Energy Storage Design and Integration in Power Systems by System-Value Optimization

Maximilian Parzen

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Agile Energy Systems Group

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Lay Summary of Thesis

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The transition to low-carbon power systems is essential to combat climate change and ensure a sustainable future. One of the biggest challenges in this transition is the integration of renewable energy sources such as wind and solar, which are intermittent and variable in nature. Energy storage technologies can play a crucial role in decarbonizing power systems by providing a reliable and flexible source of power which provides economic benefits to the system. These benefits of energy storage are nowadays assessed with system-value methods that highly depend on large-scale power system models. However, with existing methods several research questions appear: how to assess multiple energy storage technologies under competition, how to avoid appearing misleading energy storage model artefacts, is it possible to expand the geographical scope of energy models to cover other parts of the world? In this thesis, we build and solve large energy system optimization problems to explore and optimize various energy storage designs and integration's in context of system-value.

The first part of the thesis focuses on technology assessment methods and energy system modelling. We explore and discuss existing methods and develop a new complementary system-value assessment method, known as ‘market-potential method’, that works as systematic deployment analysis to also consider multiple storage technologies under competition. Because the integration of energy storage in system models can lead to unrealistic ‘unintended storage cycling’ effects that curtails electricity and increases operation of any generator, grid, and storage component, we explore its cause and suggest solutions that lead to more realistic model results by appropriate model parameterization. To enable energy system research worldwide, including system-value assessments for energy storage, we have extended the geographical scope from Europe to global coverage. The new build energy model ‘PyPSA-Earth’ is thereby demonstrated and validated in Africa.

In the second part of the thesis, we focus on applied storage design and integration system-analysis. First, the new created system-value method is introduced and demonstrated in a large-scale European transmission system. Here we focus only on Lithium battery and various hydrogen energy

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storage solutions to learn about the applicability of the method and how it differs from traditional levelised cost of storage (LCOS) methods. Second, adopting the new PyPSA-Earth model, we assess for the first time the system-value of 20 energy storage technologies with and without competition across uncertainty addressing, multiple scenarios for a representative future power system in Africa. In general, we could observe from deployment signals that not all energy storage technologies are relevant for the power system, the more energy storage can adapt to the power system the more benefits it can provide to the system, and that optimizing multiple energy storage options usually tends to significant total system cost reduction. Our findings provide insights into approaches to assess multiple energy storage technologies under competition in large-scale energy system models, and can inform decision-making for the sizing, integration, and deployment of energy storage systems in decarbonized power systems.

Abstract

Energy storage can play a crucial role in decarbonising power systems by balancing power and energy in time. Wider power system benefits that arise from these balancing technologies include lower grid expansion, renewable curtailment, and average electricity costs. However, with the proliferation of new energy storage technologies, it becomes increasingly difficult to identify which technologies are economically viable and how to design and integrate them effectively.

Using large-scale energy system models in Europe, the dissertation shows that solely relying on Levelized Cost of Storage (LCOS) metrics for technology assessments can mislead and that traditional system-value methods raise important questions about how to assess multiple energy storage technologies. Further, the work introduces a new complementary system-value assessment method called the market-potential method, which provides a systematic deployment analysis for assessing multiple storage technologies under competition. However, integrating energy storage in system models can lead to the unintended storage cycling effect, which occurs in approximately two-thirds of models and significantly distorts results. The thesis finds that traditional approaches to deal with the issue, such as multi-stage optimization or mixed integer linear programming approaches, are either ineffective or computationally inefficient. A new approach is suggested that only requires appropriate model parameterization with variable costs while keeping the model convex to reduce the risk of misleading results.

In addition, to enable energy storage assessments and energy system research around the world, the thesis extended the geographical scope of an existing European open-source model to global coverage. The new build energy system model 'PyPSA-Earth' is thereby demonstrated and validated in Africa. Using PyPSA-Earth, the thesis assesses for the first time the system value of 20 energy storage technologies across multiple scenarios in a representative future power system in Africa. The results offer insights into approaches for assessing multiple energy storage technologies under competition in large-scale energy system models. In particular, the dissertation addresses extreme cost uncertainty through a comprehensive scenario tree and finds that, apart from lithium and hydrogen, only seven energy storage are optimization-relevant technologies. The work also discovers that a heterogeneous storage design can increase power system benefits and that some energy storage are more important than others. Finally, in contrast to traditional methods that only consider single

energy storage, the thesis finds that optimizing multiple energy storage options tends to significantly reduce total system costs by up to 29%.

