yield.

Therefore, the narrative of the optimistic scenario guides the selection of input parameters discussed in the previous section. For instance, the upper arrows in Table 4.13 indicate that the higher values of input parameters from Table 4.10 should be considered. The moderate scenario adopts average when input parameters are given in ranges. The pessimistic scenario portrays a slow deployment of renewable energy. Thus, the pessimistic scenario considers higher costs. Overall, Table 4.14 illustrates main scenario assumptions in the context of this thesis. The application of these scenarios is evaluated in a case study in the Chapter 5.

Table 4.13 Scenario narratives

Parameters ESM-LCA	**Optimistic**	**Moderate**	**Pessimistic**
Electricity demand	↑	average	↓
Capacity factors	↑	average	↓
Efficiency	↑	average	↓
Lifetime	↑	average	↓
Share of renewables	↑	average	↓
Technical development	↑	average	↓
Environmental indicators	↓	average	↑
Cost (e.g., CAPEX)	↓	average	↑

.

Table 4.14 Assumptions adopted in this thesis for 2050

Fuel group	Optimistic	Moderate	Pessimistic
Hard coal	0 GW hard coal power plants for all countries	A maximum of 25% of the installed capacity over the last 10 years (2015 to 2024) is considered, based on ENTSO-E energy capacity data.	A maximum of 40 % of installed capacity in the last 10 years (2015 to 2024) is considered, based on ENTSO-E energy capacity data.
Lignite	0 GW Lignite power plants for all countries	25 % of max installed capacity (2015 to 2024) are considered as constraint. For Germany, 0 GW	40 % of max installed capacity (2015 to 2024) are considered as energy cap. For Germany, 0 GW
Natural Gas	The maximum constraint for natural gas is set equal to the country's peak load.	The maximum constraint for natural gas is set equal to the country's peak load, like current conditions	The maximum constraint for natural gas is set equal to the country's peak load, like current conditions
Nuclear	0 GW for Germany. For BE, BG, CH, CZ, ES, FR, UK, HU, NL, RO, SE, SI, SK maximum GW equal to maximum installed capacity in the last 10 years 2015 to 2024 (ENTSO-E, 2024a)	0 GW for Germany. For BE, BG, CH, CZ, ES, FR, UK, HU, NL, RO, SE, SI, SK maximum GW equal to maximum installed capacity in the last 10 years 2015 to 2024 (ENTSO-E, 2024a)	0 GW for Germany. For BE, BG, CH, CZ, ES, FR, UK, HU, NL, RO, SE, SI, SK maximum GW equal to maximum installed capacity in the last 10 years 2015 to 2024 (ENTSO-E, 2024a)
Oil	0 GW for all countries	25 % of max installed capacity (2015 to 2024) are considered as constraint. For Germany 0 GW	40 % of max installed capacity (2015 to 2024) are considered as constraint. For Germany 0 GW
Others	max installed capacity values period 2015-2024 for Biomass (ENTSO-E, 2024a)	max installed capacity values period 2015-2024 for Biomass, (ENTSO-E, 2024a)	max installed capacity values period 2015-2024 for Biomass, (ENTSO-E, 2024a)
Waste	max installed capacity values period 2015-2024 for waste, as constraints (ENTSO-E, 2024a)	max installed capacity values period 2015-2024 for waste, as constraints (ENTSO-E, 2024a)	max installed capacity values period 2015-2024 for waste, as constraints (ENTSO-E, 2024a)
Biomass	max installed capacity values period 2015-2024 for Biomass, (ENTSO-E, 2024a)	max installed capacity values period 2015-2024 for Biomass, (ENTSO-E, 2024a)	max installed capacity values period 2015-2024 for Biomass, (ENTSO-E, 2024a)

Hydro	Hydro reached potential, constraints as maximum installed capacity values 2015 to 2024	Hydro reached potential, constraints as maximum installed capacity values 2015 to 2024	Hydro reached potential, constraints as maximum installed capacity values 2015 to 2024
Geothermal	maximum GW values period 2015 to 2024 for Biomass (ENTSO-E, 2024a)	maximum GW values period 2015 to 2024 for Biomass (ENTSO-E, 2024a)	maximum GW values period 2015 to 2024 for Biomass (ENTSO-E, 2024a)
Solar	For rooftop: maximum potential 282 GW. All countries are set maximum constraints 282 GW. Open-ground PV depending available land in each country. E.g. Germany max potential 152 GW. Solar CSP in ES, IT, GR values with respect country targets or current values	PV rooftop: All countries are set max constraints 80 % of 282 GW. Open-ground PV 80 % available potential in each country. E.g. Germany max potential 80% of 152 GW. Solar CSP in ES, IT, GR values 80 % country targets or current	PV rooftop: All countries are set max constraints 50 % of 282 GW. Open-ground PV 50 % available potential in each country. E.g. Germany max potential 50 % of 152 GW. CSP in ES, IT, GR values 50 % country targets or current
Onshore wind	100 % of GW potential used as constraint. If this constraint is too large, energy cap equal to the highest GW for onshore in Europe	80 % of GW potential used as constraint	50 % of GW potential used as constraint
Offshore wind	100 % of GW potential for fixed bottom foundation as described in the literature per country, 100 % this value is used as constraint. If this constraint is too large, energy cap equal to the highest GW for offshore in Europe	80 % of GW potential for fixed bottom foundation as described in the literature per country, 100 % this value is used as constraint. If this constraint is too large, energy cap equal to the highest GW for offshore in Europe	50 % of GW potential for fixed bottom foundation as described in the literature per country, 100 % this value is used as constraint. If this constraint is too large, energy cap equal to the highest GW for offshore in Europe

4.6 Limitation

The ESM-LCA model provides a comprehensive approach for assessing the environmental and economic aspects of electricity generation technologies. However, several limitations must be acknowledged, arising from technological, geographical, and methodological considerations, data availability and model assumptions. For instance, the study omits carbon capture and storage (CCS) technologies. Although Germany has clear strategies about the role of CCS in power generation, this trend might be different in other countries (e.g., Poland). Despite hydrogen (produced through electrolysis) in the model, the electricity demand does not reflect its production. The production of electrolysis will consume electricity, yet during moments generation surplus. The study also focuses solely on mature technologies, a common approach in energy system modelling, as predicting the emergence or obsolescence of new technologies over the long term is highly uncertain. However, the framework allows for the integration of new technologies if necessary.

Another limitation concerns the geographical representation of power plant infrastructure. While the present thesis adjusts efficiency for each country during the operational phase, infrastructure assumptions remain generic without country-specific distinctions. LCA databases rely on market-based activity data to estimate material and component consumption. But their geographical coverage is limited, making it difficult to determine the precise origin of materials such as steel, copper, aluminium, and rare earth elements used in offshore wind turbines. LCA datasets often use aggregated geographical locations like Global (GLO), Rest-of-the-World (RoW), or Europe (RER), which may not fully capture regional variations in electricity generation technologies.

Technical parameter assumptions also introduce uncertainties. Some values, such as lower heating values (LHV), are assumed to be constant, even though they can vary based on resource quality and extraction methods. Similarly, efficiency and other operational parameters are not always explicitly defined in LCA databases, requiring additional assumptions. Despite improvements in documentation and transparency, it remains challenging to trace the exact methodological choices made in LCA inventories.

Regarding the estimation of the electricity demand, the study primarily follows historical consumption patterns, with only minor adjustments for Germany, and does not fully account for the impact of future sectoral electrification. The increasing adoption of electric vehicles (EVs) is limited is not reflected in demand projections for all countries. The study does not incorporate possible shifts in electricity load profiles caused by EV and heat pump adoption in other countries outside Germany, which could alter peak demand patterns and require infrastructure upgrades. Effective demand management strategies, essential for ensuring supply security and minimising costly grid expansion, are also not explicitly modelled.

Related to resource availability, the ESM-LCA framework assumes that resources such as solar, wind, and fossil fuel supplies are infinitely available, whereas, in reality, resources are finite. Future research could refine resource availability assumptions to enhance system modelling accuracy.

Despite these limitations, the ESM-LCA model provides valuable insights into energy system performance. However, incorporating additional technological, geographical, and demand-side considerations could improve its accuracy and applicability for long-term energy planning.

4.7 Summary

This chapter focuses on deriving the main input parameters and how to achieve a coherent integration of the LCA into the ESM built on the Calliope framework. The present chapter addresses the obstacles related to technical, geographical and temporal representation by homogenising input data in both parts of the model. As a result, this chapter lays the foundation for a systematic process to collect and harmonise input data through the development of Python scripts, which facilitates a structured construction of the ESM-LCA model.

This thesis employs prospective inventory data to estimate the future environmental impacts of individual supply technologies. The prospective inventory data is derived via the PREMISE framework, which modifies LCA databases to reflect evolving energy and technology systems. For instance, PREMISE aligns LCA background inventories with two IPCC scenarios—a 1.5 °C pathway (RCP2.6–SSP2) and a 3.6 °C baseline (RCP6.0–baseline)—providing consistent and regional environmental data for 2030 and 2050. In addition, one significant contribution of this thesis is the development of prospective life cycle inventories for offshore wind turbines representing offshore wind turbines of 7 MW, 9 MW, 11 MW and 15 MW.

The economic considerations of this thesis include the costs of investment in technologies, the operating and maintenance (O&M) expenses (excluding fuel costs) and the total cost of energy supply. The operating costs cover the fixed and variable maintenance expenses, excluding fuel costs. These parameters are essential to evaluate the financial viability of the ESM-LCA model.

Accurate prediction of electricity demand is essential for ensuring a secure supply, particularly given that increasing electrification in areas such as heating and transport is changing demand patterns. However, due to the complexity of reliably estimating future demand, this thesis assumes that future electricity demand will remain similar to 2019 levels. For Germany only, this thesis provides a simple estimate of future electricity demand, taking into account the increased use of electric vehicles and heat pumps.

5 A case study on integrating LCA into the ESM, with a focus on offshore wind

The chapter presents the results of integrating LCA into the ESM built on the Calliope modelling framework. The integration process requires extensive harmonisation of input parameters to ensure consistency between the LCA and ESM methodologies. Particular attention is given to offshore wind energy, which serves as a representative case study for demonstrating the integration approach. Within this context, tools are employed to manage life cycle inventories and to standardize technical, economic, and environmental inputs across both modelling domains. The analysis adopts a scenario-based methodology to address uncertainties and to explore future technological developments, thus scenarios for the years 2030 and 2050 are developed. The focus on low-carbon technologies—such as offshore wind—is crucial, as they play a key role in achieving global climate mitigation targets. However, electricity generation technologies do not operate in isolation. Their technical, economic, and environmental performance must be assessed within the broader context of the energy system in which they are embedded. Accordingly, this chapter aims to address the following research question:

- How can technological changes such as in offshore wind technology can be investigated from a technical, economic and environmental perspective within the context of an integrated energy system?

Through this investigation, the chapter seeks to demonstrate the added value of combining LCA and energy system modelling in supporting robust and holistic energy planning and policy development. The present chapter discusses the results of the integration approach and is structured to present a comprehensive comparative analysis of three distinct energy system scenarios using LCA indicators. It begins with an overview of the case study (see Section 5.1), followed by a concise summary of scenarios assessed, the modelling approach and LCA metrics applied. The results obtained for the scenarios namely current-reference, year 2030 and year 2050 are discussed in the Section 5.2, Section 5.3 and Section 5.4, respectively. The main body of the chapter is devoted to the presentation and interpretation of results for each scenario, including visualizations that illustrate the environmental contributions of various technologies. The results are disaggregated by country and technology to emphasize regional and sectoral disparities. The chapter concludes with a critical discussion of the findings and their implications for sustainable energy planning and policy formulation.

5.1 Overview of the case study

The present thesis proposes an ESM-LCA model for the consistent integration of environmental indicators derived from LCA into an energy system model. The study develops an energy system model based on the Calliope framework (see Chapter 4), which could serve as a planning or dispatch model for the electricity sector. The Calliope framework has been specifically designed to manage energy systems that comprise a significant proportion of fluctuating removable energy sources, such as offshore wind (Pfenninger & Pickering, 2018). The objective of the model is to evaluate a simplified version of the European electricity sector, with a particular focus on offshore wind technology in the years 2030 and 2050.

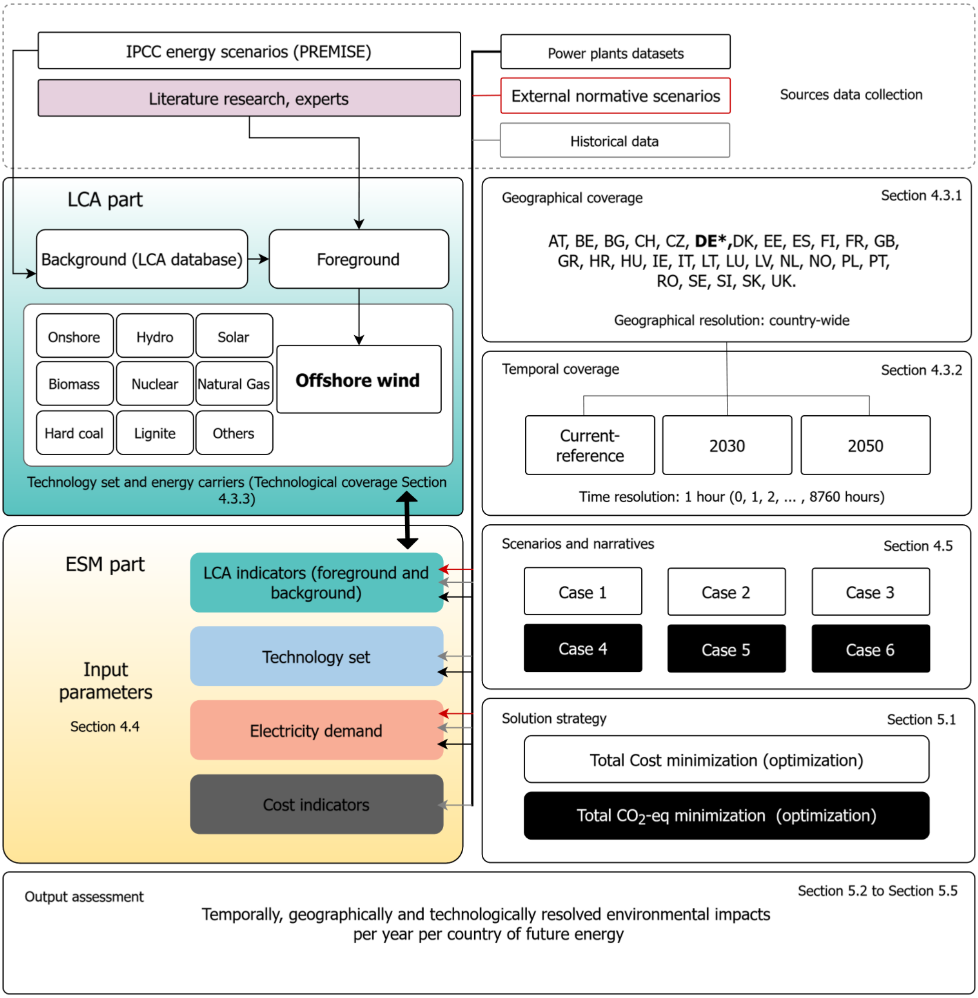


Figure 5.1 Overview case study
The case study consists of evaluating three scenarios—optimistic (Case 1), moderate (Case 2), and pessimistic (Case 3)—which are solved under a total cost minimisation objective. Alternatively, Case 4, Case 5, and Case 6 are equivalent to Case 1, Case 2, and Case 3 respectively in terms of input assumptions but are optimised for total greenhouse gas emission minimisation

Source: Own representation

The novelty of this thesis lies in the evaluation of user-defined electricity demand profiles, cost reductions due to learning effects, and prospective LCA indicators aligned with expected technological developments in the year under consideration. This thesis focuses on offshore wind as a representative case, illustrating how to address data gaps associated with this technology from both LCA and ESM perspectives (see Section 4.2). In order to achieve this objective, the ESM-LCA model can be updated to include advancements in the offshore wind sector from an economic perspective. This update considers the effects of scaling up technologies, deployment rates, learning curves and inflation, in order to estimate costs improvements for offshore wind turbines. From a technological standpoint, sectoral advancements are reflected not only in the construction of larger turbine units, but also in performance enhancements, such as higher full load hours. In order to account for the technical improvements, this thesis estimates capacity factors using wind speed data, turbine power curves and technical specifications of offshore wind turbines. Furthermore, as technological developments are intrinsically linked to environmental performance, LCA inventories are adapted by adjusting material inputs based on turbine size and technological diversity in offshore wind components. These aspects are addressed in the foreground system of the LCA model, while improvements in the supply chain (e.g. materials, energy) are captured in the background system using prospective LCA databases. In this way, technological advancements in the offshore wind sector are comprehensively integrated into the ESM-LCA framework.

The integration of both LCA and ESM methodologies into a single framework necessitates the resolution of data inconsistencies (see Chapter 3). To this end, the present thesis emphasises the importance of meticulously examining scenarios' narratives to ensure the transparency of assumptions (see Chapter 4). The study therefore proposes the evaluation of three scenarios, with the input data for these scenarios set to describe three narratives.

The structure of the case study is outlined in Figure 5.1. The assumptions guiding the selection of the relevant technology set within the ESM, as well as the derivation of corresponding technical input parameters, are discussed in Section 4.4.3. The system boundaries—covering geographical, temporal, and technical dimensions—are outlined in Section 4.3. Electricity demand for the target years (current, 2030, and 2050) is represented through time series based on the 2019 electricity consumption of each country. An exception is made for Germany, where electricity demand has been estimated to account for increased electrification of end-use sectors (see Section 4.4.1). Cost-related input data, including capital expenditures (CAPEX), operational expenditures (OPEX), and fuel prices, are detailed in Section 4.4.4. The derivation of LCA indicators, representing both infrastructure (e.g., power plants) and operational phases (e.g., fuel consumption), is presented in Section 4.4.5. Finally, the scenario framework applied in this thesis is also introduced in Section 4.5.

Table 5.1 outlines the scenarios' assumption regarding the electricity demand, LCA indicators, and other input parameters. Three scenarios have been developed in this thesis (i.e., optimistic, moderate and pessimistic) for each target year 2030 and 2050. Additionally, the scenario *current reference* represents the current status of the electricity system (see Section 4.3.2). As such, it reflects the average electricity mixes across 28 European countries plus the United Kingdom, based on data obtained from ENTSO-E.

Table 5.1 Scenarios definition

Input	**Reference (current)**	**Case 1 (Optimistic)**	**Case 2 (Moderate)**	**Case 3 (Pessimistic)**
Electricity demand	Demand reference: Hourly average based on historical data (2015 to 2023) 28-EU countries	Demand_C1: EVs + heat pumps in DE (KN 65); Rest of EU, average max	Demand_C1: EVs + heat pumps in DE (KN 60); Rest of EU average max	Demand reference: Hourly average,

LCA indicators	RCP6.5 2020 Adjusted FLH wind and solar capacity factors; moderate scenario OWE study	RCP2.6 Adjusted FLH wind and solar capacity factors; moderate scenario OWE study	RCP6.5 Adjusted FLH wind and solar capacity factors; moderate scenario OWE study	RCP6.5 (2020) Adjusted FLH wind and solar capacity factors; moderate scenario OWE study
Deployment renewables (learning)	average	strong	average	low
Interest rate	Country average (last 10 years)	Country average (last 10 years)	Country average (last 10 years)	Country average (last 10 years)
Capacity factors	Proxy 2019	Proxy 2019	Proxy 2019	Proxy 2019
efficiencies	ecoinvent; average literature	According to Premise (RCP 26)	According to Premise (RCP 65)	According to Premise (RCP 65-2020)

In the context of this thesis, the scenario narratives are structured as follows to guide the integrated assessment of future energy pathways using the ESM-LCA approach. The current-reference scenario has been designed to reflect the average installed capacity and technological diversity observed in Europe over the past decade. Scenario *Case 1* envisions an optimistic future, characterised by strong electrification of the transport sector, high renewable energy penetration, and improvements in both efficiency and cost, primarily reflected in lower investment and reduced environmental impacts. Scenario *Case 2* presents a moderate outlook, in line with current trajectories. This represents a middle ground between the optimistic and pessimistic scenarios. *Case 3*, by contrast, reflects a pessimistic pathway, such as limited progress in electrification, and continued but slow deployment of wind and solar technology.

The Calliope framework facilitates system optimisation based on various cost classes, which can be defined as either monetary expenditures or environmental emissions (see Section 4.1). In this thesis, the cost classes are defined using environmental indicators listed in Table 4.12, which are then categorised into two types: infrastructure (treated as fixed costs) and operation (treated as variable or operational costs). This means the ESM-LCA model can optimise the system to minimise total costs based on any of the defined cost classes. For example, the optimistic, moderate, and pessimistic scenarios are initially evaluated by minimising total system costs, i.e., using the monetary cost class as the objective function.

Although optimising based on LCA indicators may introduce bias – as discussed in Section 3.2.1 and Section 4.3.3 – due to varying levels of technological representativeness in LCA databases, the ability to evaluate an entire system based on emissions offers valuable insight into trade-offs between economic costs and environmental burdens. To explore these trade-offs, this thesis proposes the evaluation of three additional scenarios: Case 4 reflects the optimistic scenario; Case 5 corresponds to the moderate scenario; and Case 6 is aligned with the pessimistic scenario. The key distinction is that in these three cases, the system is optimised to minimise Global Warming Potential (GWP), as opposed to financial costs.

5.2 Outcomes of the current-reference case

The ESM-LCA integration model represents a simplified version of the European electricity system, it relies on a number of assumptions when defining input parameters. The *current-reference scenario* is intended to represent the actual conditions of the electricity system (see Section 4.3.2). However, since the ESM is based on optimization and relies on assumed inputs—such as capacity factors that reflect weather conditions—it is expected that the results may not perfectly match historical data. Nevertheless, the outcomes should be reasonably close and reflective of real-world trends. Additionally, the current-reference scenario serves a comparative purpose, providing a baseline against which the environmental impacts of low-carbon mitigation strategies for 2030 and 2050 can be evaluated.

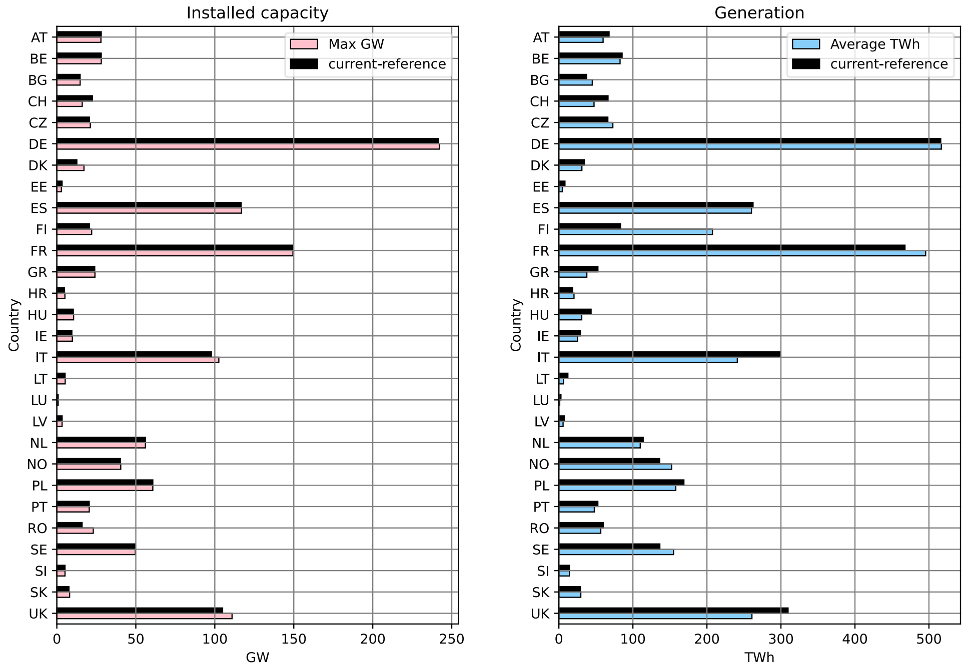


Figure 5.2 Comparison of actual installed capacity and ESM-LCA mode results
Both installed capacity values (maximum values in GW) and electricity generation (average values on TWh) per country refer to observations during the period 2015–2023, respectively. The modelled results correspond to the current-reference scenario; observed data corresponds to 2024

Source: Own representation based on ENTSO-E (2024a)

Figure 5.2 compares the maximum installed capacity (in GW) per country, as reported by ENTSO-E (2024a) from 2015 to 2023, with the values calculated by the model for the reference case (i.e., called current-reference). The maximum GW value is selected instead of an average because, in several countries—such as the United Kingdom—installed capacity growth has slowed down after the COVID pandemic, making the average less representative of the current situation. The plot on the right illustrates a comparison between the average electricity generation (in TWh) over selected years per country and the generation estimated by the model. It is important to note that electricity demand in the past four years (e.g., 2023, 2022, 2021, 2020) has declined due to the economic recession and the COVID-19 pandemic. Pre-2019 figures were generally higher; hence, an average value is used to better reflect the ongoing deviation from pre-pandemic demand levels. Overall, the results of the current scenario reasonably reflect the current power plant mix across EU and UK.

The optimisation model selects the cost-optimal mix of technologies based on minimising of total system costs. In Germany, the cost-optimal alternative represents about 240 GW, with the largest shares coming from solar (74 GW), onshore wind (60 GW) and natural gas (3 GW) (see Figure 5.3a). Although lignite represents only about 18 GW to the installed capacity, it generates around 150 TWh of electricity annually. Germany has the largest installed capacity due to its high share of renewable energy sources, followed by France with approximately 150 GW. Similarly, Germany and France lead in terms of annual electricity generation. In Germany, for example, wind and solar energy sources contribute approximately 233 TWh, accounting for 45 % of the country's total electricity generation. France, on the other hand, relies on nuclear power, with 61 GW of installed capacity generating around 193 TWh of electricity per year.

The environmental burdens describing GWP (or GHG emissions) depend on the specific technology mix selected as cost-optimal by the model. Figure 5.3c illustrates the total GWP (i.e., including infrastructure and operation) originating from the core regions represented in the ESM-LCA model, with generation technologies grouped by fuel type. Among these countries, Germany not only has the highest share of installed capacity but also accounts for the highest GHG emissions (200 million t CO_2-eq), primarily due to lignite-based generation. This aligns with reported emissions from the electricity sector between 2018 and 2019, which were approximately 220 million t CO_2-eq (UBA, 2020).

Despite its relatively small share in capacity, lignite is responsible for approximately 70 % of Germany’s total GHG emissions due to the combustion during operation (see Figure 5.3c). As a result, Germany's emissions are roughly twice as high as those from countries such as Italy, Poland, and the United Kingdom. In contrast, the associated GHG emissions from France are relatively low, less than 20 million t CO_2-eq due to its reliance on nuclear energy.

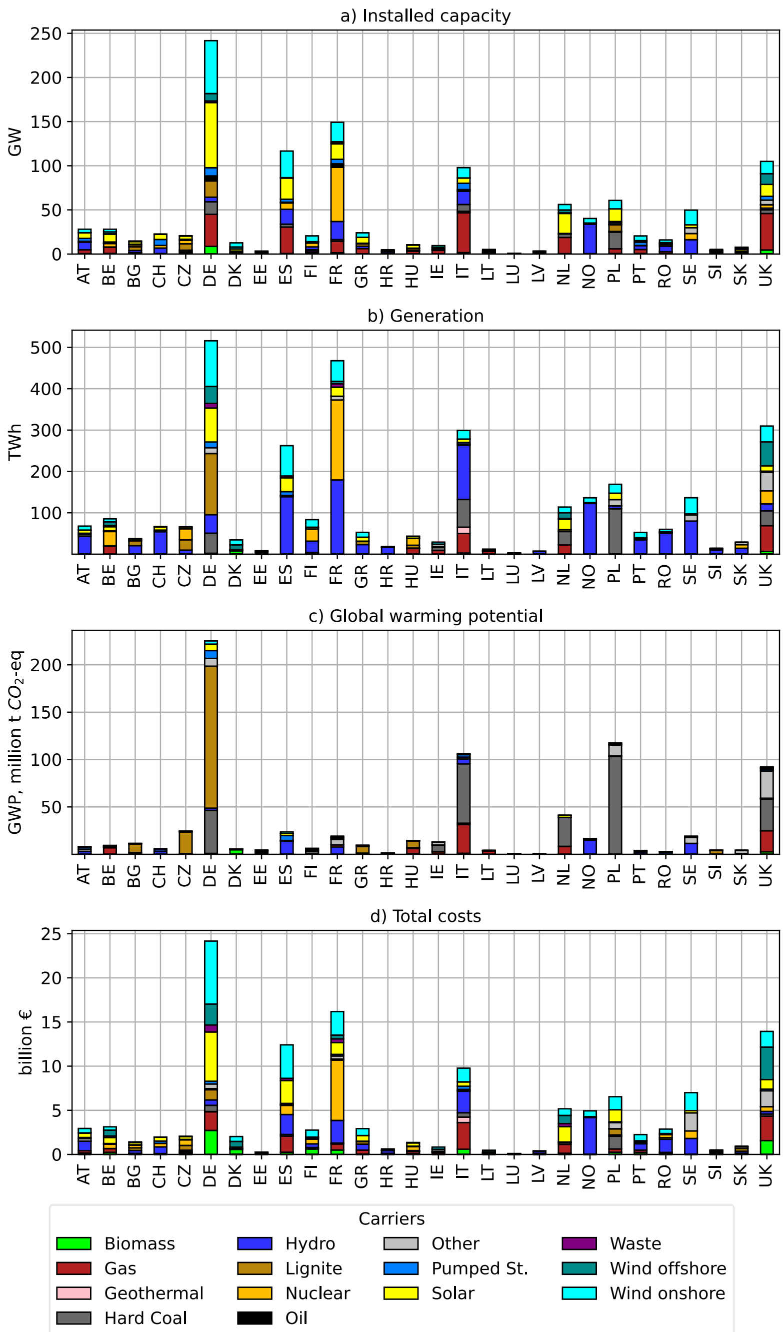


Figure 5.3 Results for the current reference scenario
a) Installed capacity b) Annual electricity generation, c) Total global warming potential emissions, and d) Total costs associated with the power plant mix per country. Current reference temporal assumptions in Section 4.3.2

Source: Own representation

While total GHG emissions reflect the overall environmental impact at the national level, GHG emissions per kWh provide a more meaningful basis for comparing the efficiency and environmental performance of different power generation technologies. In this context, Figure 5.4 presents both the total emissions with a GWP associated with each country's power plant mix and the corresponding specific emissions, expressed in kg CO_2-eq/kWh. Poland has the highest specific emissions, largely due to its dependency on hard coal-fired power plants, which supply approximately 65 % of its electricity demand. In contrast, Germany's electricity mix results to 0.43 kg CO_2-eq/kWh, consistent with reported values from 2019 (e.g., 0.40 kg CO_2-eq/kWh) (UBA, 2020). Overall, France has the lowest GWP per kWh (0.04 kg CO_2-eq/kWh).

Regarding costs, high capital expenditures are associated with renewable technologies. In Germany, onshore wind and solar account for approximately half of the total costs (see Figure 5.3d), while in the UK, offshore wind energy is a major cost driver. The total costs associated with biomass technologies – including biogas and solid biomass facilities – are relatively high. For instance, although both biomass and offshore wind account for approximately 8 GW of installed capacity and incur total costs ranging between 2,300 and 2,700 million € in Germany, their generation output differs significantly: biomass generates only about 0.34 TWh, whereas offshore wind produces around 40 TWh.

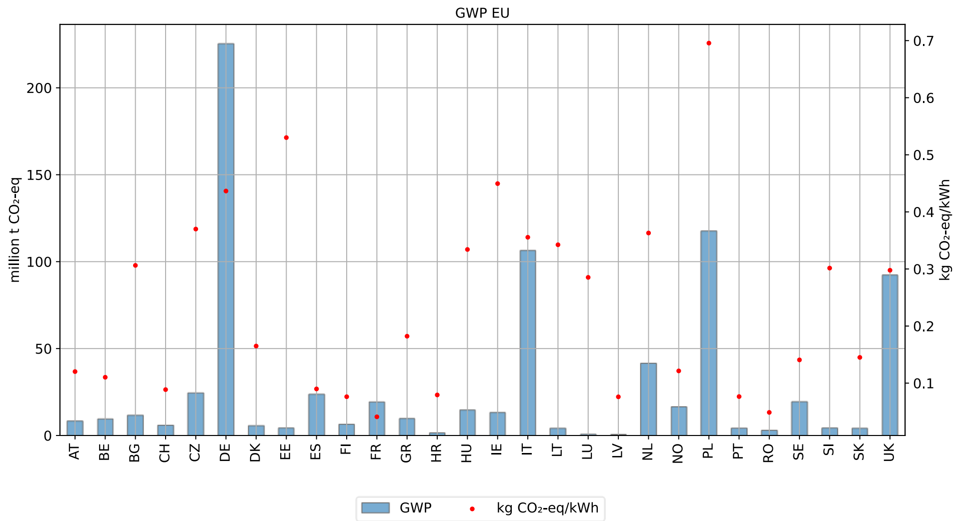


Figure 5.4 Total global warming potential (GWP) for the current reference scenario
Results per country calculated by the ESM-LCA model. Current reference temporal assumptions in Section 4.3.2

Source: Own representation

While GHG emissions are crucial for understanding the impacts of climate change, other LCA impact categories are also important for identifying potential trade-offs (see Table 4.12, section 4.4.5). Therefore, the relative contributions of each technology within the German power plant mix are presented in Figure 5.5. This illustration provides a visual representation of the proportional burdens across various LCIA impact categories, based on EF 3.0 methodology, categorized by technology type.

For example, electricity generation from natural gas includes several technology types—such as combined cycle, open cycle, and steam turbine power plants—which are individually distinguished in the figure. The analysis of relative contribution of LCA indicators demonstrates that, for the current-reference scenario, lignite is the largest contributor to emissions in 11 of the 19 LCIA categories under consideration. While lignite accounts for over 60 % of GWP, a similar pattern is observed in other impact categories, such as Freshwater Eutrophication Potential (FEP, 90 %) and Marine Eutrophication Potential (MEP, 66 %), primarily due to emissions associated with lignite combustion and mining processes. In contrast, for abiotic depletion potential (ADP), solar photovoltaics (42 %) and onshore wind (40 %) are the main contributors, due to the use of metals such as steel and copper. Minimal contributions come from offshore wind, nearly all impact categories (below 5 %), with the exception of water use (WAU). However, this indicator should be interpreted with caution, as it reflects the depletion of available water resources and requires higher geographical resolution for accurate assessment. In this case, the impact is primarily associated with upstream processes related to material extraction.

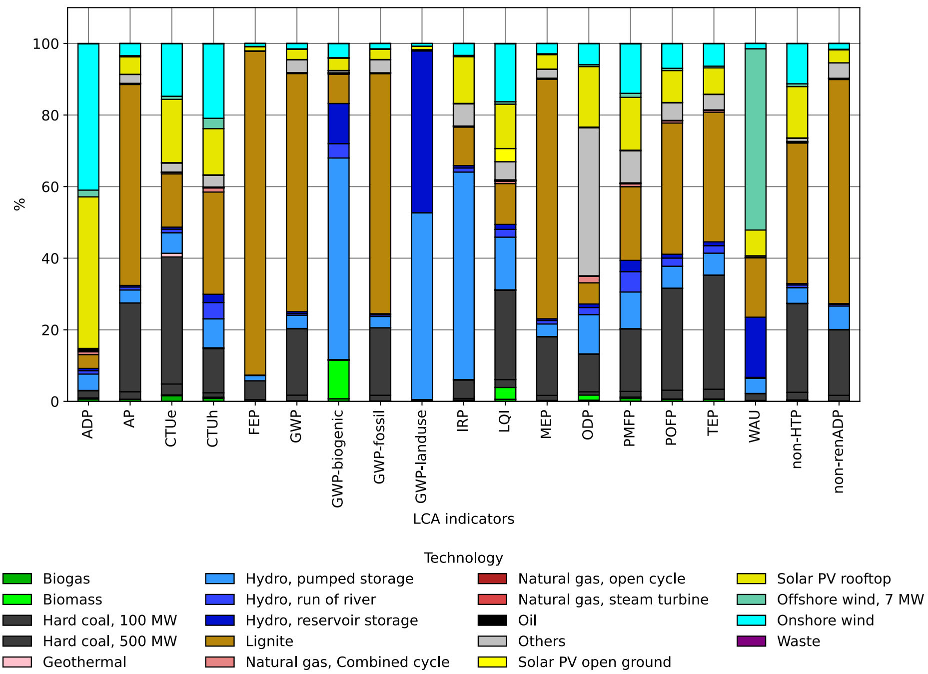


Figure 5.5 Relative contribution representing the German power plant mix for the current reference scenario

LCA indicators corresponds to the EF 3.0 LCIA including abiotic depletion potential (ADP), acidification potential (AP), ecotoxicity (CTUe), human toxicity (CTUh), freshwater eutrophication (FEP), global warming potential (GPW) including from biogenic, fossil and land use, ionizing radiation (IRP), land use soil quality index (LQI), ozone depletion potential (ODP), marine eutrophication (MEP), particulate matter (PMFP), photochemical oxidation potential (POFP), terrestrial acidification (TEP), water use (WAU), human health (non-HTTP), abiotic depletion potential non-renewables (non-ren ADP). Current reference temporal assumptions in Section 4.3.2

Source: Own representation

In addition to assessing relative contributions, LCA studies facilitate the identification of environmental hotspots, for instance, by determining which life cycle stages are most significant. This, in turn, supports the development of targeted mitigation strategies. For this reason, Figure 5.6 presents the impacts associated with the operation and infrastructure phases of electricity generation in Germany.

The Figure 5.6 shows that impact categories vary in their proportional contributions, and that their relevance differs across life cycle stages. For instance, given that lignite is the most significant contributor to GWP, it is anticipated that its most substantial impact will occur during the operation phase. This also implies that the environmental effects are concentrated in the regions where lignite power plants are located. Conversely, the impact of renewable technologies is more pronounced during the extraction and construction phases. This suggests that the majority of associated environmental burdens are concentrated in regions where raw materials are sourced and processed, a phenomenon that is particularly evident in the context of Abiotic Depletion Potential (ADP).

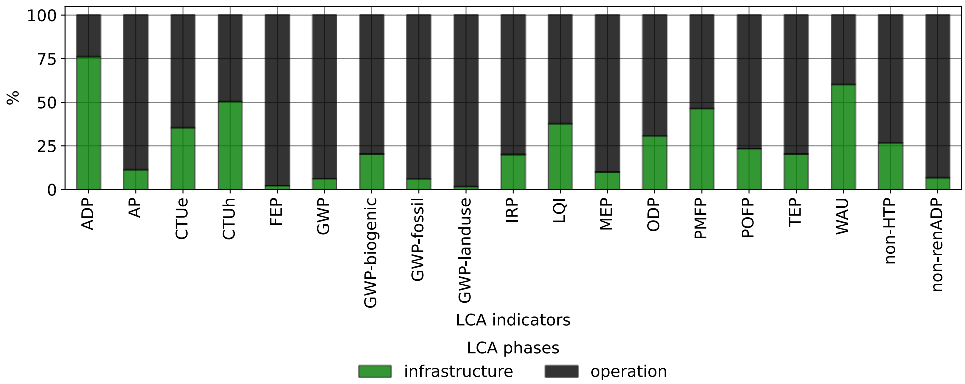


Figure 5.6 LCA indicators representing environmental burdens coming from life cycle phases
Results correspond to the infrastructure and operation phases for the current reference scenario. LCA indicators corresponds to the EF 3.0 LCIA including abiotic depletion potential (ADP), acidification potential (AP), ecotoxicity (CTUe), human toxicity (CTUh), freshwater eutrophication (FEP), global warming potential (GPW) including from biogenic, fossil and land use, ionizing radiation (IRP), land transformation (LQI), ozone depletion potential (ODP), marine eutrophication (MEP), particulate matter (PMFP), photochemical oxidation potential (POFP), terrestrial acidification (TEP), water use (WAU), human health (non-HTTP), abiotic depletion potential non-renewables (non-ren ADP). Current reference temporal assumptions in Section 4.3.2

Source: Own representation

The current reference scenario estimates offshore wind facilities in eight countries as shown in Table 5.2, which are Belgium, Germany, Denmark, France, Italy, the Netherlands, Portugal and the United Kingdom. In this case, only offshore wind turbines of 7 MW nominal capacity are considered. Table 5.2 summarises the input parameters for offshore wind technologies. The annual full load hours (FLH) are calculated based on Section 4.4.2. The location in the United Kingdom exhibits the highest resource availability, achieving 4,743 hours per year compared to 4,430 hours per year in Germany for the same type of wind turbine. Although LCA indicators per kWh are relatively small, there is a 20 % difference in the locations, primarily due to differences in wind resource availability.

Table 5.2 Results scenario current reference for offshore wind

		BE	DE	DK	FR	IT	NL	PT	UK
Inputs	Interest rate, %	0.94	0.49	0.68	0.93	2.21	0.69	2.11	1.61
	Inflation rate, %	2.48	2.52	1.72	1.98	1.97	2.58	1.82	2.2
	Lifetime, years	20	20	20	20	20	20	20	20
	CAPEX, €/kW	3605	3610	3499	3535	3533	3619	3513	3565
	OPEX, €/kWh	93	93	91	91	91	94	91	92
	FLH, hours/year	3582	4430	4419	3920	3439	4312	3555	4743
	GWP infrastructure, kg CO_2-eq/kW	828	828	828	828	828	828	828	828
	GWP operation, kg CO_2-eq/kWh	2.31E-04	1.89E-04	1.88E-04	2.35E-04	2.68E-04	2.13E-04	3.39E-04	1.94E-04
Results offshore wind	Total, GW	2.26	8.39	2.31	1.48	0.03	3.22	0.03	12.16
	Total electricity generation, TWh	9.02	40.77	11.27	5.81	0.10	13.88	0.09	57.68
	Total costs, million €	660	2377	642	424	9	927	8	3674
	Total GWP, million kg CO_2-eq	95.6	354.7	97.5	62.7	1.2	136.2	1.0	514.3
	LCOE, €/kWh	6.78	5.39	5.27	6.76	8.47	6.18	8.08	5.92
	GWP, g CO2-eq/kWh	10.61	8.70	8.65	10.79	12.30	9.81	11.98	8.92

Results are based on units of 7 MW, 154 m rotor diameter and 77 m hub height. Capital expenditure (CAPEX), operational expenditure (OPEX), Full load hours (FLH), Global warming potential (GWP). Current reference temporal assumptions in Section 4.3.2

The values of installed capacity calculated by the ESM-LCA model reflect current conditions in Germany (8 GW) as well as in the other countries (see Figure 5.7a). As the optimization of the model requires constraints—such as a maximum limit for installed capacity— historical data retrieved from ENTSO-E (2024a) are used to define the current reference scenario. However, electricity generation is determined by the ESM-LCA model based on resource availability and costs. As a result, the calculated installed capacity of 8 GW generates about 40 TWh in Germany, which is double its actual generation in 2023 (23.5 TWh) (see Figure 5.7b).