The presented research findings have the potential to inform decision-making processes for the sizing, integration, and deployment of energy storage systems in decarbonized power systems, contributing to a paradigm shift in scientific methodology and advancing efforts towards a sustainable future.

Publications

Main Publications:

- **Maximilian Parzen**. “The Value of Competing Energy Storage in Decarbonized Power Systems”. In: ArXiv (2023). DOI: https://doi.org/10.48550/arXiv.2305.09795. **Preprint**, cite as [1].

- **Maximilian Parzen**, Hazem Abdel-Khalek, Ekaterina Fedorova, Matin Mahmood, Martha Maria Frysztacki, Johannes Hampp, Lukas Franken, Leon Schumm, Fabian Neumann, Davide Poli, Aristides Kiprakis, and Davide Fioriti. "PyPSA-Earth. A new global open energy system optimization model demonstrated in Africa." (2023). In: Applied Energy 341 (2023), p.121096. DOI: https://doi.org/10.1016/j.apenergy.2023.12109. **Peer-reviewed**, cite as [2].

- **Maximilian Parzen**, Martin Kittel, Daniel Friedrich, and Aristides Kiprakis. “Reducing energy system model distortions from unintended storage cycling through variable costs”. In: iScience 26.1 (2023), p.105729. DOI: https://doi.org/10.1016/j.isci.2022.105729. **Peer-reviewed**, cite as [3].

- **Maximilian Parzen**, Fabian Neumann, Adriaan H. Van Der Weijde, Daniel Friedrich, and Aristides Kiprakis. “Beyond cost reduction: improving the value of energy storage in electricity systems”. In: Carbon Neutrality 1.1 (2022), p.26. DOI: https://doi.org/10.1007/s43979-022-00027-3. **Peer-reviewed**, cite as [4].

Further Publications:

- Davide Fioriti, **Maximilian Parzen**, Ekaterina Fedotova, Denise Giubilato, Martha Maria Frysztacki, Leon Schumm, Hazem Abdel-Khalek, Stuart Daniel James and Davide Poli. “Country-wise open energy planning in high-resolution with PyPSA-Earth”. In: SEST 2023 Conference. (2023). **Accepted**.

- Ekaterina Fedotova, Ekaterina Voronkov, Davide Fioriti and **Maximilian Parzen**. “Regional Applicability of PyPSA-Earth Framework: Case Study for Kazakhstan”. In: IEEE Smart Information Systems and Technologies Conference. (2023). **Under review**.

- Ekaterina Voronkova, **Maximilian Parzen**, Davide Fioriti, Ekaterina Fedotova. "Interconnecting the Silk Way: validation of power transmission data for Western and Central Asia". In: IEEE International Conference on Smart Energy Systems and Technologies. (2023). **Accepted**.

- Lukas Franken, Matin Mahmood, Davide Fioriti, **Maximilian Parzen**, Cesare Caputo and Gaurav Kumar. “On Transfer Learning to Detect Electric Infrastructure in Satellite Imagery”. In: ICLR 2023 Workshop: Tackling Climate Change with Machine Learning. (2023). **Under review**.

- Desen Kirli, Johannes Hampp, Koen van Greevenbroek, Rebecca Grant, Matin Mahmood, **Maximilian Parzen**, and Aristides Kiprakis. “PyPSA meets Africa: Developing an open source electricity network model of the African continent”. In: 2021 IEEE AFRICON. (2021), pp. 1–6. DOI: `https://doi.org/10.1109/AFRICON51333.2021.9570911`. **Peer-reviewed**, cite as [5].

- Desen Kirli, **Maximilian Parzen**, and Aristides Kiprakis. “Impact of the COVID-19 Lockdown on the Electricity System of Great Britain: A Study on Energy Demand, Generation, Pricing and Grid Stability”. In: Energies 14.3 (2021). `https://www.mdpi.com/1996-1073/14/3/635`. **Peer-reviewed**, cite as [6].