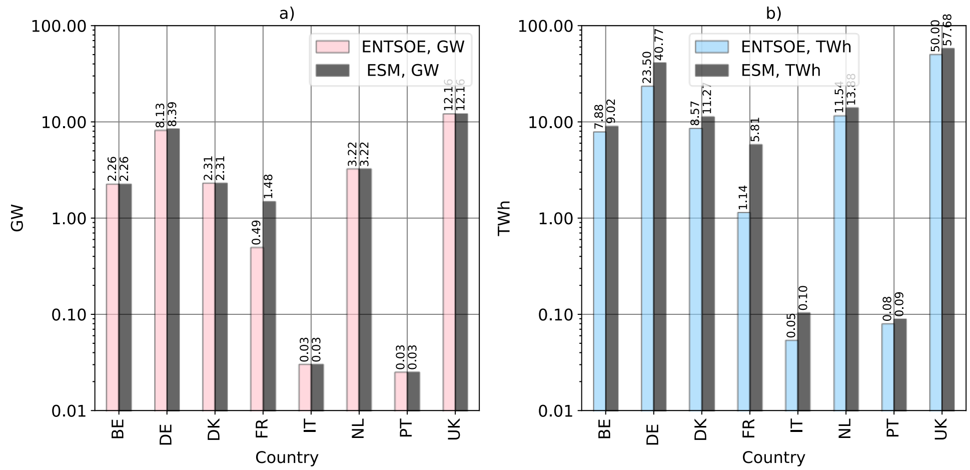


Figure 5.7 Comparison between current reference scenario outcomes and observed data
Calculated results from the ESM-LCA model (shown in black); observed data corresponds to 2024
a) Installed capacity (in GW); b) Electricity generation (in TWh) for offshore wind turbines of 7 MW in Belgium (BE), Germany (DE), Denmark (DK), France (FR), Italy (IT), the Netherlands (NL), Portugal (PT) and the United Kingdom (UK). Current reference temporal assumptions in Section 4.3.2

Source: Own representation based on ENTSO-E (2024a, 2024b)

The LCOE calculated by the model ranges from 0.06 €/kWh to 0.08 €/kWh, with the highest LCOE values for Portugal due to its lower generation. These values match literature estimates, with offshore wind turbine LCOE ranging from 0.05 €/kWh to 0.11 €/kWh in 2024 (Kost et al., 2024). Regarding total costs, CAPEX presents small variations between countries, primarily due to interest rates (see Section 4.4). Furthermore, CAPEX values do not account for variation in water depth, as the thesis assumes all offshore projects will be installed in water depths suitable for monopile foundation. The total GHG emissions per kWh are comparable in Germany, Denmark and the United Kingdom, with a mean of 8 g CO_2-eq/kWh. Despite GHG emissions coming from the construction are equivalent across countries, the total GHG emissions encompass both construction and operation. Consequently, when accounting for GHG emissions over the entire lifetime of the wind turbines, the effect of the operational phase becomes more pronounced.

5.3 Projected outcomes under future scenario assumptions

This section presents the outcomes obtained by the ESM-LCA model for the target years 2030 and 2050, respectively. For each designated target year, the results of the optimistic and pessimistic scenarios are presented for the core regions belonging to the ESM-LCA model. Despite the evaluation's primary focus on Germany due to its economic significance, results from France, Italy and the UK are also examined.

5.3.1 Target year 2030

This section presents the results of the target year 2030. To assess the impact of different assumptions on the energy system in 2030, two scenarios are compared: a pessimistic scenario (left Figure 5.8), characterized by conservative technological deployment, higher environmental burdens and higher costs, and an optimistic scenario (right Figure 5.8), assuming accelerated renewable integration and cost reductions. Additionally, the moderate scenario contains average values between optimistic and pessimistic scenarios. While Germany reaches 300 GW of installed capacity, Italy, France, and the United Kingdom exceed 100 GW (see Table 5.3). In most countries, the power plant mix is based on renewable energy sources, with the exception of Poland, where the pessimistic scenario assumes the continued operation of a small share of hard coal power plants (15 GW).

Table 5.3 ESM-LCA model results for Germany, France, Italy and the United Kingdom in 2030

		Germany			France			Italy			United Kingdom		
	Parameters	**Pess**	**Mod**	**Opt**	**Pess**	**Mod**	**Opt**	**Pess**	**Mod**	**Opt**	**Pess**	**Mod**	**Opt**
Input	Share renewables min, %		70			43			72			40	
	Demand, TWh		570			473			290			320	
	WOF 7MW CAPEX, €/kW	4,260	3,691	3,218	4,041	3,501	3,053	4,037	3,498	3,050	4,129	3,578	3,119
Output	Total, GW	306	287	285	113	113	127	122	124	116	97	129	129
	Total, TWh	635	630	630	481	480	480	308	310	309	330	334	335
	Renewables, GW	257	239	237	71	71	88	116	119	110	65	98	98
	Renewables, TWh	570	557	557	276	275	301	305	306	294	200	232	232
	Calculated share renewables, %	89	88	88	57	57	62	98	98	95	60	69	69

Pessimistic (pess), moderate (mod), optimistic (opt), wind offshore wind (WOF) represented by 7 MW wind turbine

In terms of electricity generation, the ESM-LCA model aims to meet a share of the electricity demand with renewable energy resources, aligned with government targets (see Table 5.3). The results indicate that by 2030, Germany could meet at least 80 % of its electricity demand from renewables. Due to the high cost of offshore wind, most countries prioritize more cost-effective technologies such as onshore wind and solar photovoltaics. Under the modelled cost and demand assumptions, offshore wind deployment is limited to countries with favourable conditions, including Ireland, Germany, the Netherlands, Poland, and the United Kingdom (see Figure 5.8).

Regarding total GWP, by 2030 Poland exhibits the highest emissions in the pessimistic scenario. In contrast, Germany—despite having a power plant mix exceeding 300 GW and generating over 600 TWh annually—achieves significantly lower emissions due to its reliance on renewable energy sources (38 million t CO_2-eq). In Poland, 15 GW of hard coal capacity results in approximately 60 million t CO_2-equivalent emissions. However, in the optimistic scenario, these emissions are reduced by half (27 million t CO_2-eq) through the substitution of hard coal with natural gas and a diversified mix of renewable energy technologies.

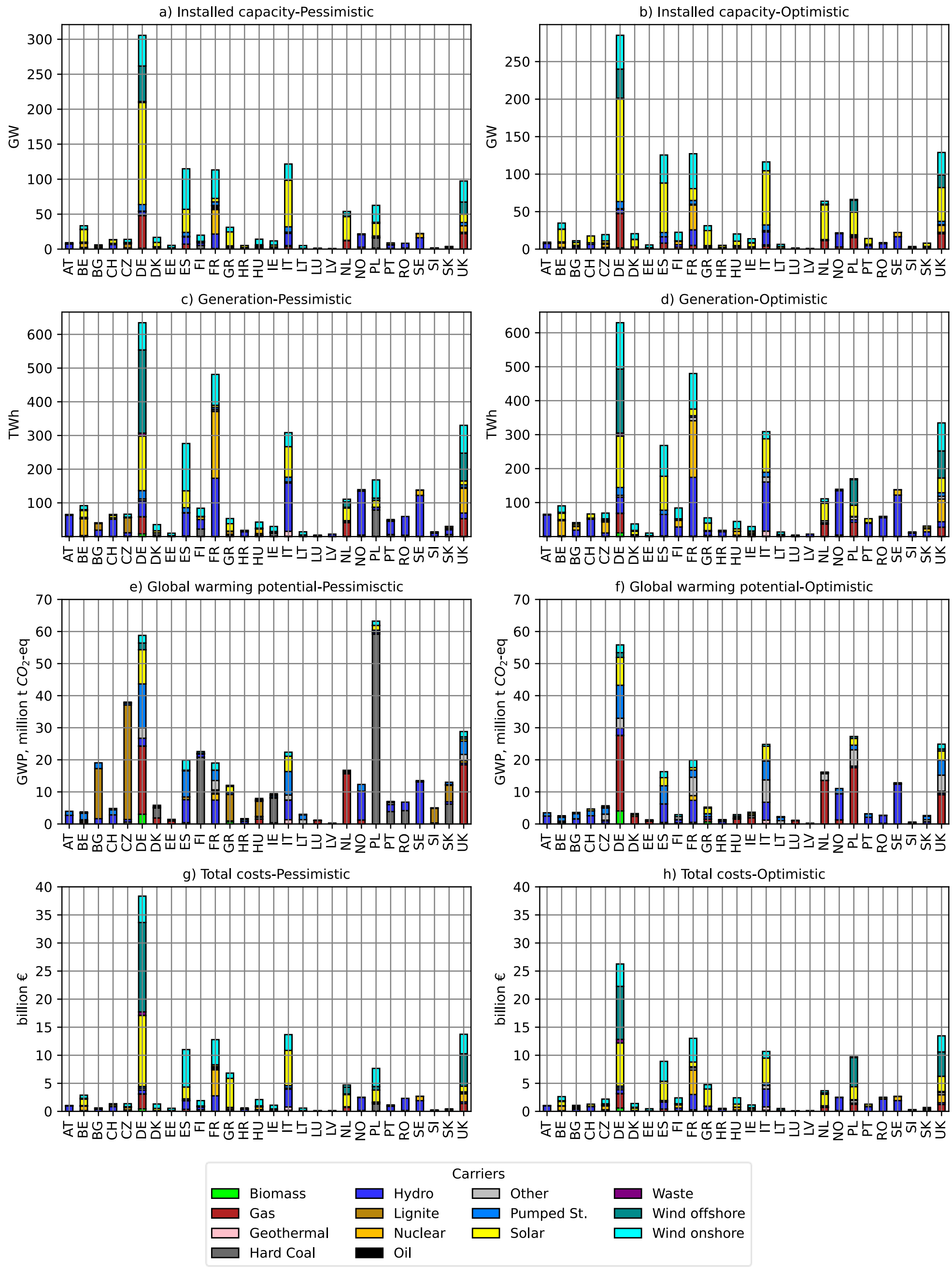


Figure 5.8 ESM-LCA model results for 2030 under cost minimisation
Comparison between pessimistic (left) and optimistic (right) scenarios

Source: Own representation

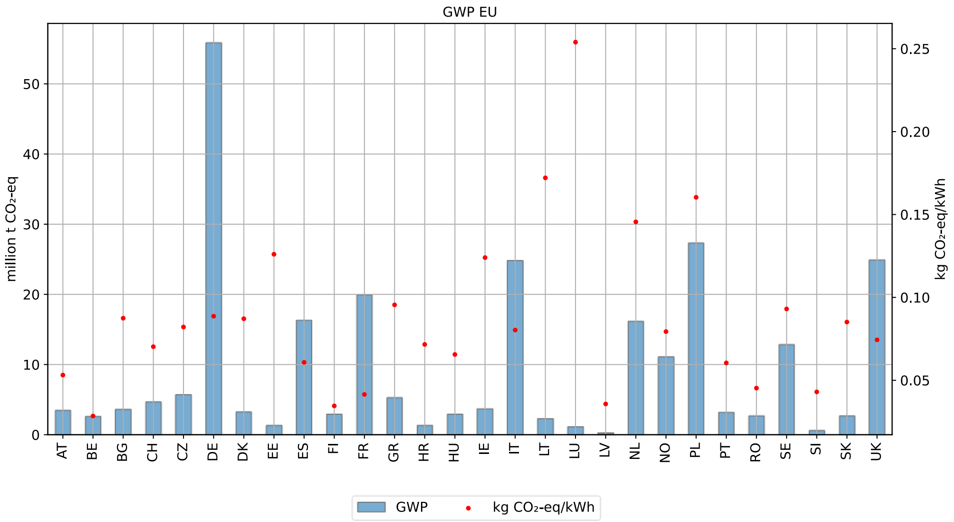


Figure 5.9 Total global warming potential (GWP) in 2030
Results per country calculated by the ESM-LCA model correspond to the optimistic scenario under cost minimisation

Source: Own representation

Overall, the GHG emissions per kWh generated in the optimistic scenario are below 0.25 kg CO_2-eq/kWh. For instance, Germany could reach 0.08 kg CO_2-eq/kWh in 2030 (see Figure 5.9). As this thesis focuses on Germany, Figure 5.10 illustrates the relative contribution of the LCA indicators for the optimistic scenario in 2030. The majority of the contribution to climate change comes from combined cycle gas turbines (NG-CCGT), which account for approximately 20 GW of installed capacity and 55 TWh of electricity generation.

Despite this, NG-CCGTs represent 38 % of total GWP. In contrast, solar and wind energy, with a combined installed capacity of 220 GW generating around 470 TWh, contribute to only about 20 % of the total GWP. In addition, natural gas has the largest contribution to ozone depletion potential (ODP), while solar makes the highest contribution to abiotic resource depletion, acidification, freshwater ecotoxicity (CTUe) and human health. Regarding the LCA phases, the results diverge. For GWP, the operation phase remains the most relevant due to the burning of natural gas and biomass, while for toxicity-related and resource-related indicators, the infrastructure phase is more significant (see Figure 5.11).

Because the optimistic scenario assumes a higher deployment of renewables and consequently lower renewable energy costs, there are only minor differences in the electricity mix in Germany between the optimistic and pessimistic scenarios. However, in terms of total system costs, the optimistic scenario achieves a reduction of nearly 32 % (see Table 5.4).

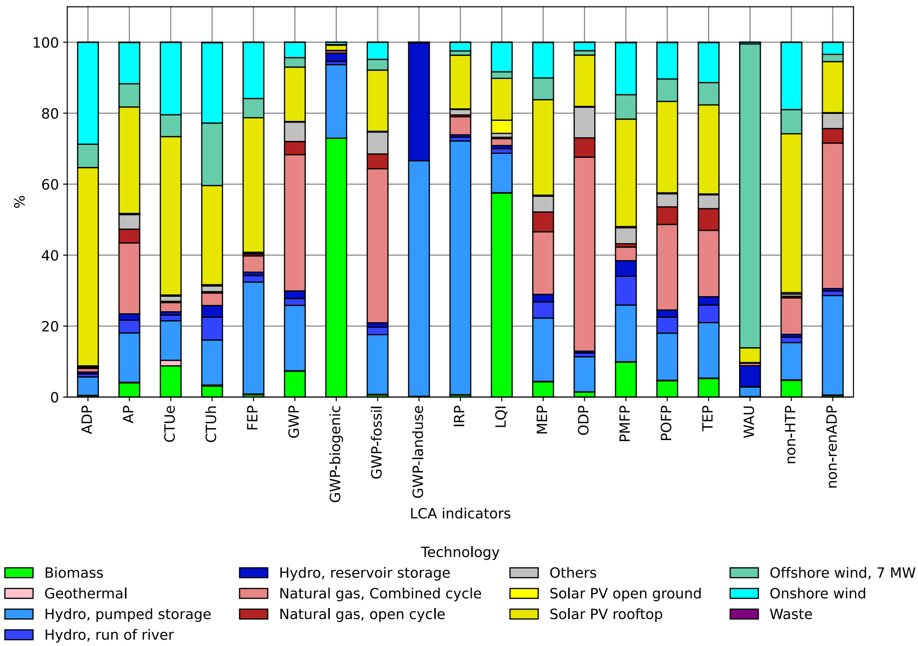


Figure 5.10 Relative contribution representing the German electricity mix in 2030
The results correspond to the optimistic scenario in 2030 under cost minimisation. LCA indicators corresponds to the EF 3.0 LCIA including abiotic depletion potential (ADP), acidification potential (AP), ecotoxicity (CTUe), human toxicity (CTUh), freshwater eutrophication (FEP), global warming potential (GPW) including from biogenic, fossil and land use, ionizing radiation (IRP), land use soil quality index (LQI), ozone depletion potential (ODP), marine eutrophication (MEP), particulate matter (PMFP), photochemical oxidation potential (POFP), terrestrial acidification (TEP), water use (WAU), human health (non-HTTP), abiotic depletion potential non-renewables (non-ren ADP). Absolute values in Table A. 4

Source: Own representation

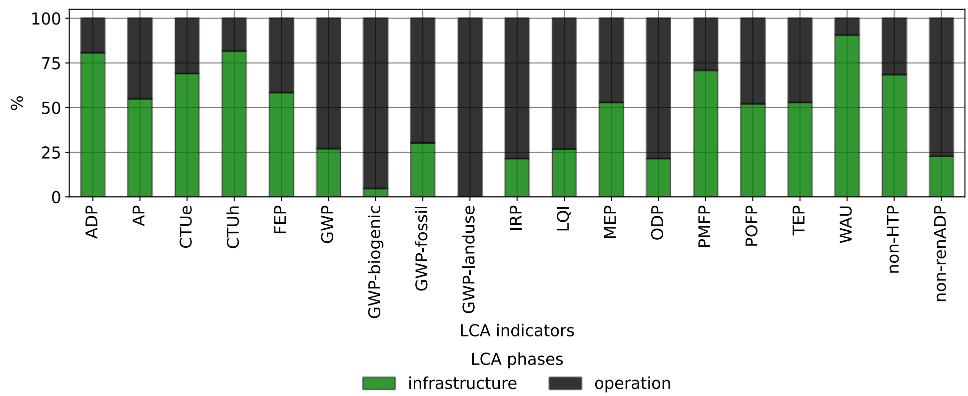


Figure 5.11 LCA indicators representing environmental burdens coming from life cycle phases in 2030

Results correspond to the infrastructure and operation phases for the optimistic scenario in 2030. LCA indicators corresponds to the EF 3.0 LCIA including abiotic depletion potential (ADP), acidification potential (AP), ecotoxicity (CTUe), human toxicity (CTUh), freshwater eutrophication (FEP), global warming potential (GPW) including from biogenic, fossil and land use, ionizing radiation (IRP), land transformation (LQI), ozone depletion potential (ODP), marine eutrophication (MEP), particulate matter (PMFP), photochemical oxidation potential (POFP), terrestrial acidification (TEP), water use (WAU), human health (non-HTTP), abiotic depletion potential non-renewables (non-ren ADP)

Source: Own representation

Table 5.4 Summary results for the target year 2030 in Germany under cost minimisation.

Germany 2030		Pessimistic	Moderate	Optimistic	Difference*
Inputs	Annual demand, TWh	570	570	570	0 %
	WOF11MW CAPEX, €/kW	6,129	5,311	4,631	24 %
	WOF15MW CAPEX, €/kW	9,726	8,428	7,349	24 %
	WOF7MW CAPEX, €/kW	4,260	3,692	3,672	14 %
	WOF9MW CAPEX, €/kW	5613	4864	4,241	24 %
	Share renewables, min	70 %	70 %	70 %	0 %
	Constraint onshore wind, GW	80	80	80	0 %
	Constraint offshore wind, GW	inf	inf	inf	-
	FLH solar PV, h-a	1,109	1,109	1,109	0 %
	FLH onshore, h-a	1,842	2,719	3,025	-64 %
	FLH WOF11MW, h-a	6,128	5,310	5,298	14 %
	FLH WOF15MW, h-a	9,726	8,428	7,348	24 %
	FLH WOF7MW, h-a	4,260	3,692	3,218	24 %
	FLH WOF9MW, h-a	5,612	4,863	4,240	24 %
Total results	Installed capacity, GW	305.59	287.09	285.08	7 %
	Electricity generation, TWh	634.72	629.56	629.54	1 %
	GWP million t CO_2-eq	58.79	59.36	55.82	5 %
	billion €	38.35	30.63	26.26	32 %
Wind offshore results (7 MW)	Installed capacity, GW	50.75	42.35	38.75	24%
	Electricity generation, TWh	246.73	205.89	188.41	24 %
	GWP, million t CO_2-eq	2.08	1.73	1.49	28 %
	Costs, billion €	15.93	11.64	9.45	41 %

Wind offshore (WOF) represented by offshore wind turbines 7 MW, 9 MW, 11 MW and 15 MW. Full load hours (FLH). Capital expenditure (CAPEX). *Difference between the pessimistic and optimistic scenarios.

When the ESM-LCA model is configured to evaluate the same scenarios with the objective of minimising GWP, the most immediate impact is on the composition of the power plant mix across all countries (see Figure 5.12). For instance, Italy could achieve an average 90 % reduction in GWP (from 90 million t CO_2-eq under cost optimisation to 12 million t CO_2-eq under GHG emissions optimisation) with only a 10 % increase in total system costs. This enhancement can be achieved by substituting the technology categorised as "Others" with natural gas. The "Others" category encompasses technologies that cannot be readily classified and are presumed to exhibit equivalent environmental performance to that of oil-fired power plants and comparable costs to those of solid biomass power plants. Overall, countries experience significant reduction of GWP but at the expense of a substantial cost increase (see Table 5.5). For Germany, a 45 % reduction in GWP could result in an average cost increase of 42 %.

While the composition of the power plant mix remains comparable, the primary distinction is found in the allocation of GW assigned to each technology. For example, offshore wind capacity increases by 44 %, rising from 44 GW under cost optimization to 83 GW under GHG emissions optimization.

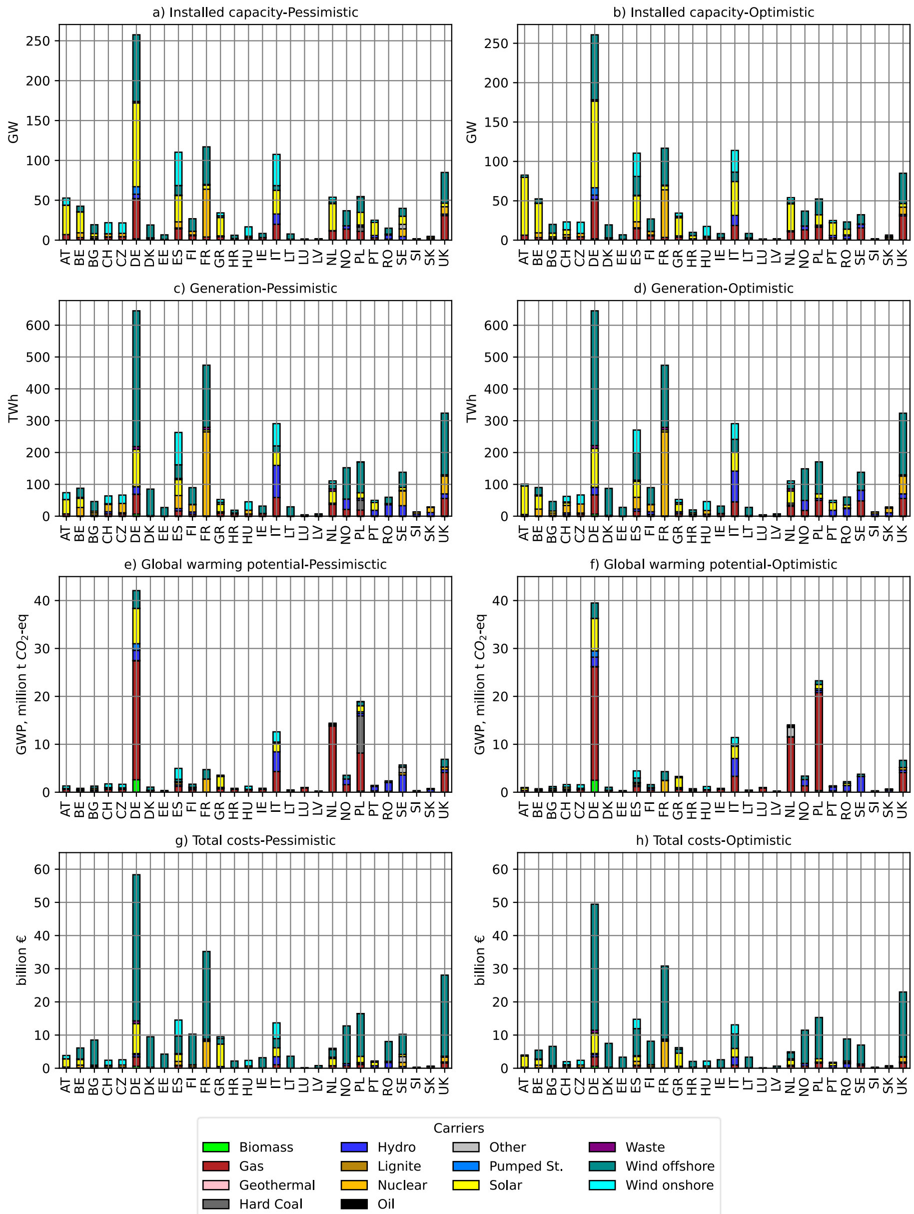


Figure 5.12 ESM-LCA model results for 2030 under GWP minimisation
Comparison between pessimistic (left) and optimistic (right) scenarios

Source: Own representation

Table 5.5 Comparison of average results under GWP and total cost minimisation in 2030

Solution strategy	*Installed capacity, GW*		*Electricity generation, TWh*		*GWP, million t CO_2-eq*		*Total costs. billion €*	
	GWP	*Monetary*	*GWP*	*Monetary*	*GWP*	*Monetary*	*GWP*	*Monetary*
AT	68	9	88	66	1	4	4	1
BE	49	33	89	91	1	3	6	3
BG	20	8	46	41	1	14	8	1
CH	23	16	63	66	2	5	2	1
CZ	22	16	66	68	2	26	2	2
DE	259	293	646	631	41	58	55	32
DK	19	19	86	36	1	6	8	1
EE	7	5	27	10	0	1	4	1
ES	110	122	266	271	5	18	15	10
FI	27	21	90	84	2	10	9	2
FR	117	118	474	480	5	19	33	13
GR	34	31	52	54	3	10	8	6
HR	8	5	20	18	1	2	2	1
HU	17	17	45	43	1	5	2	2
IE	8	13	32	30	1	6	3	1
IT	109	121	291	309	12	23	13	12
LT	8	6	28	14	0	3	4	1
LU	1	1	4	4	1	1	0	0
LV	2	1	7	7	0	0	1	0
NL	54	61	111	111	14	16	5	4
NO	37	22	151	139	3	12	12	3
PL	53	64	171	169	22	56	16	8
PT	25	12	50	52	1	5	2	1
RO	20	8	60	59	2	6	9	2
SE	37	22	138	138	5	13	9	3
SI	2	2	13	14	0	4	0	0
SK	6	7	29	31	1	7	1	1
UK	85	118	324	333	7	26	25	14

The average values are calculated based on the results of the Optimistic, Moderate, and Pessimistic scenarios under GWP and total cost minimisation (monetary)

5.3.2 Target year 2050

The results for the target year 2050 are presented in Figure 5.13, which illustrates the expected installed capacity, electricity generation, total GWP, and total costs for both the pessimistic (Figure 5.13-left) and optimistic (Figure 5.13-right) scenarios. In this case, hydrogen produced via electrolysis is used as a replacement for natural gas in power plants—but only in Germany—in line with climate neutrality scenarios proposed by Prognos et al. (2021). To meet an electricity demand of approximately 600 TWh, nearly 300 GW of installed capacity are required for Germany, which is expected to generate around 670 TWh of electricity. In the optimistic scenario, fossil-fuelled power plants—such as those using natural gas—are excluded. Instead, the system relies on biogas, biomass, hydropower, waste, and hydrogen-based power plants for flexible generation. A significant share of the installed capacity, approximately 220 GW, consists of wind and solar technologies.

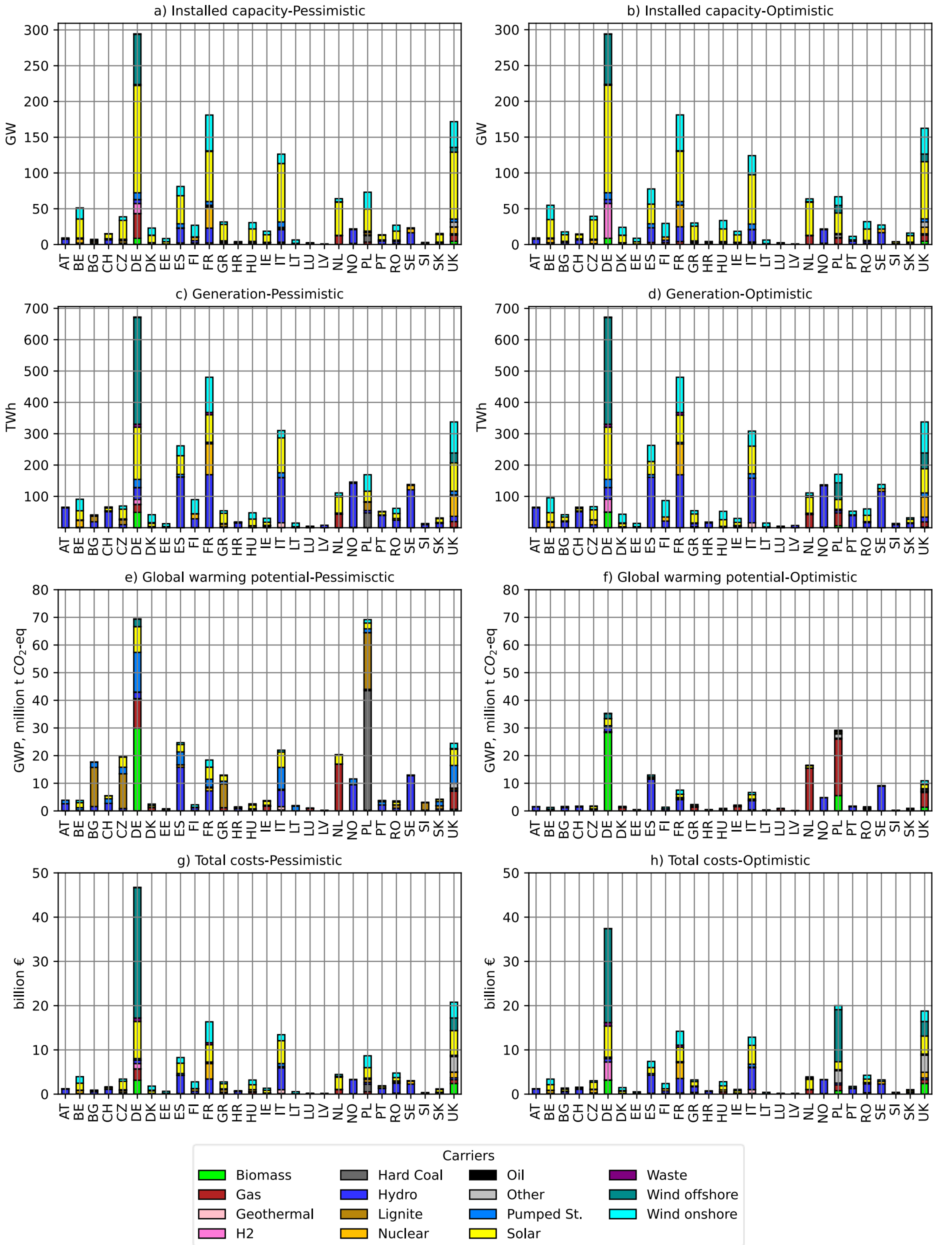


Figure 5.13 ESM-LCA model results for 2050 under cost minimisation
Comparison between pessimistic (left) and optimistic (right) scenarios

Source: Own representation

In terms of installed capacity, France, the UK, and Italy follow Germany, with 180 GW, 170 GW and 126 GW, respectively. Although nuclear power (30 GW) remains in the Frech electricity mix, onshore wind and solar energy have a significant share (66 %) of the country's power plant mix. Similarly, in the UK wind and solar constitute about 80 % of its installed capacity, while in Italy, these sources accounts for approximately 95 GW. With respect of electricity generation, offshore wind could potentially supply 50 % of the electricity demand in Germany. In contrast, France and Italy rely on hydropower, generating approximately 160 TWh. Despite solar power accounting for an average of 86 GW of installed capacity in the UK, it generates approximately 80 TWh, while 9 GW of nuclear power produces around 65 TWh. Although the ESM-LCA model is configured to phase out fossil-fired power plants by 2050 (see Table 4.5), the pessimistic scenario includes a small share of fossil-fired power generation in Poland, with an average of 2 GW from lignite and 5 GW from hard coal. As a result of the phasing out of fossil-fired power plants and the transition to gas-fired and renewable energy sources, Poland could achieve a 58 % reduction in GWP. However, this transition could lead to a 131 % increase in total system costs.

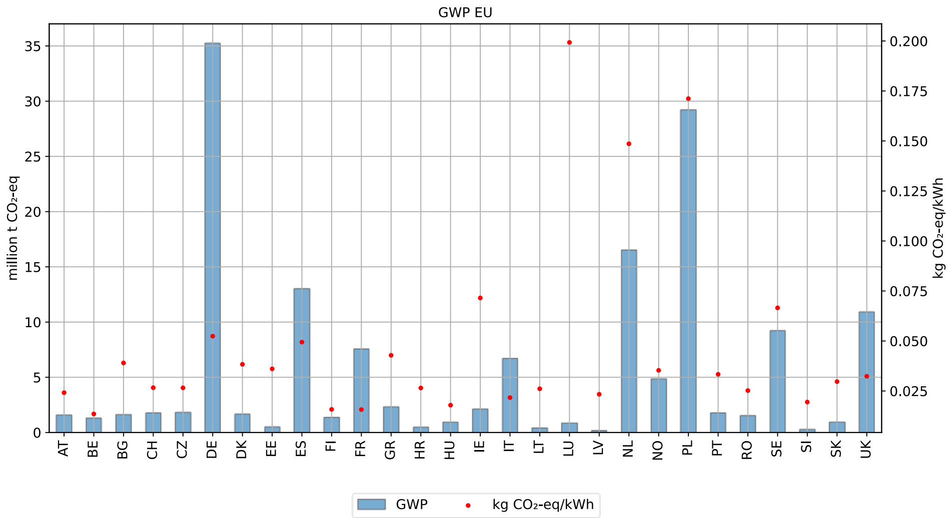


Figure 5.14 Total global warming potential (GWP) in 2050
Results per country calculated by the ESM-LCA model correspond to the optimistic scenario under cost minimisation

Source: Own representation

In Germany, GWP could be reduced from 80 million t CO_2-eq to 35 million t CO_2-eq by limiting the use of natural gas and biomass and incorporating hydrogen into the energy mix. In the case of the UK, the power plant mix consists of natural gas, nuclear, hydro, wind, and solar technologies, with a similar composition in both scenarios. However, the total GWP differ significantly— with the optimistic scenario producing nearly half the emissions of the pessimistic scenario. For Italy, GHG emissions decrease significantly, primarily due to reduced impacts associated with hydro pumped storage. Cement, as a key component in the infrastructure of pumped storage power plants, is a major contributor to environmental burdens. In the optimistic scenario, these impacts are lower due to improvements in the cement production process, which reflects Western European practices. This reduction is primarily attributed to the lower LCA environmental burdens (e.g., GWP) associated with more efficient cement manufacturing.

Concerning the specific GWP, Germany could reach 0.05 kg CO_2-eq/kWh in 2050 (see Figure 5.14), while France and Italy are projected to reach 0.02 kg CO_2-eq/kWh, and the United Kingdom approximately 0.03 kg CO_2-eq/kWh. Despite the significant reduction in GWP that Germany experiences, its total emissions remain the highest among the analysed countries. However, it is important to note that, within the context of this thesis, Germany's electricity demand is assumed to increase substantially due to sector electrification. In Germany, the relative contribution of LCA indicators under the optimistic scenario shows that biomass and biogas are the primary contributors to GWP—accounting for approximately 80 %—despite representing only about 8 GW of installed capacity and generating around 50 TWh. In contrast, wind and solar account for just 12 % of GWP while supplying approximately 75 % of the electricity demand. The use of green hydrogen as a fuel in natural gas power plants makes a minimal contribution to GWP; however, it becomes a significant contributor to acidification, marine and terrestrial eutrophication, and photochemical ozone formation potential, due to nitrogen oxide emissions associated with hydrogen combustion. Similarly, renewable technologies such as solar and wind are significant contributors to abiotic resource depletion due to their high demand for metals (e.g., steel, copper), which is associated with increased impacts on freshwater ecotoxicity and human health as a result of intensified mining activities. Additionally, water use emerges as a key concern for offshore wind technologies (see Figure 5.15).

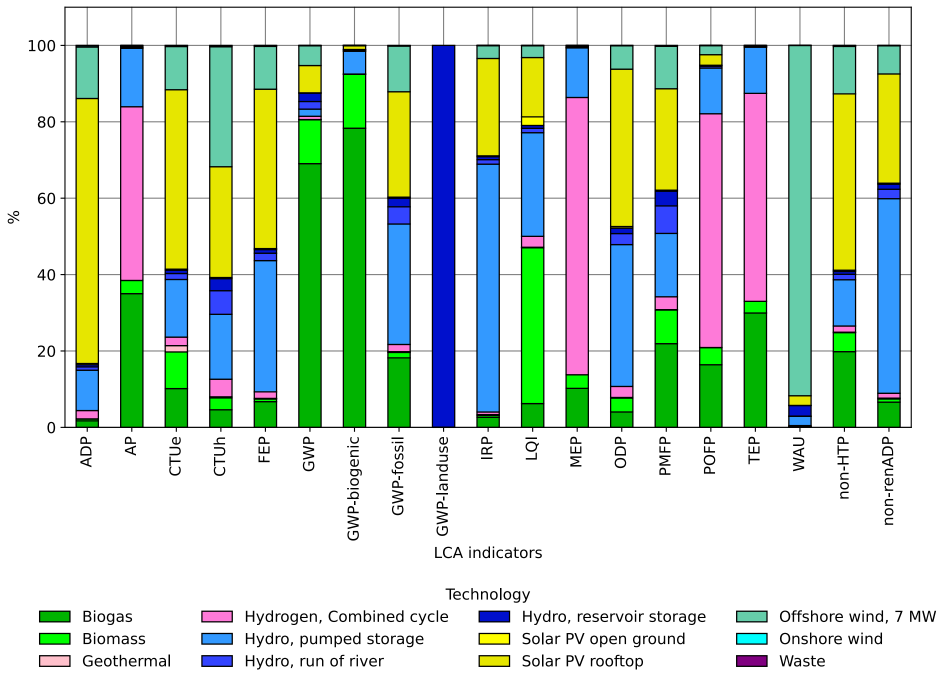


Figure 5.15 Relative contribution representing the German power plant mix in 2050
The results correspond to the optimistic scenario in 2050. LCA indicators corresponds to the EF 3.0 LCIA including abiotic depletion potential (ADP), acidification potential (AP), ecotoxicity (CTUe), human toxicity (CTUh), freshwater eutrophication (FEP), global warming potential (GPW) including

from biogenic, fossil and land use, ionizing radiation (IRP), land use soil quality index (LQI), ozone depletion potential (ODP), marine eutrophication (MEP), particulate matter (PMFP), photochemical oxidation potential (POFP), terrestrial acidification (TEP), water use (WAU), human health (non-HTTP), abiotic depletion potential non-renewables (non-ren ADP). Absolute values in Table A. 5

Source: Own representation

Regarding the environmental burdens across the LCA phases, less than 25 % of the GHG emissions originate from the infrastructure phase of the German electricity mix (see Figure 5.16), with the remaining majority attributed to the combustion of solid biomass and biogas during the operation phase. Similarly, the environmental indicators such as freshwater ecotoxicity, human health impacts, and abiotic resource depletion are primarily associated with the infrastructure phase, which aligns with the presence of renewable energy sources.

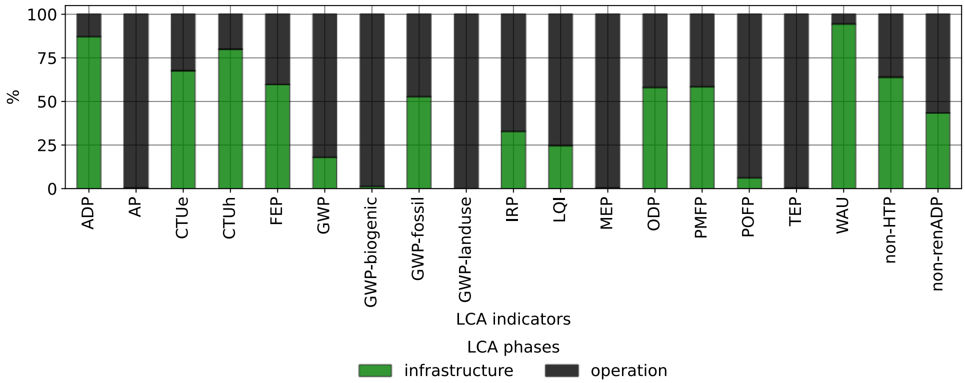


Figure 5.16 LCA indicators representing environmental burdens coming from life cycle phases in 2050 Results correspond to the infrastructure and operation phases for the optimistic scenario in 2050. LCA indicators correspond to the EF 3.0 LCIA including abiotic depletion potential (ADP), acidification potential (AP), ecotoxicity (CTUe), human toxicity (CTUh), freshwater eutrophication (FEP), global warming potential (GPW) including from biogenic, fossil and land use, ionizing radiation (IRP), land transformation (LQI), ozone depletion potential (ODP), marine eutrophication (MEP), particulate matter (PMFP), photochemical oxidation potential (POFP), terrestrial acidification (TEP), water use (WAU), human health (non-HTTP), abiotic depletion potential non-renewables (non-ren ADP)

Source: Own representation

Table 5.6 Summary results for Germany scenario 2050 under cost minimisation

Germany 2050		Pessimistic	Moderate	Optimistic	*Difference
Inputs	Annual demand, TWh	622	622	622	0%
	WOF11MW CAPEX, €/kW	4,556		3,442	24%
	WOF15MW CAPEX, €/kW	14,678	12,261	10,319	30%
	WOF7MW CAPEX, €/kW	9,547	7,975	4,520	53%
	WOF9MW CAPEX, €/kW	6,543	5,466	4,600	30%
	Share renewables, min	70%	70%	70%	0%
	Constraint onshore wind, GW	80	80	80	0%

	Constraint offshore wind, GW	inf	inf	inf	-
	FLH solar PV, h-a	1,109	1,109	1,109	0%
	FLH onshore, h-a	1,842	2,719	3,025	-64%
	FLH WOF11MW, h-a	5,041	5,041	5,041	0%
	FLH WOF15MW, h-a	5,140	5,140	5,140	0%
	FLH WOF7MW, h-a	4,862	4,862	4,862	0%
	FLH WOF9MW, h-a	4,430	4,430	4,430	0%
Total results	Installed capacity, GW	295	326	294	0%
	Electricity generation, TWh	672	675	673	0%
	GWP million t CO_2-eq	69	58	35	49%
	Total costs, billion €	47	39	37	20%
Wind offshore results (7 MW)	Installed capacity, GW	70	60	70	0%
	Electricity generation, TWh	340	291	340	0%
	GWP, million t CO_2-eq	3	2	2	32%
	Total costs, billion €	30	21	21	28%
Fossil-fired results	Installed capacity, GW	35	33	0	100%
	Electricity generation, TWh	25	19	0	100%
	GWP million t CO_2-eq	11	7	0	100%
	Total costs, billion €	3	2	0	100%
Renewables results	Installed capacity, GW	260	293	294	-13%
	Electricity generation, TWh	647	656	673	-4%
	GWP million t CO_2-eq	59	50	35	40%
	billion €	44	37	37	15%
H_2 results	Installed capacity, GW	14	15	49	-247%
	Electricity generation, TWh	16	19	40	-160%
	GWP million t CO_2-eq	0.14	0.13	0.30	-115%
	Total costs, billion €	1.20	1.24	4.07	-240%

Wind offshore (WOF) represented by offshore wind turbines 7 MW, 9 MW, 11 MW and 15 MW. Full load hours (FLH). Capital expenditure (CAPEX). *Difference presents the percentage change between the pessimistic and optimistic scenarios.

In Germany, the difference in GWP between the pessimistic and optimistic scenarios is close to 50 %, with a corresponding cost difference of approximately 20 %. Offshore wind is identified as the primary cost driver (see Table 5.6). The evaluation of the scenarios under GWP minimisation reveals a significantly different technological mix in most countries (see Figure 5.17). In the case of Germany, onshore wind plays a minor role, while the system relies more heavily on solar and offshore wind. A comparison between Case 4 (pessimistic scenario under GWP minimisation) and Case 6 (optimistic scenario under GWP minimisation) shows that Germany could achieve a 14 % reduction in GWP by 2050, albeit with an average increase of 53 % in total system costs. Additionally, GWP associated with pumped storage are relatively higher in the pessimistic scenario due to assumptions in the background data (see Section 5.3.1). Conversely, Hungary stands to achieve a 49 % reduction in emissions with a mere 15 % increase in total costs by leveraging solar and onshore wind technologies. In the UK, the energy system relies more on nuclear, natural gas, solar, onshore and offshore wind, and GWP could be reduced by 138 % with a cost increase of 49 %. In Spain, total GWP are, on average, three times higher when the system is optimised based on cost. A 189 % reduction in GWP could imply a 66 %

increase in total system costs, driven by the inclusion of 7 GW of nuclear energy and approximately 30 GW of offshore wind capacity.

Figure 5.17 ESM-LCA model results for 2050 under GWP minimisation
Comparison between pessimistic (Case 6, left) and optimistic (Case 4, right) scenarios

Source: Own representation

5.3.3 Offshore wind in 2030 and 2050

The results for the target year 2030 in the three analysed scenarios under cost minimisation indicate that offshore wind emerges as a cost-optimal solution in a few countries, namely Ireland, Germany, the Netherlands, Poland, and the United Kingdom, although the model allows for offshore wind deployment in a wider range of countries (Table 4.8, Section 4.4.2). This outcome is driven by the high capital expenditure associated with offshore wind, as the capital expenditure reflects the nominal capacity, inflation and technology learning associated with rapid technology deployment. Table 5.4 shows some of the inputs considered and results obtained for the year 2030 in Germany. The CAPEX for offshore wind varies in 24 % (between the pessimistic and optimistic scenarios), which in turn results in a 41 % difference in total costs. Although the ESM-LCA model considers four wind turbine sizes, the cost-optimal solution includes only the 7 MW offshore wind turbines.