- **Maximilian Parzen**, Julian Hall, Jesse Jenkins, and Tom Brown. “Optimization solvers: the missing link for a fully open-source energy system modelling ecosystem.” In: Zenodo (2022). DOI: `https://zenodo.org/record/6534004#.Y6inJ6fP1Qo`. **Open funding proposal** (successful, 600k€+ for Julian Hall’s group at the University of Edinburgh), cite as [7].

- Robbie Morrison and **Maximilian Parzen**. “Open energy system modelers call for CC-BY-4.0 data licensing wherever possible — our world needs comprehensive usable and reusable data to transition to net-zero” In: Zenodo (2023). DOI: `https://doi.org/10.5281/zenodo.7549853`. **Open letter** (74+ signatures), cite as [8].

- **Maximilian Parzen**, Fabian Hofmann and Ekatarina Fedotova. "13 power systems around the world." In openmod (2022). Url: `https://forum.openmod.org/t/13-power-systems-around-the-world/3528`. **Blog post**, cite as [9].

Contributions to Scientific Open-Source Software:

The list below shows software packages to which I contributed significant open-source code. To cross-check the contributions in detail, one can click on one of the GitHub repository links, then move to "Pull Requests", and click on "Closed". Entering there in the search bar my GitHub account name "pz-max", will reveal all my contributions.

- Atlite, https://github.com/PyPSA/Atlite. A tool to convert weather data to energy systems data. Contribution: bug fixes.
- Earth-osm, https://github.com/pypsa-meets-earth/earth-osm. Tool to extract & standardize power infrastructure data from OpenStreetMap (OSM). Contribution: Co-creator, feature development, bug fixes, usability and documentation.
- Linopy, https://github.com/PyPSA/Linopy. Linear optimization interface for Python. Contribution: Feature development, bug fixes and usability and documentation.
- Powerplantmatching, https://github.com/PyPSA/Powerplantmatching. Toolbox to combine multiple powerplant databases. Contribution: feature development, bug fixes, usability and documentation.
- PyPSA, https://github.com/PyPSA/PyPSA. Python framework for energy system optimization. Contribution: feature development, bug fixes, usability and documentation.
- PyPSA-Earth, https://github.com/PyPSA-meets-Earth/PyPSA-Earth. A flexible open sector-coupled optimization model of the global energy system. Contribution: Co-creator, feature development, bug fixes, usability and documentation.
- PyPSA-Eur, https://github.com/PyPSA/PyPSA-Eur. A flexible open sector-coupled optimization model of the European energy system. Contribution: Feature development, bug fixes, usability and documentation.
- Technology-data, https://github.com/PyPSA/technology-data. A tool that compiles assumptions on energy system technologies. Contribution: Feature development, bug fixes, usability and documentation.
- Zenodopy, https://github.com/lgloege/zenodopy. A tool to push data over the terminal to Zenodo. Contribution: Feature development, bug fixes, usability and documentation.

Figure 1 shows the coding activity from Monday to Sunday during the dissertation, where one contribution can include several lines of code. Next to these code development, I have also contributed to building up a popular energy system modelling community called PyPSA meets Earth (https://pypsa-meets-earth.github.io/) to empower others and enhance collaborative work.