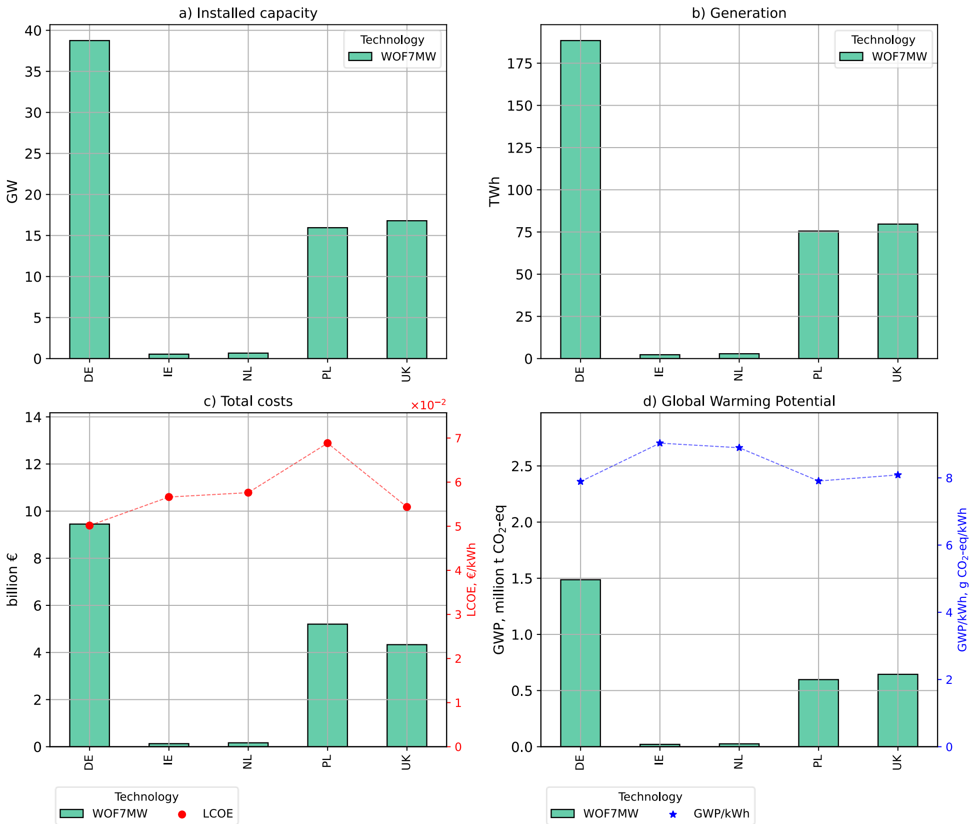


Figure 5.18 Results for wind offshore (WOF) technology in 2030 under cost minimisation
The results are composed by wind turbines of 7 MW in the Optimistic Scenario for 2030 under cost minimisation – a) Installed Capacity, b) Electricity Generation, c) Total Costs, including levelized cost of electricity (LCOE, in red dots) d) Global Warming Potential, including specific GWP (blue starts) for Germany (DE), Ireland (IE), the Netherlands (NL), Poland, and the United Kingdom (UK)

Source: Own representation

Under the ESM-LCA model assumptions, the values in terms of offshore wind installed capacity calculated by the model for Germany vary between 38 and 50 GW. In contrast, a current target for Germany is to achieve 30 GW by 2030 (Agora Energiewende et al., 2020). Despite the anticipated higher costs for renewables (e.g. solar, onshore and offshore wind), this situation in the pessimistic scenario appears to favour the inclusion of offshore wind in Germany (50 GW).

In the optimistic scenario, there is a 24 % reduction in CAPEX compared to the pessimistic scenario. However, offshore wind remains more expensive than onshore wind and solar energy (see Table 4.10, Section 4.4.4). Consequently, the optimistic scenario includes only 38 GW of offshore wind. Offshore wind targets vary significantly across countries. According to several literature sources, by 2030, Ireland, the Netherlands, Poland, and the United Kingdom are expected to reach offshore wind capacity targets of 5 GW, 21 GW, 6 GW, and 50 GW, respectively.

Overall, the LCOE in the optimistic scenario is on average below 0.05 €/kWh in 2030 (see Figure 5.18c). This amount considers inflation and learning effects. Similarly, GWP per kWh remain close to 8 g CO_2-eq/kWh (see Figure 5.18d).

Table 5.7 Summary offshore wind results target year 2050 under cost minimisation.

Country	**DE**			**NL**			**PL**			**UK**		
Parameters	**Pess**	**Mod**	**Opt**	**Pess**	**Mod**	**Opt**	**Pess**	**Mod**	**Opt**	**Pess**	**Mod**	**Opt**
Share renewables min, %	95	95	95	a)	a)	a)	a)	a)	a)	a)	a)	a)
Demand, TWh	622	622	622	110	110	110	167	167	167	320	320	320
7 MW OWT CAPEX, €/kW	6,429	5,371	4,520	6,543	5,466	4,600	9,086	7,592	6,390	5,854	4,890	4,115
15 MW OWT CAPEX, €/kW	14,678	12,261	10,319	14,938	12,478	10,502	20,751	17,334	14,588	13,364	11,163	9,395
Total installed capacity, GW	295	326	294	64	64	64	73	86	67	172	167	162
Total electricity generation, TWh	672	675	673	111	111	111	169	174	171	338	337	338
Renewables, GW	245	277	244	51	51	51	57	70	55	147	142	137
Renewables, TWh	622	627	622	62	63	63	95	106	128	250	252	256
Offshore, GW	70	60	70	0.21	0.67	0.67	0	0	11	7	9	11
Offshore, TWh	340	291	340	0.9	3	3	0	0	53	32	41	51

a) Share renewables in EU 85 %

By 2050, offshore wind energy emerges as a cost-optimal solution in Germany, the Netherlands, Poland, and the United Kingdom. In particular, Germany is projected to reach approximately 70 GW of installed offshore wind capacity. Although the model includes four offshore wind turbine sizes (e.g., 7 MW, 9 MW, 11 MW and 15 MW), the cost-optimal configuration suggests the deployment of 7 MW turbines in Germany, as well as in the Netherlands and the UK. The exception is Poland, where the model recommends installing 15 MW offshore wind turbines to achieve the proposed 15 GW capacity (see Figure 5.19a). The ESM-LCA model is configured to meet 95 % of Germany's electricity demand from renewable sources, while the remaining countries in the system are expected to achieve a minimum of 85 % renewable energy. Under these conditions, offshore wind contributes almost half Germany's electricity demand, 31 % in Poland and around 15 % in the UK (see Table 5.7).

The cost of offshore wind turbines increases over time, despite learning effects, due to inflation. As a result, cost reductions are insufficient to make offshore wind more competitive than onshore wind or solar energy. The LCOE for a 7 MW offshore wind turbine is slightly above 0.05 €/kWh, whereas for a

15 MW turbine, the LCOE exceeds 0.20 €/kWh (see Figure 5.19c). These results are highly dependent on annual electricity generation, and in this thesis, only a single year is used as a proxy. From an environmental perspective, specific GWP per kilowatt-hour decrease to approximately 5 g CO_2-eq/kWh (see Figure 5.19d).

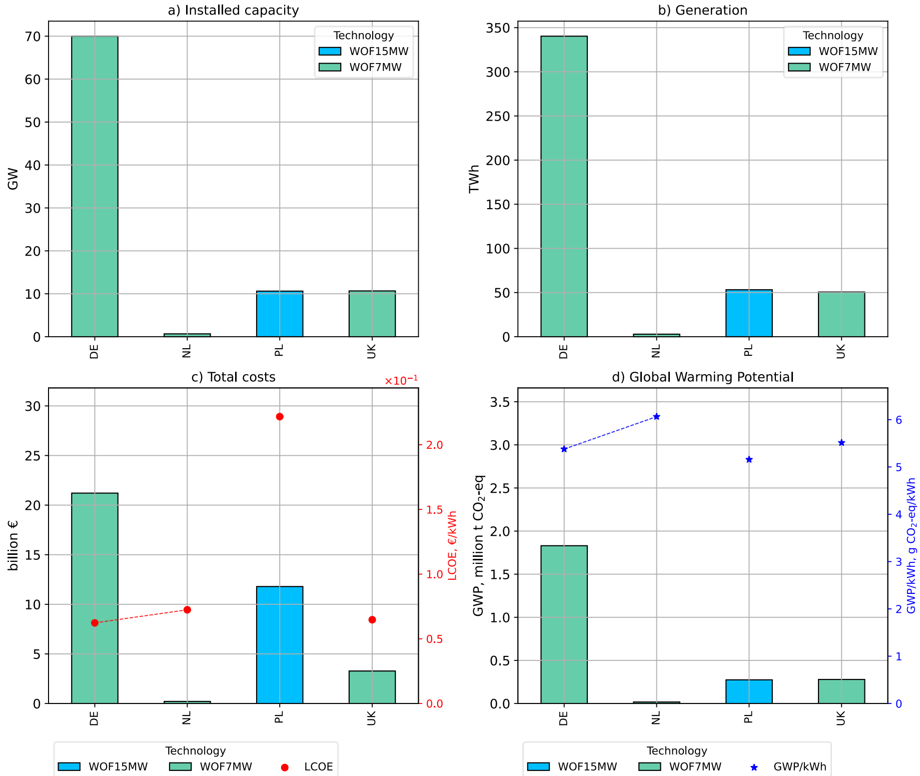


Figure 5.19 Results for wind offshore (WOF) technology in 2050 under cost minimisation
The results are composed by wind turbines of 7 MW and 15 MW in the Optimistic Scenario for 2050 under cost minimisation – a) Installed Capacity, b) Electricity Generation, c) Total Costs, including levelized cost of electricity (LCOE, red dots) d) Global Warming Potential, including specific GWP (blue starts) for Germany (DE), Ireland (IE), the Netherlands (NL), Poland, and the United Kingdom (UK)

Source: Own representation

When the system is configured to minimise GWP, offshore wind becomes a relevant option and emerges as an optimal solution in several countries for both the 2030 and 2050 target years (see Figure 5.20 and Figure 5.21, respectively). The results suggest variations in the configuration of offshore wind technologies, including a mix of wind turbine sizes. For instance, by 2030, Germany could reduce total GWP by 42 % by installing 83 GW of offshore wind capacity, including 11 MW and 15 MW turbines. However, this would come at the expense of a 42 % increase in total system costs. In comparison to the cost-effective solution, this level of offshore wind deployment appears ambitious, taking into consideration the existing 2030 target of 30 GW. The selection of larger wind turbines results in elevated levels of GWP per kWh in regions characterised by inadequate wind resources. For instance, in Bulgaria, the installation of 15 MW units to cover 11 GW is estimated to generate approximately

15 kg CO_2-eq per kWh, and the LCOE is predicted to be almost 0.20 € per kWh (see Figure 5.20c). In the case of Spain, the ESM-LCA model suggests that the optimal solution for the installation of offshore wind turbines is 11 MW, 15 MW, 7 MW and 9 MW turbines, respectively, with a total capacity of 24 GW (see Figure 5.20a). These turbines could generate up to 85 TWh per year, with an LCOE ranging from 0.05 €/kWh to 0.10 €/kWh. In Germany, the average LCOE is below 0.10 €/kWh.

By 2050, in Germany, the results under the GWP minimisation suggest that the 70 GW of offshore wind capacity could be predominantly covered by 15 MW offshore wind turbines (see Figure 5.21a). This is in contrast with the results under the cost minimisation scenario, which suggest that the same 70 GW could be covered only by 7 MW units. Nevertheless, the discrepancy in financial expenditure is multiplied by a factor of two, from 20 billion € to above 40 billion €. In both scenarios, the total GWP attributable to offshore wind is approximately 2 million t CO_2-eq. Nevertheless, the total GWP from the electricity mix calculated based on GWP minimisation could be up to 63 % lower than the electricity mix calculated based on cost minimisation.

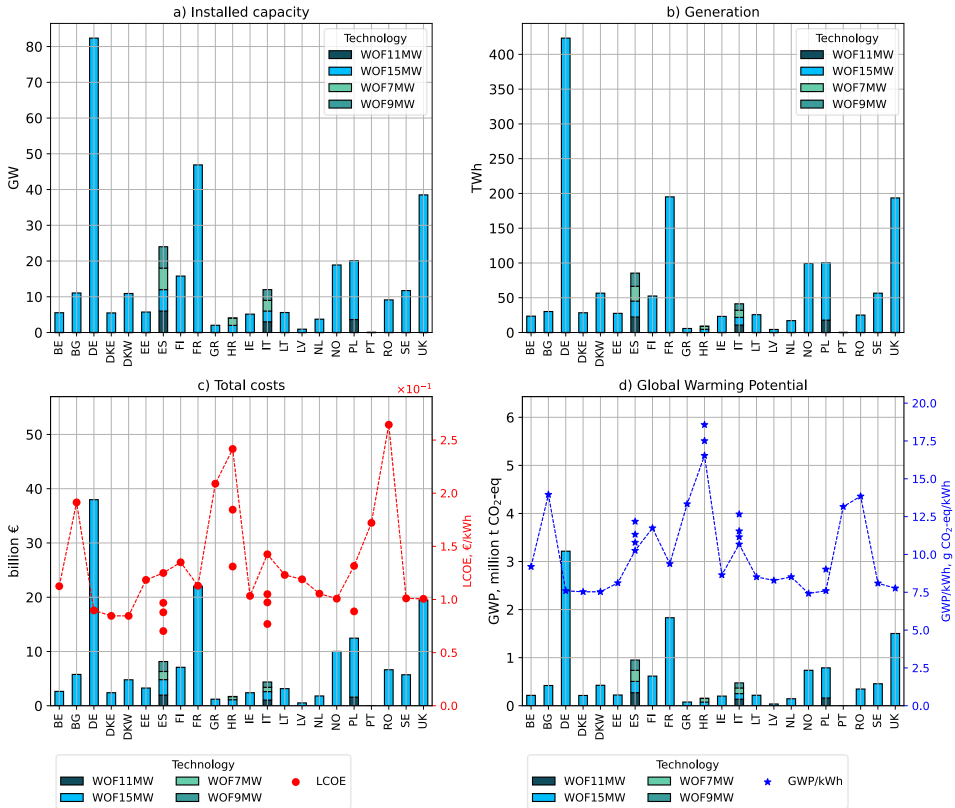


Figure 5.20 Results for wind offshore (WOF) technology in 2030 under GWP minimisation
The results are composed by wind turbines of 7 MW, 9 MW, 11 MW and 15 MW in the Optimistic Scenario in 2030 under GWP minimisation: a) Installed capacities, b) Electricity generation, c) Total cost and levelized cost of electricity (LCOE) for offshore wind turbines (red dots), d) Total Global Warming Potential and specific GWP (blue starts)

Source: Own representation

The ESM-LCA model is configured with a constraint on the total installed capacity in Europe for offshore wind, limited to a maximum of 1,000 GW based on expected deployment projections (IRENA, 2019)(see section 2.5), and Germany is set to its specific national target (e.g., 70 GW by 2050).

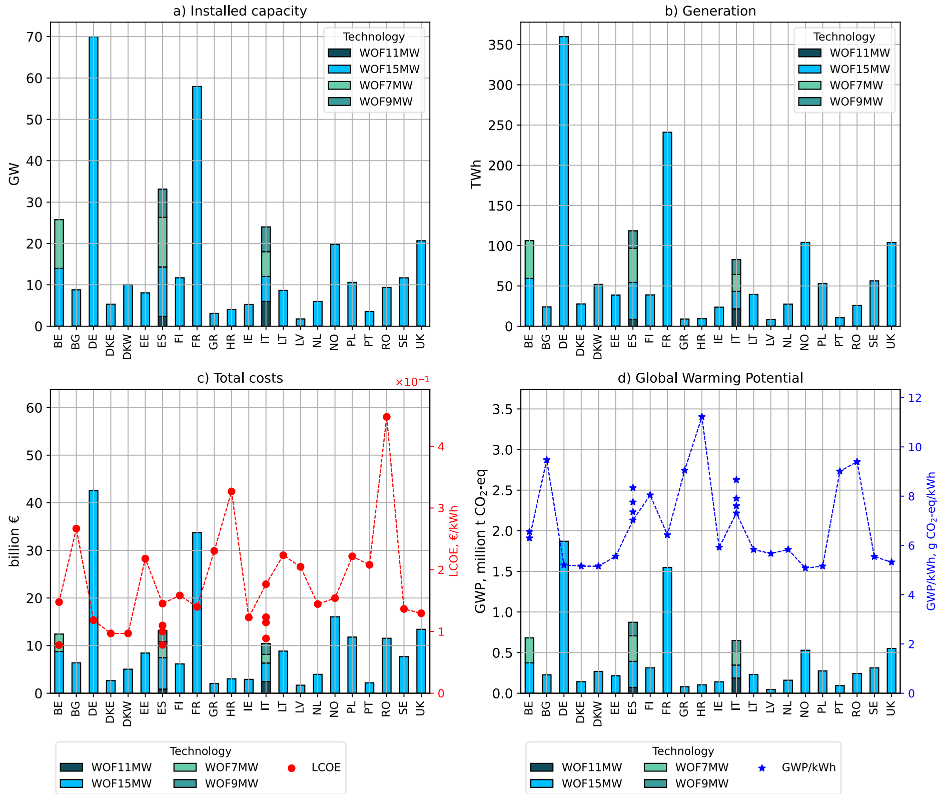


Figure 5.21 Results for wind offshore (WOF) technology in 2050 under GWP minimisation
The results are composed by wind turbines of 7 MW, 9 MW, 11 MW and 15 MW in the Optimistic Scenario in 2050 under GWP minimisation: a) Installed capacities, b) Electricity generation, c) Total cost and levelized cost of electricity (LCOE) for offshore wind turbines (red dots), d) Total Global Warming Potential and specific GWP (blue starts)

Source: Own representation

Figure 5.22 compares national targets for offshore wind installed capacity. The term 'current' is used to denote the actual installed capacity in 2024 (ENTSO-E, 2024a). The values for 2030 and 2050 are based on data collected from various sources (IEA, 2019; IRENA, 2019; WFO, 2023). The offshore wind installed capacity calculated by the ESM-LCA model under the GWP minimisation reveals discrepancies when compared to national targets. With the exception of Germany, the ESM-LCA model estimates 70 GW, which aligns with its national targets. Denmark, on the other hand, exhibits a marginally elevated value of 19 GW, in comparison to its 18 GW target. In contrast, the ESM-LCA model estimates a mere 21 GW of offshore wind installed capacity for the UK, a figure that falls considerably short of the government's target of 80 GW. The calculated offshore wind installed capacity for Sweden (nearly 10 GW) is considerably lower than the expected national target (41 GW).

The ESM-LCA model estimates offshore wind capacity of 60 GW in France, in comparison to the target of 45 GW by 2050.

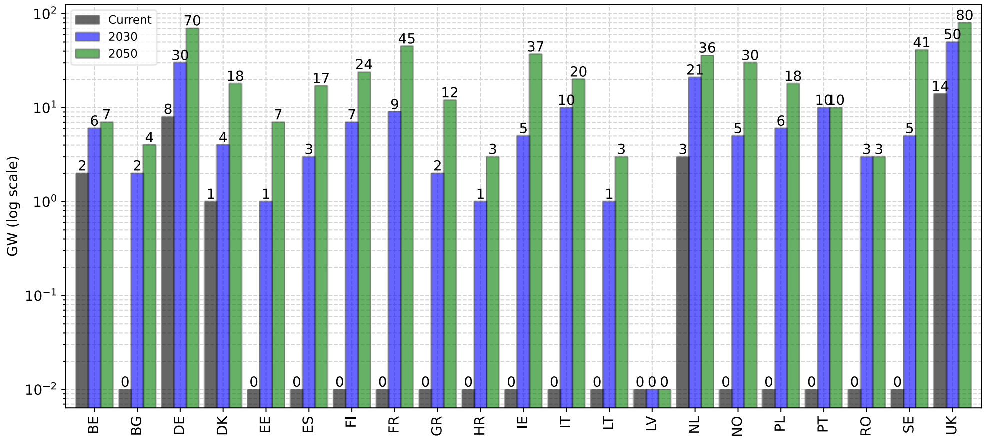


Figure 5.22 Offshore wind installed capacity targets for 2030 and 2050
Current represents observed data in 2024

Source: Own representation based on ENTSO-E (2024b); IEA (2019); IRENA (2019); WFO (2023)

5.4 Overview future scenarios in Germany

This section is concerned with an analysis of the results obtained for Germany, with a view to drawing comparisons between developments over time. To this end, the results for 2030 and 2050 represent average values across optimistic, moderate, and pessimistic scenarios, both under cost minimisation and GWP minimisation. The objective of this thesis is to evaluate the development of the German power plant mixes over time and across various scenarios. In addition, the study will highlight the trade-offs between costs and GWP.

Figure 5.23 illustrates the results for installed capacity cluster by technology type. The current-reference scenario holds 242 GW, with a significant share of solar technology (74 GW), including 7 GW of open ground or utility-scale systems. Overall, renewables represent 164 GW, while conventional power plants account for 76 GW. Depending on the solution strategy, the composition of the German power plant mix varies significantly in 2030. The cost-optimal solution, on average, relies equally on onshore and offshore wind technologies, each with approximately 44 GW of installed capacity. In contrast, the GWP-optimal solution suggests a greater emphasis on offshore wind, including 11 MW wind turbines accounting for 12 GW and 15 MW wind turbines accounting for 72 GW. Overall, by 2030 a significant increase of renewables between 205 GW and 243 GW is expected, depending on the solution strategy. While cost-optimal solutions, on average, rely on solar energy (138 GW), minimising GWP leads to a doubling of offshore wind capacity – from 44 GW (cost-optimal) to 83 GW. This thesis estimates that by 2030, the demand of electricity in Germany would reach 570 TWh. To meet the demand, the installed capacity required need to be 259 GW and 293 GW, respectively, in order to generate an average of

646 TWh and 631 TWh (see Figure 5.23). The differences in technology mix could result in a 42 % variation in GWP and a corresponding 42 % increase in total system costs by 2030. Independently of the solution strategy, offshore wind is a main cost driver. From the environmental perspective, most GHG emissions comes from biomass and natural gas (e.g., open-cycle and combined-cycle natural gas power plants).

By 2050, the German power plant mix may require, on average, between 242 GW and 254 GW of installed capacity to generate approximately 673 TWh of electricity, meeting an estimated demand of 622 TWh. Around 20 % of this capacity is expected to come from conventional power sources, including approximately 7 GW from biogas and 2 GW from solid biomass, under both optimization strategies—cost minimisation and GWP minimisation. In a cost-optimal scenario, hydrogen is projected to be used as fuel in 25 GW of natural gas power plants, compared to 44 GW in the emissions minimisation scenario. The electricity mixes calculated by the two solution strategies result in a 74 % difference in GHG emissions: 33 million t CO_2-eq from GWP minimisation versus 58 million t CO_2-eq from cost minimisation. However, the GWP minimisation alternative is approximately 38 % more expensive than the cost minimisation alternative.

Under these circumstances, in Germany GWP could be reduced from its electricity sector by up to 82 % by 2030 compared to the current level of 225 million t CO_2-eq, as indicated by the GWP minimisation scenario (41 million t CO_2-eq). In the case of the cost-optimal pathway, a reduction of approximately 74 % is projected, resulting in total GWP of 58 million t CO_2-eq. By 2050, the cost-optimal solution could achieve 84 % reduction in GWP (37 million t CO_2-eq), while the GWP minimisation pathway could result in an 85 % reduction (33 million t CO_2-eq) (see Figure 5.23c).

From an economic standpoint, the implementation of these pathways could require investments ranging from 41 billion € (cost-optimal) to 67 billion € (GWP-optimal). A significant share of these expenditures is associated with offshore wind development, with estimated costs of 24 billion € in the cost-optimal case and 51 billion € under the GWP minimisation scenario (see Figure 5.23d).

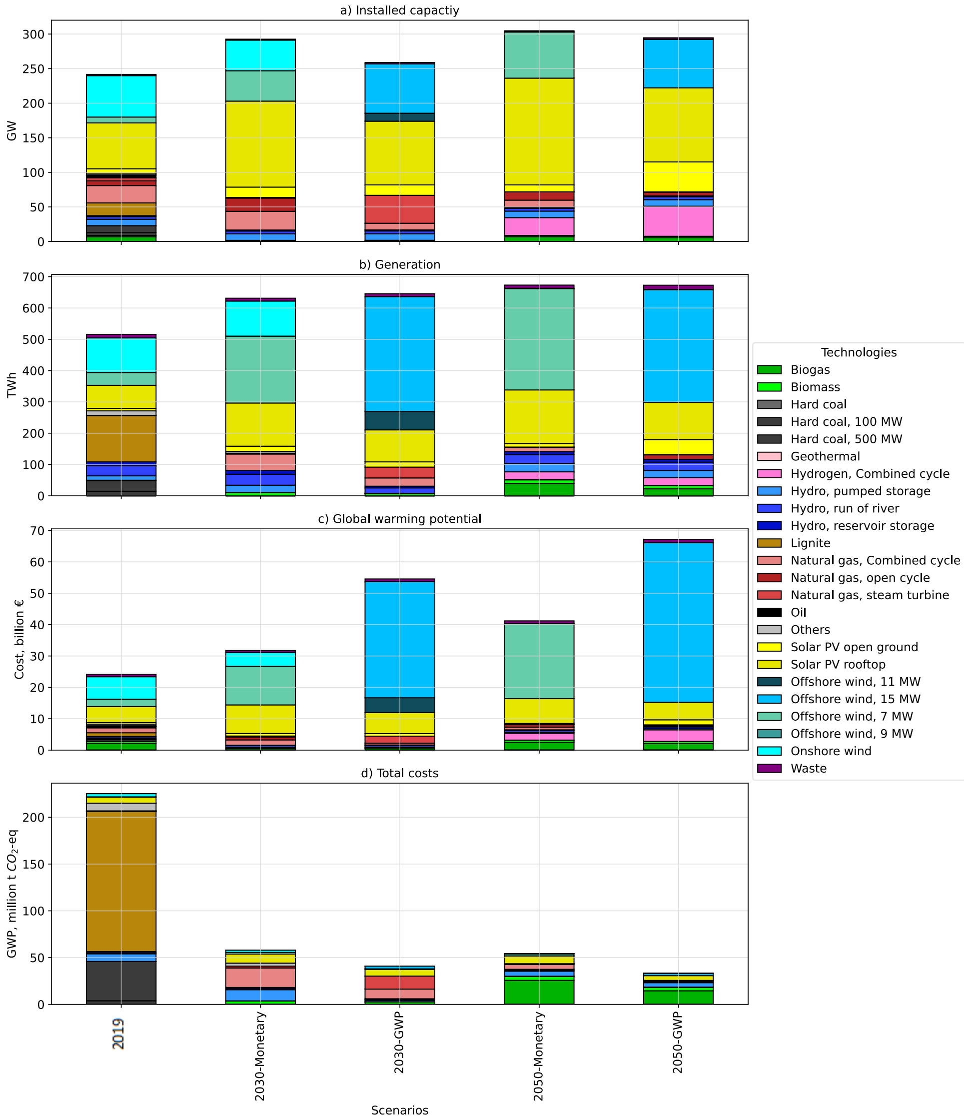


Figure 5.23 Summary of results for Germany

The results correspond to the scenarios Current Reference (2019), 2030 Average, and 2050 Average under cost minimisation (Monetary) and GWP minimisation (GWP): a) Installed Capacity, b) Electricity Generation, c) Global warming potential (GWP), and d) System Cost. Values are shown in Table A. 3.

Source: Own representation

5.5 Understanding uncertainty

The ESM-LCA model requires the definition of numerous input parameters, such as technology cost, fuel prices, technical parameters, technology development, electricity demand, etc (see Chapter 4).

Moreover, long-term projections (e.g., to 2030 and 2050) cannot be exact. Thus, the evaluation of ranges of possible outcomes becomes essential to capture the inherent uncertainty and to support robust, flexible decision-making in energy system planning. This thesis deals with uncertainty by analysis extreme scenarios for instance optimistic versus pessimistic under two solution strategies, one based on cost minimisation and the other based on GWP minimisation. This section explores the uncertainty surrounding projections for Germany's electricity system through 2030 and 2050 by analysing expected ranges for key metrics such as installed capacity (GW), electricity generation (TWh), total system costs (billion €), and total GWP (million t CO_2-eq). While the optimistic scenario is designed to represent the best economic and environmental condition, the pessimistic represents higher cost and environmental indicators. In this way, the solutions proposed by this thesis capture a range of possible outcomes. The results displayed in Figure 5.24 include average results across all scenarios runs for each year, with error bars illustrating the range based on different assumptions and solution strategies. As seen in Figure 5.24, while total installed capacity increases steadily from current levels to 2050, the GWP declines significantly, yet its uncertainty widens over time. This reflects the influence of varying technology mixes and the sensitivity of long-term planning to assumptions about offshore wind investment. Since investment in the model are adjusted for inflation to align with the target years (2030 and 2050), and only renewable technologies (i.e., solar, onshore, and offshore wind) incorporate learning effects, both total system costs and their associated uncertainties increase over time.

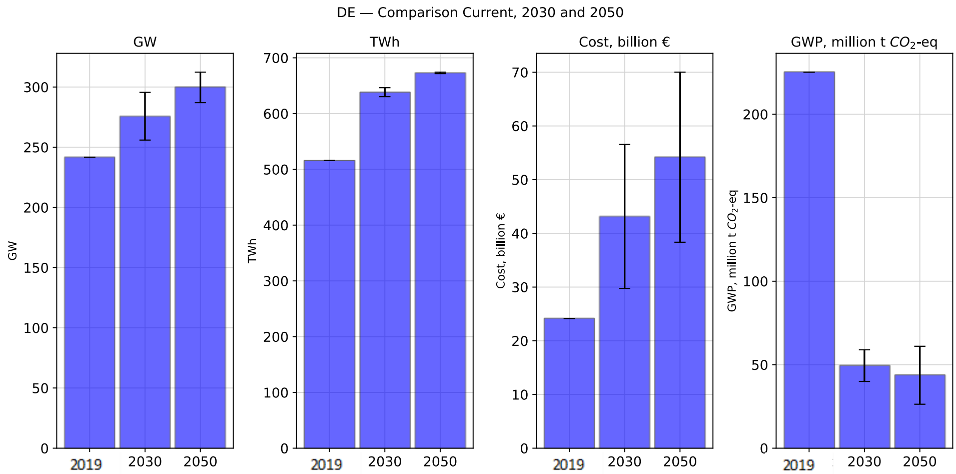


Figure 5.24 Summary of average results obtained for Germany (DE)

Source: Own representation

These findings highlight the trade-offs between minimising GWP and minimising system costs within the German electricity sector. While both optimization approaches—cost-optimal and GWP-optimal—can lead to significant reductions in GHG emissions by 2030 and 2050, the level of ambition and the associated financial requirements differ notably. For example, GWP minimisation can achieve up to 85 % emission reductions by 2050 compared to the current scenario, but at a higher system cost—driven largely by increased offshore wind deployment. Conversely, the cost-optimal pathway achieves nearly the same emission reductions (84 %) but relies on a different technology mix, emphasizing affordability. The primary distinctions between the two solution alternatives pertain to the technology selection. For instance, by 2050 the cost-optimal solution relies on biogas (7 GW), combined-cycle natural gas (10 GW), solar photovoltaics (154 GW), and offshore wind (66 GW)—primarily using 7 MW turbines. In contrast, the GWP-optimal solution places greater emphasis on combined-cycle fuelled with hydrogen (43 GW), solar photovoltaics (150 GW), and offshore wind (70 GW) with larger 15 MW turbines. For instance, the cost-optimal alternative.

For policymakers, these results underscore the importance of aligning climate targets with realistic investment frameworks. If Germany prioritizes rapid and deep decarbonization, higher upfront investments may be justified, especially in offshore wind infrastructure and hydrogen technologies. However, if fiscal constraints or political feasibility demand cost-efficiency, a balanced approach leveraging onshore wind, solar, and system flexibility could still deliver substantial emissions cuts. The study thus provides quantitative evidence to support more informed, flexible, and forward-looking energy policy design.

5.6 Discussion

The results of this thesis provide important insights into the role of offshore wind power in future energy systems, particularly within the context of evolving technological, economic, and environmental conditions. This section contextualizes the findings by addressing key dimensions influencing offshore wind deployment, including technological advancements, life cycle environmental impacts, and modelling assumptions.

Investment (or CAPEX) for offshore wind reported in the literature reflect wind turbines of around 6 MW capacity (Fraunhofer, 2021). These costs play a crucial role in decision-making and are highly sensitive to the size of the wind turbine (Fingersh et al., 2006), inflationary pressures, and learning effects. The learning effect is directly related to technological advancements, as manufacturers improve their processes and designs, leading to more efficient wind turbines. In turn, this also improves the environmental performance of offshore wind power. Although the results of this thesis incorporate these dynamics, in the cost-optimal solution, offshore wind is economically favourable only in countries with particularly strong wind conditions. Overall, offshore wind remains more expensive than solar and onshore wind, whose costs in this thesis were adjusted only for inflation and learning effects. While the model includes four different offshore wind turbine sizes and allows deployment across 21 regions, the cost-optimal scenarios indicate significant offshore wind installations in only a few countries. In contrast, when the focus shifts to minimising GWP, offshore wind emerges as a highly favourable low-carbon technology, contributing significantly to emissions reductions. The LCA results further reveal that although offshore wind has low GWP, it is also relevant in other environmental impact categories. Notably, freshwater ecotoxicity and water use are affected—the latter due to the use of epoxy resin in the nacelle components.

This thesis uses capacity factors based on weather conditions from a single year (e.g., proxy: 2019). In Germany, the resulting full load hours for onshore wind are approximately 1,800 hours per year, whereas reported values typically range between 1,800 and 3,200 hours per year (Kost et al., 2024). This may explain the relatively low share of onshore wind in the pessimistic scenarios for Germany. In contrast, the modelled offshore wind capacity for Germany in 2030 reaches up to 80 GW—significantly higher than the official target of 30 GW (Prognos et al., 2020). One reason for this discrepancy is the setup of the ESM-LCA model, which allows unrestricted offshore wind capacity expansion in 2030. However, for 2050, a cap of 70 GW is applied, limiting further expansion.

Regarding hydrogen in the electricity mix, this thesis includes hydrogen as a potential replacement for natural gas in power plants, assuming it is produced via electrolysis. However, the electricity demand required for hydrogen production is not included in the user-defined electricity demand profile. The 2050 scenario suggests that between 25 GW and 44 GW of capacity is used to generate approximately 24 TWh of electricity by burning hydrogen in gas turbines. This would require roughly 1.31 million t of hydrogen, implying a need for at least 10 GW of installed electrolysis capacity. Although Germany's current target is to reach 10 GW of electrolyser capacity by 2030, the current installed capacity however is only 0.3 GW,

Based on the insights and limitations identified in this thesis, several recommendations can be made to improve future modelling efforts. Although this thesis includes inflation and learning effects to estimate investment for offshore wind, the analysis is centred on Germany, and key site-specific factors—such as water depth—were not considered. Similarly, the LCA inventory is tailored to German conditions, relying on monopile foundations and excluding other foundation types. This limits the applicability of the findings to countries where floating foundations are expected to play a significant role. While some CAPEX refinements were made, a more comprehensive adjustment to account for offshore characteristics such as foundation type and water depth is necessary to improve the accuracy of both cost and environmental assessments in diverse regional contexts.

The application of broad system-wide constraints, such as the 85 % renewable electricity share by 2050 (except for Germany), leads to uneven technology allocation across regions. To improve the realism of future scenarios, there is a clear need for more harmonized and detailed national targets beyond 2030. These targets should be aligned with country-specific policies, ambitions, and grid capabilities, allowing models to better reflect national energy planning trajectories.

The model results project a need for up to 10 GW of electrolysers by 2050 to meet hydrogen demand in the power sector. However, the electricity required to produce this hydrogen is not reflected in user-defined electricity demand. This highlights a need for integrated planning between the hydrogen and electricity sectors to avoid future mismatches and infrastructure bottlenecks. While hydrogen is included in the model as an energy carrier, its production dynamics—such as reliance on surplus electricity—are not fully captured. A more detailed analysis is needed to assess how much hydrogen can realistically be produced from available renewable excess, particularly within national boundaries like Germany.

The static electricity demand assumptions used in this thesis do not reflect the likely increase in demand due to the electrification of heating, transport, and industrial sectors in other countries except for Germany. However, the electricity demand is modelled in a simplified manner. As electricity demand is user-defined in the model, it can be adapted based on the availability of more detailed or future-oriented data.

Although ESM-LCA model's short-term horizon is well-suited for systems with a high share of renewables—due to its effective handling of time-series data—the model is not designed to capture long-term development dynamics. For example, while it includes a planning mode, it assumes that all construction occurs in the target year and does not account for asset end-of-life or decommissioning. Despite these limitations, the ESM-LCA model is well-suited for illustrating the importance of integrating LCA into ESM. The ESM-LCA model can evaluate a range of LCA impact categories and assess trade-offs between cost and environmental performance. This is achieved by treating any LCA indicator as a cost class, allowing for the optimization of environmental impacts and enabling a more holistic understanding of sustainability implications in system design.

Despite the significant effort to minimise data limitations by using prospective LCA data to calculate environmental indicators for the ESM, these data primarily reflect changes in the background systems of the LCA model, with the exception of offshore wind. As demonstrated in this thesis, fully adjusting life cycle inventories remains a complex task. Offshore wind serves as an illustrative case, as its LCA inventories are adjusted in the foreground and background part of the LCA model in order to update commercial LCA databases at the time this thesis was conducted.

5.7 Summary

This chapter presents a case study on integrating LCA into an ESM, using a simplified representation of the European electricity system. Offshore wind is used as an illustrative example to explore the challenges of combining LCA with system modelling, particularly in addressing data inconsistencies—most notably geographic and technological. Capital expenditure (CAPEX) for offshore wind is adjusted based on wind turbine size, inflation, and learning rates, but despite these efforts, it remains more expensive than solar PV and onshore wind, limiting deployment to countries with strong policy alignment, such as Germany.

The ESM-LCA model applied both cost and GWP optimization to explore trade-offs, revealing that high-level constraints and static demand assumptions strongly influenced technology choices. For instance, onshore wind was underrepresented in Germany, likely due to outdated input data or spatial limitations. Offshore wind deployment was also uneven across countries, sometimes diverging from real-world targets. Additionally, hydrogen use in 2050 emerged as a critical factor, with the model indicating a need for at least 10 GW of electrolysers to produce sufficient hydrogen that can replace natural gas.

The ESM-LCA model facilitates the evaluation of trade-off between cost and environmental burdens, and findings underscore the importance of improving data accuracy, aligning model constraints with real-world policy, and preparing infrastructure for sector coupling to achieve a balanced and feasible energy transition.

6 Conclusion

This chapter presents a synthesis of the preceding chapters, which are outlined in Section 6.1. In Section 6.2, the results obtained contribute directly to answering the research questions posed at the outset of the thesis. Utilising these insights, the chapter derives methodological and practical conclusions and engages in a discussion regarding the broader applicability of the findings. Finally, it outlines potential avenues for future research to extend and deepen the work presented in this thesis.

6.1 Summary

Effective climate mitigation requires interdisciplinary collaboration across environmental science, engineering, economics, and policy. Evaluating strategies involves modelling frameworks like energy system models and Life Cycle Assessment to estimate cost, assess environmental impacts, and explore technological pathways. Identifying viable solutions, such as low-carbon technologies, necessitates integrating data and expertise from multiple domains. The use of various models and scenarios highlights the need for analysis at different levels, from global trends to national or local developments. Each level provides distinct insights: global scenarios guide overarching climate goals, while national and local analyses inform policy, assessing specific technological or environmental impacts. In Germany, a key climate mitigation strategy focuses on developing an electricity sector with minimal greenhouse gas emissions (Agora Energiewende, 2022; Prognos et al., 2021), as the electricity sector is one of the major contributors to greenhouse gas emissions (UBA, 2023) and highly adaptable to transformation (BMUB, 2016; Prognos et al., 2021). Central to this transformation is the shift toward renewable energy, with offshore wind emerging as a significant low-carbon technology option (Agora Energiewende et al., 2020; Prognos et al., 2021).

In this context, the first chapter of this thesis outlines its objectives and defines the research questions that guide the development of the work. The objective of this thesis is to investigate how to integrate life cycle assessment into an energy system model, with particular attention to the German electricity sector and a special focus on offshore wind energy technology. For this purpose, two fundamental tasks are undertaken. First, a systematic process is developed for the collection and harmonization of input data relevant to both Life Cycle Assessment and the energy system model. This systematic process facilitates the generation of scenarios. The second task is to assess and quantify future energy scenarios. For this purpose, this thesis develops an integrated approach that combines Life Cycle Assessment with an energy system model.

Given the complexities involved in integrating Life Cycle Assessment into an energy system model, Chapter 2 explores key topics essential for understanding and addressing the associated challenges. These topics include the classification of scenarios based on their underlying narratives, key insights from the IPCC scenario framework, an overview of energy scenarios relevant to the German energy sector, fundamental concepts related to offshore wind energy, and a review of modelling frameworks commonly applied in climate mitigation studies. Collectively, these topics provide the necessary background to address the first and second research questions outlined in Section 6.2.

The importance of integrating energy system models and Life Cycle Assessment is examined in Chapter 3. A review of the literature highlights recommendations to address these challenges. Chapter 3 explores integration approaches to combine ESMs and LCA, emphasising their relevance in the context of climate mitigation. This chapter is particularly important as it assists in elucidating which types of energy system models—especially those used in practice—are most suitable for integration with LCA. Accordingly, the second and third chapters of this thesis provide the necessary knowledge to facilitate the selection of the energy system model. The content presented in Chapter 3 is essential for addressing the third research question outlined in Section 6.2.

Chapter 4 describes the main considerations when setting up the ESM-LCA model regarding input parameters, as well as the harmonisation of input data to overcome temporal, geographical and technological mismatches. In addition, Chapter 4 introduces the approach to define economic, technical and environmental input parameters in the context of the energy system model adopted in this thesis, which is built on the Calliope framework (Pfenninger & Pickering, 2018). Furthermore, the explorative scenarios for the evaluation in the study case are introduced in Chapter 5. The topics discussed in Chapter 4 are necessary to reply the fourth question in Section 6.2

Chapter 5 presents the case study, which involves the quantification of three scenarios in the model developed in this thesis. The model is a simplified representation of the European electricity sector. With the case study, this thesis aims to evaluate the technical, environmental, and economic performance of the energy system, with a particular focus on offshore wind turbines operating in Germany within an interconnected electricity system. In this way, Chapter 5 addresses the fifth research question outlined in Section 6.2.

6.2 Addressing the research questions

The objective of this thesis is to investigate how the integration of Life Cycle Assessment into an energy system model contributes to a more profound understanding of the environmental burdens associated with electricity generation technologies operating as a system. This thesis formulates five research questions. These questions serve to clarify the objective and highlight the contributions of the present thesis.

1. How can environmental impacts of energy systems be effectively assessed through the integration of environmental assessment frameworks such as Life Cycle Assessment into energy system modelling?

An effective assessment of the environmental impacts of energy systems through an integrated approach that combines Life Cycle Assessment with an energy system model necessitates a systematic process for managing relevant input data. A significant challenge in integrating Life Cycle Assessment and energy system models is resolving structural data inconsistencies arising from methodological differences, particularly with respect to system boundaries. This thesis proposes a novel approach, which establishes a systematic process for the collection of technical, environmental and economic data. It tackles the issue of environmental data mismatches by managing life cycle inventory data using PREMISE, a Python-based framework that contextualises commercial Life Cycle Assessment databases according to climate change scenarios. In this way, the PREMISE framework allows for the inclusion of technological advancements in life cycle inventories (Sacchi et al., 2022). Accordingly, this thesis proposes a Python-based approach for collecting, organising, and harmonising environmental, technical, and economic input data. This systematic approach facilitates the generation of scenarios that follow clear and coherent narratives. In order to evaluate and quantify these scenarios, this thesis develops an ESM-LCA model, which represents a simplified version of the European electricity sector and serves as a basis for integrating environmental indicators. While the ESM-LCA model represents the European context, the exemplar application focuses technologically on offshore wind energy in Germany. The response to this initial research question will be elaborated upon in the subsequent research questions.