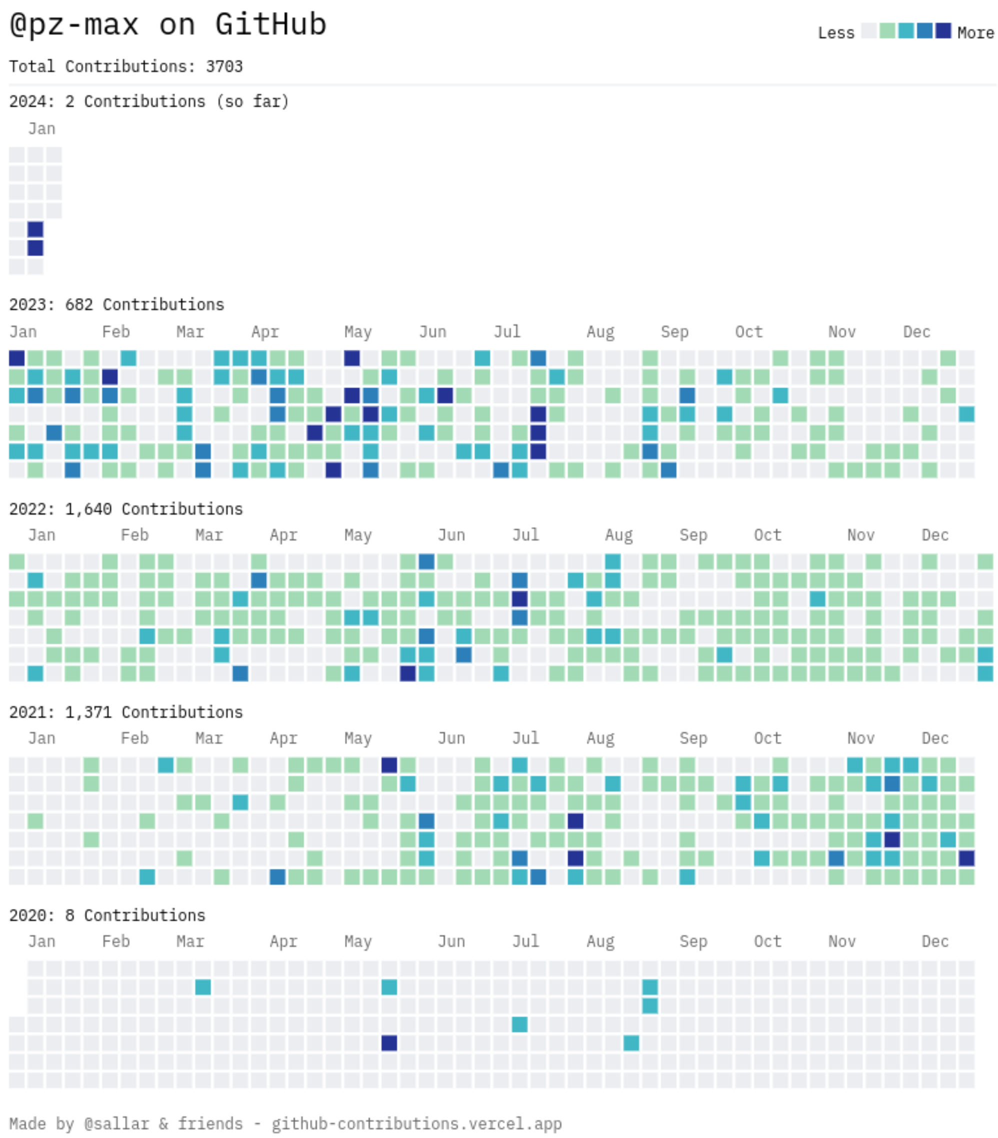

Fig. 1.: GitHub contributions from Monday to Sunday over the past 4 years.

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The thesis represents a research journey that wouldn't be possible without the support of many people.

First of all, I want to thank my supervisor Prof. Aristides Kiprakis and co-supervisor Prof. Daniel Friedrich. They inspired me, believed in me and gave me all the freedom and guidance needed to go and find my research path. Working with you is a pure pleasure. Second, I want to thank Prof. Davide Fioriti, the co-leader of the grassroots initiative PyPSA meets Earth that I founded during the process of the research journey. Many things wouldn't be possible without him and the amazing PyPSA community within and outside of TU Berlin. Talking about Berlin, third, I thank Prof. Tom Brown for co-creating and co-maintaining PyPSA. When I talk about PyPSA, friends tell me it sounds like a church. Well, if we call it a church, you certainly represent the pope. Forth, I appreciate and acknowledge all co-authors, colleagues, friends, open-source and open-data contributors who contributed to this thesis. To name a few: Fabian Neumann, Davide Fioriti, Mousa Zerai, Desen Kirli, Martin Kittel, Hazem Abdel-Khalek, Ekaterina Fedotova, Matin Mahmood, Martha Maria Frysztacki, Johannes Hampp, Lukas Franken, Leon Schumm and Robbie Morrison. Fifth, I would also like to extend my thank you to my enemies for pushing me to work harder and reminding me of the importance of perseverance in the face of adversity. Sixth, I would like to express my deepest gratitude and appreciation to my family Helmut Parzen, Ksenija Parzen and Daniel Parzen and many of my friends, who have supported and encouraged me throughout my academic journey. I could not have achieved this milestone without you. Seventh, following Snoop Dogg's philosophy, I want to thank me for believing in me, I want to thank me for doing all this hard work. I wanna thank me for having no days off. I wanna thank me for never quitting. I wanna thank me for always being a giver and trying to give more than I receive. I wanna thank me for trying to do more right than wrong. I wanna thank me for being me at all times.

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Declaration

I declare that (a) the thesis has been composed by myself, (b) the work is either my owns work or clearly indicated if not, (c) the work has not been submitted for any other degree or professional qualification except as specified and (d) any included publications are my own work or marked as collaborative work.

Edinburgh, August 23, 2023

Maximilian Parzen

Contents

Nomenclature

Abbreviations

BAU Business as Usual
CSP Concentrated Solar Power
EP Energy to Power
FLH Full Load Hours
GADM Database of Global Administrative Areas
GDP Gross Domestic Product
GHG Greenhouse Gas
H2 Hydrogen
HVAC High Voltage Alternative Current
HVDC High Voltage Direct Current
H2 Hydrogen
IRR Internal Rate of Return
IPM Interior Point Method
LCOS Levelized Cost of Storage
MILP Mixed Integer Linear Program
MPI Market Potential Indicator
MPM Market Potential Method
NPV Net Present Value
PEM Proton Exchange Membrane
PV Photovoltaic
ROI Return of Investment
SOFC Solid-Oxide Fuel Cell
UC Unit Commitment
USC Unintended Storage Cycling
VRE Variable Renewable Energy
WSB Whole System Benefit

Nomenclature

Subscripts

i Location

l Line number

r Generator technology

s Storage technology

t Time step

Variables

H^+ Storage charge capacity (MW)

h^+ Storage charge (MWh)

H^- Storage discharge capacity (MW)

h^- Storage discharge (MWh)

$H_{i,s}^{store}$ Store capacity (MWh)

$\overline{T}$ Energy to discharging power ratio (MWh/MW)

e Stored energy (MWh)

F Transmission line capacity (MW)

G Generator capacity (MW)

g Generated energy (MWh)

Parameters

η	Efficiency
c	Specific investment cost (€/MW)
o	Variable cost (€/MWh)
T	Optimization period
w	Weighted duration

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1 Introduction

> *Climate change is, simply, the greatest collective challenge we face as a human family*
>
> — **Ban Ki-Moon**
> (Politician and diplomat)

1.1 Background

The global demand for energy has reached unprecedented levels, as depicted in Figure 1.1. However, the accompanying GHG emissions produced by predominately fossil fuel energy generators exert significant pressure on the atmosphere, making the transition to low-carbon power systems a critical imperative for combating climate change and securing a sustainable future. One of the biggest challenges in this transition is the integration of renewable energy sources, such as wind and solar, which are intermittent and variable in nature.

Energy storage technologies can play a crucial role in decarbonising power systems by providing a reliable and flexible source of power that can balance out mismatches between supply and demand while also leading to economic benefits in the power system [10]. However, with the proliferation of new energy storage technologies, it becomes increasingly difficult to identify which technologies are most economically viable and how to design and integrate them effectively.

One point making the economic assessment and integration of energy storage difficult is that power systems are complex machines. The power system consists of demand and supply devices interconnected through grid infrastructure. The continuous matching of demand and supply in real-time is crucial for the stable and efficient operation of the system. However, this task is complicated by the fact that demand and supply vary across regions, depending on a multitude of factors such as environmental conditions (e.g., weather, temperature, seasonal effects), social conditions (e.g., cultural preferences and acceptance of certain technologies), and technology advancements (e.g., electrification of transport). In addition, the transport of electricity across the grid is driven by physical principles such as the alternating current optimal power flow, which further adds to the system's complexity.