2. Which solutions are proposed in energy scenarios to reduce greenhouse gas emissions? What role does offshore wind energy play in these scenarios? Which modelling frameworks are available to assess climate mitigation solutions?

This thesis examines the types and roles of scenarios. While various scenario classifications exist, this thesis adopts the categorization of scenarios into predictive, normative, and explorative, as this approach is applied within the field of Life Cycle Assessment (Börjeson et al., 2005; Langkau et al., 2023). These scenarios are particularly valuable because they support effective data exchange across disciplines and methodologies, guide the selection of appropriate models and improve the clarity of results. Specifically, the adoption of explorative scenarios—namely optimistic, moderate, and pessimistic—helps in managing input parameters (e.g., electricity demand, efficiency, CAPEX, fuel costs, environmental indicators), central to this thesis.

An effective assessment of environmental impacts necessitates the integration of Life Cycle Assessment and energy system models, with the support of scenario analysis. This approach is essential for capturing uncertainties (e.g., incomplete data, quality of inventory, uncertain system boundaries, etc.), data variability and alternative future states, in order to ensure robustness and comprehensiveness. Given the large number of uncertain input parameters and the complexity of projecting future outcomes, explorative scenarios (i.e., optimistic, moderate and pessimistic) offer the advantage of presenting a range of plausible futures. In this thesis, each scenario is built upon a narrative that guides the selection and calibration of quantitative input data. For example, the optimistic scenario reflects a future with the lowest environmental burdens, rapid deployment of renewable technologies, and reduced costs (e.g., CAPEX and OPEX) values for key technologies such as wind and solar. Conversely, the pessimistic scenario assumes slower deployment of renewables, higher costs and environmental impacts, while the moderate scenario represents an intermediate trajectory, reflecting average values between the two extremes.

In addition, Chapter 2 has a focus on energy scenarios, including those developed by the IPCC and those specific to Germany. The IPCC scenarios describe how the world might evolve under different potential futures in terms of greenhouse gas emissions, which are estimated through various energy system models, such as integrated assessment models and bottom-up energy system models. These emission estimates are then used to model atmospheric concentration pathways and assess potential environmental and societal impacts. Accordingly, two climate change scenarios are utilised to derive prospective life cycle inventories in this thesis. One scenario sets a limit of 1.5 °C increase to the global temperature, while the other sets a target of 2.9 °C increase by the middle of the century (Sacchi, 2023). As climate and energy policies are implemented at the country level, more detailed energy system models tailored to specific regions, countries, or sectors are essential. These models allow for a more precise estimation of potential environmental burdens and support more effective and context-specific mitigation strategies. For this reason, this thesis examines energy scenarios for Germany, particularly those aimed at achieving net-zero greenhouse gas emissions or climate neutrality. In these scenarios, a balance between greenhouse gas emissions and the strategies used to mitigate them is aimed for. They are typically defined by a specific climate target and, as a result, offer various possible pathways or ideal alternatives to reach those goals. In most of the scenarios analysed, a common conclusion is the need to phase out fossil fuel-based power generation and accelerate the deployment of renewable energy sources (see Table 2.4). In this context, offshore wind appears as a key low-carbon technology with significant potential to contribute to emissions reductions. For instance, for Germany an installed capacity for offshore between 30 GW and 70 GW by 2045 can be expected (see Table 2.4). Therefore, this thesis recapitulates the fundamental concepts of offshore wind energy, including its technological diversity. This is crucial as it provides clarity and guidance on the steps required to incorporate the estimated future technical advancements in offshore wind into the ESM-LCA model.

After identifying relevant climate mitigation scenarios and the role of offshore wind, this thesis shifts focus to the tools used to generate these scenarios. In the context of climate mitigation, several modelling frameworks are commonly employed. Integrated Assessment Models (IAMs), for example, are widely used to estimate greenhouse gas emissions across multiple sectors of the economy, including land use. In addition, bottom-up energy system models focus on specific sectors—such as electricity—allowing for a more detailed representation of individual technologies. In addition, LCA is used to evaluate the potential environmental impacts of technologies.

3. How can the integration of Life Cycle Assessment into energy system models improve the representation of emissions and enhance the evaluation of climate mitigation strategies? What are the current approaches for integrating LCA and ESMs?

While the aforementioned modelling frameworks often include greenhouse gas emissions, they typically only account for emissions in a limited manner, focusing mainly on direct emissions during operation. To address this limitation, Life Cycle Assessment is used to evaluate the environmental impacts of processes or technologies throughout their entire life cycle. Accordingly, the inclusion of Life Cycle Assessment allows for the consideration of greenhouse gas emissions from upstream processes—such as material extraction and construction—as well as the evaluation of broader environmental concerns, including impacts on human health and resource use. This thesis adopts the impact categories from the Environmental Footprint (EF) 3.0 impact method (European Commission, 2020).

The importance of an integration approach becomes evident, as both methodologies offer complementary perspectives that can enrich and broaden analyses. Energy system models provide system-level insights into energy planning and technology deployment, while Life Cycle Assessment captures a broad range of environmental impacts across a technology's life cycle. Therefore, this thesis investigates existing integration approaches. Several studies have already explored this integration, particularly within the electricity sector and using bottom-up models. In this context, the present thesis selects the Calliope framework to develop the ESM-LCA model due to its suitability for analysing systems with a high share of renewables (Pfenninger & Pickering, 2018). Despite its short-term temporal resolution, Calliope offers flexibility in optimization, allowing the minimization of different cost classes— whether expressed in monetary terms or as environmental indicators derived from LCA.

This thesis identifies two major challenges in linking ESM and LCA: first, data structure inconsistencies; and second, the need for tools to manage and adapt life cycle inventories for use in energy system modelling. A discussion of the main methodological aspects of energy system models and Life Cycle Assessment is essential to clarify discrepancies between the two approaches. Current integration approaches involve avoiding double counting, which is tackled by the separation of LCA inventories into LCA stages, for instance LCA inventories that only contain data describing the infrastructure (e.g., power plants) and other LCA inventories describing the operation phase. Tackling data inconsistencies requires flexibility to adjust commercial Life Cycle Assessment databases to the temporal, geographical scope of the energy system model. While technical inconsistencies are related to the level of representation or level of detail in which the technology is represented, often LCA is more technical specific. A solution to this issue resulted in the development of PREMISE (Sacchi et al., 2022). Therefore, inventories derived from PREMISE contain inventory data which represent the years 2020 to 2060, including to some extend novel technologies (e.g., direct air capture), and regionalized inventories for geographical representatives of the scenarios used to derive the prospective database.

4. How can future input parameters, particularly those related to offshore wind, be derived and applied within an integrated ESM-LCA modelling approach?

The response to this question outlines the general methodological steps undertaken to develop the integration approach. This thesis focuses on offshore wind as part of a simplified European electricity system comprising 29 interconnected countries. Consequently, the model incorporates a range of technologies currently available in the European electricity system (ENTSO-E, 2024a). Therefore, this thesis investigates how input parameters such as future electricity demand, renewable energy resources, costs, and environmental indicators can be derived and applied within the ESM-LCA model. A fundamental contribution lies in the harmonisation of input parameters to address temporal, geographical, and technological mismatches between ESM and LCA input data. This includes the alignment of input parameters with consistent target years (2030 and 2050), the adaptation of input parameters to regional contexts, and the ensuring that technological representations reflect comparable levels of detail and development. The study adopts the technological representations found in LCA databases and incorporates national energy policies, including commitments to phase out fossil fuels and nuclear energy, to assess future scenarios. As result, dedicated Python scripts have been developed for the purpose of automating the compilation of relevant input data from a variety of literature sources. These scripts are also employed to create all the necessary supporting files for building the ESM-LCA model and the scenarios.

In the ESM-LCA model, the demand for electricity is defined by the user and consequently treated as an input parameter. Given the complexity of projecting future demand, historical data are used for all countries except Germany, where projections for 2030 and 2050 account for increased electrification due to electric vehicles and heat pumps. Wind and solar resources are represented through capacity factor time series from proxy years, sourced from open databases (Pfenninger & Staffell, 2016; Tröndle & Pfenninger, 2020).

The estimation of CAPEX, OPEX, and fuel costs involves adjusting literature values to the target years using the time value of money principle. This is accomplished by applying country-specific interest and inflation rates. To assess the environmental impacts within the ESM, prospective environmental indicators—representing the model's temporal (e.g., 2030 and 2050), regional, and technological scope—are integrated in the ESM-LCA model. In this thesis, the life cycle inventories representing infrastructure components—such as power plants—are typically based on average European or global data. As a result, general parameters like efficiency and lifetime are assumed to reflect European averages. However, for the operational phase, life cycle indicators are tailored to national conditions.

5. How can technological changes such as in offshore wind technology be investigated from a technical, economic and environmental perspective within the context of an integrated energy system?

To investigate technological changes in offshore wind from technical, economic, and environmental perspectives, this thesis employs an integrated ESM-LCA model for a system-wide assessment of offshore wind's role within a future electricity mix. From a technical perspective, developments in the offshore wind sector—such as the expected deployment of turbines ranging from 7 MW to 15 MW—are considered. These advancements reflect ongoing trends in material efficiency, improved manufacturing processes, and component diversification, all of which support the emergence of larger, more efficient turbines with higher full-load hours. From an economic perspective, technical improvements are associated with learning effects and economies of scale that contribute to cost reductions (e.g. CAPEX, OPEX), which can help offset inflationary pressures over time. From an environmental perspective, technical developments are captured through prospective life cycle inventories that reflect the evolving supply chain including critical materials for the construction of offshore wind turbine components. However, in the case of offshore wind, prospective inventories still typically reflect outdated turbine capacities (2–3 MW). To address this gap, this thesis develops new life cycle inventories representing offshore wind turbines of 7 MW, 9.5 MW, 11 MW, and 15 MW. A key output of this work is a peer-reviewed publication titled *Scenario-based LCA for assessing the future environmental impacts of wind offshore energy: An exemplary analysis for a 9.5-MW wind turbine in Germany*, which serves as a case study for integrating technological development into prospective Life Cycle Assessment. Country-specific wind resources are utilized to calculate annual full-load hours, ensuring that energy yields are accurately represented for each location.

The integration approach also supports the identification of burden-shifting effects, which take place when the reduction of environmental impacts in one area, LCA phase (e.g. material extraction, construction, operation, end of life) or LCA impact category leads to increased burdens elsewhere. Burden-shifting effects can occur across all life cycle stages. A second type of burden-shifting arises across LCA impact categories, while a third type takes place across geographical locations. Accordingly, the associated reduction in domestic emissions may come at the cost of environmental degradation elsewhere due to the global nature of supply chains. For instance, copper mining activities contribute to eutrophication, which typically manifests at the local level in regions where these materials are sourced—for instance, in Chile. Thus, the identification of burden-shifting effects helps to highlight potential unintended consequences—where presenting offshore wind expansion as a solution to one environmental issue, such as reducing global warming potential, may inadvertently create or exacerbate other environmental burdens elsewhere.

Moreover, the integration approach facilitates the identification of environmental hotspots—specific technologies, processes, or life cycle stages that contribute most significantly to a given environmental impact. The purpose of identifying hot spots is to prioritize improvement efforts and target the most impactful areas of a product or system's life cycle. For instance, the current scenario (e.g., 2019) identifies that 28 % of the total electricity generation in Germany comes from lignite, which represents 67 % of the total greenhouse gas emissions. Therefore, phasing out this technology by 2030 could reduce in 82 % of the impact to climate change.

The ESM-LCA model allow for the calculation of scenarios based on different optimised targets, and thus analysing trade-offs between potential environmental impacts and costs. Accordingly, it can be seen how reducing costs might increase environmental impacts, or vice versa. By including both economic and environmental aspects in one model, the search for energy solutions that are both affordable and in line with climate mitigation targets is supported. This integration approach strives for a better planning for the energy transition by showing the full effects of different technology choices. In this thesis, the ESM-LCA model is developed as a tool to assess trade-offs between total system costs and any LCA impact category defined within the model. For instance, the outcomes of the case study highlight the potential of offshore wind to significantly reduce greenhouse gas emissions, albeit at much higher system costs. By comparing outcomes of these optimization modes, the ESM-LCA model offers insights into how different scenario assumptions influence the role of offshore wind and other technologies in achieving climate targets.

6.3 Discussion and outlook

The integration of energy system models and Life Cycle Assessment provides a comprehensive approach for assessing future electricity supply. However, this integration presents significant challenges, and further research is needed to enhance the analysis and address these complexities. In addition to expanding the case study and adapting the model to different levels of aggregation (e.g., cities, regions) and system boundaries as regards considered energy technologies, there are several potential extensions to the developed method, such as refining the focus of the proposed solution.

To enhance the assessment of offshore wind technology, wind resources could be represented with greater spatial and temporal resolution, for the evaluation of the model under varying wind speed profiles. For example, using location-specific wind profiles to estimate capacity factors for turbines ranging from 7 MW to 15 MW highlights the variability of wind resources even for the same technology (see Table 5.2 on page 109). From an environmental perspective, offshore wind inventories could be extended to include alternative foundation types. This thesis focuses on monopile foundations, which are representative for Germany; however, foundation selection depends on site-specific conditions such as water depth and entails different material requirements for its construction (Benitez et al., 2024; Li et al., 2022a). This thesis study indicates that for renewable technologies, most environmental impacts stem from infrastructure—particularly material extraction—with the effect most pronounced for climate change. The results are in line with those of previous studies (Baumgärtner et al., 2021; Reinert et al., 2021; Volkart, 2017). For example, this thesis finds that the operation of offshore wind turbines in Germany results in negligible greenhouse gas emissions (e.g., 2.31E-04 kg CO_2-eq/kWh). Yet, despite the efforts of improving the offshore wind life cycle inventory for instance by better representing the impacts during the operation, it requires improvement especially to describe maintenance activities.

The ESM-LCA model includes all environmental categories expressed in the life cycle impact assessment method Environmental Footprint EF 3.0. In this thesis, offshore wind accounts for 44 GW in Germany's 2030 optimistic scenario (i.e., 15 % of the total installed capacity) but contributes only 3 % to the total global warming potential of the national electricity mix. Conversely, it accounts for 18 % of human toxicity impacts and 85 % of water use. Notably, the production of epoxy resin used in components such as nacelles is identified as a major contributor to offshore wind's water use. However, as water use is considered an impact category recommended to be applied with caution (Baumgärtner et al., 2021), further evaluation of its completeness, relevance, robustness, transparency, and applicability is necessary for proper interpretation.

One advantage of the model is its ability to optimize the system based on cost classes, which can include monetary values or any LCA indicator. In the case study, two distinct optimizations were performed: one minimizing total system costs and the other minimizing global warming potential emissions.

However, optimization based on other impact categories may produce misleading results, as the impact categories do not share the same level of completeness. Additionally, results from the optimization based on global warming emissions may be biased, as discussed in Chapter 3, due to the incompleteness of life cycle inventories. Therefore, the optimization based on minimization of life cycle impacts should be further investigated. A further advantageous feature of the ESM-LCA model is that electricity demand can be defined by the user, with demand profiles being calculated externally. A potential avenue for further research would be to assess the system with demand profiles that more accurately reflect high sectoral electrification, such as the increasing share of electric vehicles, not only in Germany but also in other countries.

In this thesis, hydrogen is considered as a fuel that can be burned in natural gas power plants. Nevertheless, despite the fact that hydrogen is produced via electrolysis, this process is not reflected in the demand for electricity. Whilst the majority of approaches in Germany advocate the generation of hydrogen through the utilisation of surplus electricity from renewable sources (BMWK, 2024; Prognos et al., 2021), the calculated amount of hydrogen for the electricity sector alone (e.g., 1.31 Mio t) is substantial and necessitates further evaluation. Furthermore, the emissions resulting from the combustion of hydrogen in gas turbines, specifically NOx, have the potential to become a problematic aspect of the process if the exhaust gas treatment is deemed inadequate (Benitez et al., 2024). This, in turn, could have a detrimental effect on impact categories such as terrestrial and marine eutrophication, as well as photochemical ozone formation. These indicators are linked to ecosystem quality and air quality, respectively (see Table 4.12 on page 89).

The present thesis places particular emphasis on the environmental assessment of offshore wind turbines, while economic aspects – such as CAPEX – are addressed through scaling, inflation, and learning effects to reflect technological advancements within the ESM-LCA model. However, the analysis reveals that even with learning effects, offshore wind does not consistently outperform solar or onshore wind in terms of cost-competitiveness, particularly under long-term inflation assumptions. For example, while the levelized cost of electricity for a 7 MW offshore turbine is around 0.05 €/kWh, it can exceed 0.20 €/kWh for a 15 MW turbine under less favourable generation conditions. Although offshore wind yields low greenhouse gas emissions—approximately 5 g CO_2-eq/kWh—this environmental benefit must be balanced against its comparatively higher costs. Further refinement is possible, as CAPEX is also influenced by site-specific factors such as water depth and tower height (Shields et al., 2022). These could be better explored through improved geographical disaggregation of offshore wind deployment across the countries included in the model.

The majority of studies, including the present one, omit to consider the temporal evolution of impact categories and regional characterisation factors. This remains a key challenge that requires expert attention to improve LCA integration within energy system models (Vandepaer & Gibon, 2018). In this thesis, the Python-based LCA software Activity Browser is employed, which offers sufficient flexibility to integrate prospective LCA databases and support scenario-based analysis. However, at the time of this thesis, the software lacked the flexibility to add impact categories. The advancement of integration will necessitate the utilisation of tools that facilitate not only the management of inventory and databases but also the adaptation and refinement of impact assessment methodologies. As discussed in Chapter 2, the relative nature of LCA means that assessments are based on comparisons and cannot guarantee the sustainability of a given alternative, even if it presents the lowest environmental impact. In order to address this limitation, frameworks such as Planetary Boundaries have been proposed (see

Section 2.5). The framework offers quantified thresholds that, if respected, reduce the risk of destabilising Earth system processes. Nevertheless, the integration into ESM-LCA approaches remains challenging. Further research is required to support the downscaling of boundaries to national or sectoral levels, to resolve conflicts between local and global effects, and to develop impact categories aligned with planetary boundaries concept (Ryberg et al., 2016). Finally, this thesis demonstrates that an integrated approach offers a holistic view of trade-offs between cost, environmental performance, and technological feasibility, supporting more informed energy policy and investment decisions.

Appendix A

Table A. 1 Summary results ESM-LCA model year 2030 under cost minimisation

	GW			TWh			Total GWP, million t CO_2-eq			Total Costs, billion €		
Country	Pess	Mod	Opt	Pess	Mod	Opt	Pess	Mod	Opt	Pess	Mod	Opt
AT	9.28	9.28	9.28	65.65	65.65	65.65	3.95	3.86	3.49	1.04	1.05	1.05
BE	33.38	30.92	34.72	91.83	91.55	90.32	3.76	3.41	2.57	2.89	2.68	2.63
BG	6.08	6.08	11.18	40.87	40.87	41.05	19.06	18.57	3.59	0.61	0.61	1.08
CH	13.60	17.53	17.53	65.70	66.49	66.49	4.84	5.24	4.67	1.37	1.36	1.29
CZ	13.99	13.99	19.42	66.39	67.74	69.07	38.00	33.61	5.67	1.36	1.39	2.19
DE	305.59	287.09	285.08	634.72	629.56	629.54	58.79	59.36	55.82	38.35	30.63	26.26
DK	16.81	18.14	20.62	35.45	35.57	37.19	5.83	9.89	3.24	1.32	1.27	1.40
EE	5.36	5.42	5.55	10.03	10.10	10.30	1.43	1.39	1.30	0.56	0.52	0.48
ES	114.88	125.45	125.45	276.21	268.18	268.18	19.91	18.25	16.31	11.01	10.18	8.92
FI	19.92	20.50	22.46	84.07	84.07	84.10	22.60	4.31	2.91	1.92	2.18	2.40
FR	113.23	113.23	127.18	481.22	480.18	480.01	19.00	17.73	19.90	12.78	12.57	13.02
GR	31.15	31.16	31.28	53.44	53.47	54.97	12.04	11.48	5.25	6.82	5.36	4.76
HR	5.18	5.20	5.06	18.45	18.45	18.41	1.63	1.58	1.32	0.58	0.55	0.52
HU	14.20	17.97	20.24	42.95	42.91	44.45	7.97	5.23	2.91	2.11	2.41	2.42
IE	11.83	13.98	13.85	29.98	29.48	29.56	9.44	5.61	3.67	1.10	1.17	1.15
IT	121.64	124.30	116.23	308.48	309.89	308.91	22.38	22.80	24.81	13.68	12.11	10.68
LT	5.15	5.87	6.39	14.07	13.61	13.37	3.02	2.58	2.30	0.59	0.57	0.51
LU	1.48	1.48	1.48	4.38	4.38	4.38	1.15	1.13	1.11	0.14	0.13	0.12
LV	0.99	0.99	0.99	7.22	7.22	7.22	0.28	0.28	0.26	0.15	0.15	0.15
NL	53.84	63.84	63.84	110.80	111.16	111.17	16.74	16.26	16.18	4.69	4.00	3.68

NO	21.78	21.78	21.78	139.24	139.24	139.24	12.33	12.12	11.05	2.52	2.51	2.51
PL	62.54	62.54	66.27	168.08	168.25	170.13	63.24	76.69	27.28	7.66	7.21	9.71
PT	8.89	13.16	14.14	50.30	52.41	52.63	6.97	3.93	3.18	1.15	1.35	1.29
RO	8.36	8.36	8.59	59.49	59.49	59.49	6.80	7.63	2.69	2.32	2.35	2.51
SE	22.26	22.26	22.26	138.06	138.06	138.06	13.52	13.55	12.84	2.70	2.70	2.68
SI	1.81	1.81	3.57	13.55	13.55	13.62	5.04	5.02	0.59	0.22	0.22	0.32
SK	3.89	10.15	7.98	30.17	30.92	30.89	13.01	6.51	2.63	0.42	0.72	0.70
UK	97.30	128.83	128.83	330.14	333.92	334.51	28.81	23.93	24.89	13.74	14.87	13.46

Corresponding Figure 5.8

Table A. 2 Summary results ESM-LCA model year 2050

	GW			TWh			Total GWP, million t CO_2-eq			Total Costs, billion €		
Country	**Pess**	**Mod**	**Opt**	**Pess**	**Mod**	**Opt**	**Pess**	**Mod**	**Opt**	**Pess**	**Mod**	**Opt**
AT	9.28	9.28	9.28	65.65	65.65	65.65	3.88	2.80	1.59	1.24	1.24	1.24
BE	51.25	54.94	54.87	90.97	91.70	95.48	3.81	3.19	1.29	3.95	3.69	3.41
BG	7.22	10.24	17.71	41.04	41.02	41.70	17.73	11.23	1.63	0.92	1.09	1.38
CH	15.16	15.16	14.82	65.97	65.97	65.70	5.46	3.50	1.75	1.62	1.57	1.57
CZ	38.78	42.12	39.43	69.44	71.04	67.46	19.75	8.14	1.79	3.41	3.07	3.04
DE	294.53	325.53	294.23	672.27	674.95	672.51	69.41	57.79	35.24	46.74	39.42	37.43
DK	23.03	23.46	24.05	41.71	40.86	43.18	2.50	2.43	1.66	1.82	1.64	1.49
EE	8.34	8.53	8.76	12.99	13.12	13.86	0.80	0.82	0.50	0.65	0.64	0.53
ES	81.22	81.82	77.65	261.35	261.95	262.86	24.70	19.84	12.99	8.28	7.79	7.40
FI	26.95	27.04	29.45	89.81	85.19	86.80	2.23	2.06	1.37	2.78	2.60	2.40
FR	181.06	181.06	181.06	480.25	480.25	480.25	18.42	15.46	7.54	16.35	15.19	14.21
GR	31.62	31.94	30.15	54.22	54.37	54.46	12.98	7.09	2.33	2.77	2.93	3.22
HR	4.20	4.20	4.30	18.32	18.32	18.30	1.43	0.99	0.48	0.74	0.76	0.73
HU	30.63	31.63	33.52	47.72	48.64	52.36	2.58	1.34	0.94	3.20	2.96	2.82
IE	18.70	18.84	18.53	30.20	29.73	29.75	3.76	2.81	2.13	1.34	1.19	1.08
IT	126.39	126.00	124.15	310.13	309.60	308.52	21.99	14.74	6.69	13.44	12.86	12.87
LT	6.48	6.76	6.34	14.97	14.39	15.02	1.95	0.58	0.39	0.56	0.52	0.41
LU	2.23	2.23	2.23	4.38	4.38	4.38	1.04	0.96	0.87	0.16	0.14	0.14
LV	0.99	0.99	0.99	8.03	7.22	7.22	0.27	0.27	0.17	0.19	0.19	0.19
NL	64.15	63.84	63.84	111.12	111.09	111.12	20.38	18.91	16.51	4.46	4.08	3.92
NO	21.92	21.89	21.89	145.92	137.37	137.17	11.59	9.03	4.85	3.33	3.31	3.31
PL	73.16	86.30	66.80	169.20	174.44	170.53	69.19	60.64	29.19	8.67	8.64	20.02

PT	13.66	14.14	11.43	52.27	52.63	52.94	3.77	2.89	1.76	1.89	1.82	1.76
RO	27.09	33.44	31.95	61.90	60.20	60.08	3.65	3.25	1.51	4.78	4.31	4.27
SE	23.39	25.01	27.33	138.06	138.06	138.06	13.00	12.93	9.19	3.05	3.16	3.23
SI	2.96	3.74	4.05	13.45	13.57	13.73	3.11	1.86	0.27	0.36	0.39	0.41
SK	15.48	16.00	16.00	31.42	31.75	31.69	4.22	1.95	0.94	1.20	0.96	1.02
UK	171.81	166.97	162.33	337.55	337.15	337.66	24.44	16.80	10.92	20.78	19.62	18.78

Corresponding Figure 5.13

Table A. 3 Summary of Results for Germany (Corresponding Figure 5.23)

		GW					TWh					GWP, Mio ton CO2-eq					Total costs, Billion €				
locs	techs	2019	2030-gwp	2030-cost	2050-gwp	2050-cost	current-reference	2030-gwp	2030-cost	2050-gwp	2050-cost	current-reference	2030-gwp	2030-cost	2050-gwp	2050-cost	current-reference	Cost_2030-gwp	Cost_2030-cost	Cost_2050-gwp	Cost_2050-cost
DE	ConELC-CHP_BIO-GAS	6.91	0.00	0.00	5.74	6.91	0.00	0.00	0.00	22.29	39.49	0.21	0.00	0.00	14.57	0.73	2.19	0.00	0.00	2.06	2.48
DE	ConELC-CHP_BIO-MASS	1.73	1.73	1.59	1.73	1.73	0.35	6.63	9.81	9.92	11.38	0.16	2.53	3.72	3.65	0.56	0.54	0.60	0.55	0.66	0.66
DE	ConELC-CHP_COA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DE	ConELC-CHP_COA100MW	2.08	0.00	0.00	0.00	0.00	9.76	0.00	0.00	0.00	0.00	2.41	0.00	0.00	0.00	0.02	0.07	0.00	0.00	0.00	0.00
DE	ConELC-CHP_COA500MW	4.85	0.00	0.00	0.00	0.00	23.07	0.00	0.00	0.00	0.00	28.33	0.00	0.00	0.00	0.09	0.27	0.00	0.00	0.00	0.00
DE	ConELC-CHP_GEO	0.06	0.06	0.06	0.06	0.06	0.49	0.27	0.36	0.39	0.41	0.05	0.04	0.04	0.03	0.02	0.02	0.02	0.02	0.03	0.03
DE	ConELC-CHP_LIG	0.65	0.00	0.00	0.00	0.00	3.67	0.00	0.00	0.00	0.00	3.67	0.00	0.00	0.00	0.01	0.04	0.00	0.00	0.00	0.00
DE	ConELC-CHP_NG-CCGT	7.27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.15	0.45	0.00	0.00	0.00	0.00
DE	ConELC-CHP_NG-OCGT	2.69	0.00	0.56	5.32	3.86	0.00	0.00	0.01	14.52	0.20	0.00	0.00	0.00	0.01	0.05	0.12	0.00	0.03	0.33	0.24
DE	ConELC-CHP_NG-ST	2.50	40.43	0.00	0.00	0.00	0.00	34.70	0.00	0.00	0.00	0.00	13.85	0.00	0.00	0.79	0.14	2.23	0.00	0.00	0.00
DE	ConELC-CHP_OIL	0.96	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.00	0.00
DE	ConELC-CHP_OTH	0.82	0.00	0.40	0.00	0.00	7.08	0.00	2.53	0.00	0.00	5.10	0.00	1.81	0.00	0.16	0.31	0.00	0.17	0.00	0.00
DE	ConELC-CHP_WST	0.49	0.52	0.00	0.52	0.06	0.00	2.44	0.00	3.60	0.24	0.01	0.01	0.00	0.00	0.15	0.21	0.23	0.00	0.25	0.03
DE	ConELC-PP_COA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DE	ConELC-PP_COA100MW	2.19	0.00	0.00	0.00	0.00	4.56	0.00	0.00	0.00	0.00	1.13	0.00	0.00	0.00	0.03	0.08	0.00	0.00	0.00	0.00
DE	ConELC-PP_COA500MW	5.10	0.00	0.00	0.00	0.00	11.12	0.00	0.00	0.00	0.00	13.51	0.00	0.00	0.00	0.09	0.28	0.00	0.00	0.00	0.00
DE	ConELC-PP_GEO	0.06	0.06	0.06	0.06	0.06	0.48	0.27	0.36	0.39	0.41	0.04	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.03
DE	ConELC-PP_HYD-PST	9.28	9.42	9.42	9.42	9.42	13.96	0.63	23.51	23.16	26.69	8.25	1.36	11.92	4.67	0.32	0.31	0.32	0.32	0.36	0.36
DE	ConELC-PP_HYD-ROR	3.72	4.01	4.01	4.01	4.01	32.29	17.55	34.99	26.62	28.53	1.12	1.13	1.14	0.99	0.50	0.46	0.52	0.52	0.57	0.57
DE	ConELC-PP_HYD-STO	1.43	1.52	1.52	1.52	1.52	12.48	5.58	11.92	8.74	9.43	1.26	0.93	1.22	0.96	0.16	0.15	0.16	0.16	0.18	0.18
DE	ConELC-PP_LIG	17.71	0.00	0.00	0.00	0.00	144.09	0.00	0.00	0.00	0.00	146.14	0.00	0.00	0.00	0.37	1.11	0.00	0.00	0.00	0.00
DE	ConELC-PP_NG-CCGT	17.89	9.65	27.06	0.00	10.34	0.86	26.20	52.50	0.00	13.13	0.45	10.33	20.86	0.00	1.12	1.11	0.59	1.67	0.00	0.88
DE	ConELC-PP_NG-OCGT	4.13	0.00	18.53	0.00	8.17	0.00	0.00	2.68	0.00	1.19	0.01	0.00	2.01	0.00	0.36	0.19	0.00	0.90	0.00	0.52
DE	ConELC-PP_NG-ST	1.78	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.09	0.00	0.00	0.00	0.00
DE	ConELC-PP_OIL	3.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.04	0.11	0.00	0.00	0.00	0.00
DE	ConELC-PP_OTH	0.82	0.00	0.50	0.34	0.02	7.08	0.00	3.17	0.52	0.11	3.11	0.00	1.31	0.22	0.12	0.21	0.00	0.15	0.17	0.01
DE	ConELC-PP_SPVopenground	7.38	15.00	15.00	43.33	10.00	8.19	16.64	16.64	48.08	11.09	0.06	0.10	0.10	0.24	0.68	0.47	0.79	0.79	1.59	0.38
DE	ConELC-PP_SPVrooftop	66.44	92.09	124.33	107.21	154.38	73.71	102.17	137.94	118.94	171.28	6.38	7.11	9.62	5.09	6.97	5.11	6.69	9.12	5.59	7.90
DE	ConELC-PP_WOF7MW	8.39	0.00	43.95	0.00	66.62	40.77	0.00	213.68	0.00	323.89	0.35	0.00	1.77	0.00	4.90	2.38	0.00	12.34	0.00	23.95
DE	ConELC-PP_WON	59.92	0.00	44.23	0.42	0.45	110.38	0.00	112.01	0.96	1.03	3.36	0.00	2.43	0.02	3.83	7.13	0.00	4.37	0.03	0.04
DE	ConELC-PP_WST	1.32	1.40	1.40	1.40	1.40	11.50	6.73	9.16	9.87	9.86	0.01	0.01	0.01	0.01	0.61	0.57	0.63	0.63	0.80	0.80
DE	ConELC-PP_WOF11MW	0.00	11.61	0.00	0.00	0.00	0.00	58.52	0.00	0.00	0.00	0.00	0.56	0.00	0.00	1.58	0.00	4.75	0.00	0.00	0.00
DE	ConELC-PP_WOF15MW	0.00	71.44	0.00	70.00	0.00	0.00	367.21	0.00	359.83	0.00	0.00	2.90	0.00	2.46	12.34	0.00	37.02	0.00	50.85	0.00
DE	ConELC-PP_WOF9MW	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DE	ConELC-PP_H2-CCGT	0.00	0.00	0.00	43.55	25.77	0.00	0.00	0.00	24.89	24.89	0.00	0.00	0.00	0.27	0.00	0.00	0.00	0.00	3.68	2.17

Table A. 4 Absolute LCA results for optimistic scenario year 2030 under cost minimisation.

LCA impact category	Units	Biomass	Geothermal	Pumped storage	Hydro, run on river	Hydro, reservoir storage	Natural gas, combined cycle	Natural gas, open ccyle	Others	PV-openground	PV-rooftop	Offshore wind (7MW)	Onshore wind
ADP	kg Sb-Eq x 1E6	11,061	913	132,078	21,224	13,162	26,246	6,987	2,521	8,269	1,414,543	166,727	726,163
AP	mol H+-Eq x 1E6	47,862	1,623	165,878	42,839	21,129	238,230	46,104	49,045	3,728	357,498	78,035	138,613
CTUe	CTUe x 1E6	1,237,933	220,551	1,567,853	226,304	128,096	365,005	53,530	203,449	44,682	6,286,852	867,577	2,869,769
non-HTP	CTUh x 1E6	14,793	1,385	60,872	30,953	15,587	16,983	1,800	7,804	1,592	134,018	84,350	108,622
FEP	kg PO4-Eq x 1E6	1,183	360	57,137	3,312	1,733	8,330	980	341	533	68,651	9,839	28,629
GWP	kg CO_2-eq x 1E6	40,623	700	102,955	10,835	11,779	214,416	20,672	30,559	934	85,658	14,866	24,029
GWP-biogenic	kg CO_2-eq x 1E6	375,946	71	106,992	4,523	12,138	3,203	344	294	91	7,657	859	3,316
GWP-fossil	kg CO_2-eq x 1E6	2,997	695	83,044	10,443	5,968	214,073	20,636	30,531	927	85,145	14,794	23,728
GWP-landuse	kg CO_2-eq x 1E6	3,213	0	926,838	0	464,191	2,397	236	0	0	0	0	0
IRP	kg U235 eq x 1E6	663	120	83,700	1,263	762	5,966	602	1,805	180	17,729	1,405	2,851
LQI	dimensionless x 1E6	2,519,350	3,987	486,853	58,994	37,151	84,577	16,670	48,777	162,538	517,034	80,787	363,318
MEP	kg N-Eq x 1E6	13,236	407	54,973	14,078	6,504	54,338	17,219	13,766	831	83,009	18,852	30,799
ODP	kg CFC-11-Eq x 1E6	10,116	333	71,309	7,722	3,664	393,604	39,080	62,512	1,235	104,251	8,895	17,024
PMFP	Disease incidence per kg PM2.5 x 1E6	13,919	166	22,620	11,505	6,183	5,466	1,305	6,381	491	42,891	9,732	20,793
POFP	kg NMVOC eq x 1E6	49,283	1,453	142,019	48,574	21,455	258,498	52,875	39,434	3,015	276,055	67,762	110,046
TEP	mol N-Eq x 1E6	159,554	3,868	479,406	152,065	71,022	573,555	187,188	119,221	7,941	768,730	193,007	345,625
WAU	m3 world eq. deprived x 1E6	3,329	306	68,492	2,944	150,906	18,337	1,719	1,391	1,406	106,536	2,194,548	12,222
non-HTP	CTUh x 1E6	49,480	1,277	110,322	15,874	8,366	108,009	4,658	6,656	4,021	469,839	71,646	198,619
non-renADP	MJ, net calorific value x 1E6	41,186	9,380	2,461,366	111,566	59,955	3,601,683	358,345	379,222	13,431	1,263,951	178,199	298,784

Table A. 5 Absolute LCA results for optimistic scenario year 2050 under cost minimisation.

LCA impact category	Units	Biogas	Biomass	Geothermal	H2, combined cycle	HYD-PST	Hydro, run on river	Hydro, reservoir storage	PV-opengrou nd	PV-rooftop	Offshore wind (7MW)	Onshore wind	Waste
ADP	kg Sb-Eq x 1E6	37,876	10,419	1,149	48,376	234,399	19,382	11,969	7,802	1,541,062	299,153	8,294	1,177
AP	mol H+-Eq x 1E6	396,859	39,200	14	515,460	173,936	410	197	31	3,397	3,641	446	8
CTUe	CTUe x 1E6	1,335,621	1,261,594	217,574	292,638	1,985,346	205,568	113,194	36,544	6,178,503	1,487,383	32,034	6,454
non-HTP	CTUh x 1E6	22,056	14,837	1,382	22,050	81,333	29,585	15,121	1,404	138,789	150,244	1,226	548
FEP	kg PO4-Eq x 1E6	9,771	998	239	2,480	49,843	2,805	1,380	387	60,519	16,251	309	74
GWP	kg CO_2-eq x 1E6	243,318	40,561	132	3,019	6,600	7,024	7,689	303	25,191	18,302	162	108
GWP-biogenic	kg CO_2-eq x 1E6	2,135,244	385,533	229	1,001	162,433	3,326	9,137	237	25,796	3,266	44	33
GWP-fossil	kg CO_2-eq x 1E6	32,325	2,521	361	3,348	56,013	7,997	3,986	508	49,001	21,243	198	117
GWP-landuse	kg CO_2-eq x 1E6	0	0	0	0	0	0	366,484	0	0	0	0	0
IRP	kg U235 eq x 1E6	2,062	383	174	529	50,735	928	606	173	19,930	2,632	33	11
LQI	dimensionless x 1E6	395,165	2,586,620	9,022	180,987	1,720,618	73,059	47,063	142,729	985,302	194,724	4,782	1,819
MEP	kg N-Eq x 1E6	31,673	11,039	3	225,105	40,230	130	60	7	958	804	81	2
ODP	kg CFC-11-Eq x 1E6	11,062	9,979	428	7,907	101,813	7,910	3,889	1,166	112,930	16,737	205	115
PMFP	Disease incidence per kg PM2.5 x 1E6	34,449	13,850	157	5,283	26,082	11,316	6,071	418	41,727	17,472	235	136
POFP	kg NMVOC eq x 1E6	157,341	43,159	139	587,219	114,814	4,626	2,199	254	26,503	22,870	367	78
TEP	mol N-Eq x 1E6	135,331	13,778	4	246,077	54,764	144	68	7	784	871	109	2
WAU	m3 world eq. deprived x 1E6	4,071	3,421	364	12,614	104,093	3,119	119,586	1,263	109,414	3,964,394	146	47
non-HTP	CTUh x 1E6	199,493	50,118	1,102	16,270	121,883	14,421	7,397	3,396	464,430	124,995	2,227	454
non-renADP	MJ, net calorific value x 1E6	267,832	33,515	9,022	51,561	2,065,222	99,985	53,709	10,886	1,159,155	298,347	3,170	1,477

Table A. 6 Results under cost and GWP minimisation

	2019				Installed capacity, GW				Electricity generation, TWh				GWP, million t CO_2-eq				Total costs, billion €			
Country	GW	TWh	million t CO_2-eq	billion €	GW_2030-gwp	GW_2030-cost	GW_2050-gwp	GW_2050-cost	TWh_2030-gwp	TWh_2030-cost	TWh_2050-gwp	TWh_2050-cost	GWP_2030-gwp	GWP_2030-cost	GWP_2050-gwp	GWP_2050-cost	Cost_2030-gwp	Cost_2030-cost	Cost_2050-gwp	Cost_2050-cost
AT	28	68	8	3	68	9	32	9	88	66	78	66	1	4	2	4	4	1	2	1
BE	28	85	9	3	49	33	36	54	89	91	124	93	1	3	1	3	6	3	15	4
BG	15	37	11	1	20	8	19	12	46	41	46	41	1	14	1	14	8	1	10	1
CH	23	66	6	2	23	16	11	15	63	66	64	66	2	5	1	5	2	1	1	2
CZ	21	66	24	2	22	16	16	40	66	68	67	69	2	26	1	26	2	2	2	3
DE	242	516	225	24	259	293	295	305	646	631	673	673	41	58	33	58	55	32	67	41
EE	3	8	4	0	7	5	9	9	27	10	39	13	0	1	0	1	4	1	10	1
ES	117	262	24	12	110	122	124	80	266	271	281	262	5	18	4	18	15	10	20	8
FI	21	83	6	3	27	21	27	28	90	84	93	87	2	10	1	10	9	2	10	3
FR	149	468	19	16	117	118	123	181	474	480	480	480	5	19	3	19	33	13	45	15
GR	24	53	10	3	34	31	26	31	52	54	59	54	3	10	2	10	8	6	7	3
HR	5	19	1	1	8	5	10	4	20	18	28	18	1	2	1	2	2	1	5	1
HU	10	44	15	1	17	17	33	32	45	43	60	50	1	5	1	5	2	2	4	3
IE	10	29	13	1	8	13	8	19	32	30	32	30	1	6	0	6	3	1	3	1
IT	98	299	106	10	109	121	138	126	291	309	329	309	12	23	11	23	13	12	23	13
LT	5	12	4	0	8	6	10	7	28	14	39	15	0	3	0	3	4	1	10	0
LU	1	3	1	0	1	1	2	2	4	4	4	4	1	1	1	1	0	0	0	0
LV	3	7	1	0	2	1	3	1	7	7	13	7	0	0	0	0	1	0	2	0
NL	56	114	41	5	54	61	40	64	111	111	111	111	14	16	11	16	5	4	9	4
NO	40	136	17	5	37	22	38	22	151	139	170	140	3	12	3	12	12	3	20	3
PL	61	169	118	7	53	64	60	75	171	169	172	171	22	56	28	56	16	8	28	12
PT	21	53	4	2	25	12	20	13	50	52	54	53	1	5	1	5	2	1	4	2
RO	16	60	3	3	20	8	18	31	60	59	70	61	2	6	2	6	9	2	19	4
SE	50	136	19	7	37	22	32	25	138	138	138	138	5	13	4	13	9	3	12	3
SI	5	14	4	0	2	2	4	4	13	14	14	14	0	4	0	4	0	0	0	0
SK	8	29	4	1	6	7	7	16	29	31	29	32	1	7	1	7	1	1	1	1
UK	105	310	92	14	85	118	142	167	324	333	340	337	7	26	14	26	25	14	33	20

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1. Benitez, A.; Wulf, C.; Geldermann, J.; Kuckshinrichs, W. (2023):
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2. Benitez, A.; Wulf, C.; Geldermann, J.; Steubing, B.; Kuckshinrichs, W. (2022):
   Dealing with future developments of wind offshore energy: how to incorporate their environmental aspects? 14th International Conference on Applied Energy. Bochum, Germany 08.08 – 11.08.2022.

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   Integrating Life Cycle Assessment into the electric model Stella: A case for Germany. How to include the Planetary Boundaries concept, The 10th International Conference on Life Cycle Management, Stuttgart, Germany 05.09 – 08.09.2021.

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