Due to the inherent complexity of decision-making within large-scale systems, capacity expansion models, also known as macro-energy system models, emerged as a critical tool for supporting decision-making [11]. They aim to effectively suggest and compare investment alternatives considering heterogeneous power system conditions. In particular, these models are built to provide a simplified representation of the actual system and enable the exploration of optimal power system configurations that can be modified to satisfy a range of environmental, societal, and technological constraints as well as techno-economic uncertainties. Consequently, the application of these models has expanded in recent years, with increasing emphasis placed on assessing energy storage solutions in addition to other critical energy infrastructure investments [12, 13, 14].

Even though complex decision-support models are now applied, one long-standing challenge remains: predicting the future with certainty is impossible [15]. Retrospective modelling exercises have shown that least-cost optimization rarely matched with real system observations [16]. Uncertainty in models can be understood as 'structural uncertainty' related to an imperfect or simplified mathematical description of the physics and constraints and 'parametric uncertainty' associated with imperfect knowledge of input values, i.e. impacted by innovation or behaviour. Both compromise every mathematical model with increasing uncertainty looking into the more distant future [17, 18]. Several efforts to reduce uncertainty are actively tackled. One example is the sensitivity analysis approach that requires input parameter changes, also known as parameter sweeps, or the modelling to generate alternatives approaches that hold input parameter constants while exploring the near-optimal solution space [19]. Reducing uncertainty will remain essential for successfully adopting these support decision tools.

1.2 Research Questions

Building on the high-level topic introduction from the previous section, this dissertation addresses pressing research questions concerning energy storage using energy system models. While each chapter in this thesis thoroughly examines the background, research gap and more detailed research questions, this section only introduces the high-level research questions and aims driving this work.

The thesis aims to improve applied energy storage system-value optimization and improve the underlying decision-support models. Regarding improving applied energy storage system-value optimization, the study aims to investigate and provide answers to the following critical research questions:

- What is the economic viability of different energy storage technologies?
- How can energy storage systems be effectively designed and integrated into the larger energy system?

Energy system models are required tools for addressing these questions. However, for attaining useful answers, the models' accuracy and reliability are critical. The thesis provides answers to the following energy modelling relevant research questions:

- Can energy system models be easily applied everywhere around the world?
- How to avoid unintended storage cycling in energy system models?

It is of utmost importance to continuously improve and expand these models in all dimensions, which is most effectively possible with open research, open data and open source models [20].

Fig. 1.1.: The world is hungry for energy. Own illustration.

1.3 Outline and Contributions

The thesis focuses on two main parts: energy system modelling and energy storage system-value optimization which requires system modelling. In particular, the two main themes are flanked by a foundational layer and closing remarks. Throughout the thesis, readers will gain valuable insights into the design and integration of energy storage systems in power systems and the use of advanced modelling techniques to optimize their value within these systems.

Part I, focuses on improving energy system modelling with energy storage. Driven by the need to enable energy system research in unexplored areas, including storage assessments, the chapters extended the model scope from an established open source EU power system model to planetary coverage while seeking to answer questions arising from misleading model distortions that arise when energy storage are integrated into models.

Part II, concerns about energy storage system-value optimization methods and their implications when being applied in Europe and Africa. Here, the chapters seek to answer what are suitable energy storage assessments methods and how they compare to traditional LCOS and Whole System Benefit (WSB) methods. In the context of these investigations, the work derives energy storage design and integration recommendations of up to 20 energy storage, explores magnitudes of power system benefits, and applies sensitivity analysis to address uncertainty.

Chapter 2 - Foundations, conveys the foundational knowledge necessary for this thesis. It includes knowledge about power systems, energy storage modelling, various energy storage designs, and algorithms to optimize power system operation and investment. These topics are consistently referred to throughout the manuscript. This chapter serves as an introduction to these concepts, which are critical for understanding the research presented in this study.

Chapter 3 - Modelling Power Systems with High Resolution Data - PyPSA-Earth [2] (**Part I**), focuses on the introduction and demonstrations of a new global energy system model. The tool, PyPSA-Earth, has been introduced as the first open global energy system model with data in high spatial and temporal resolution. The model provides two main features: customizable data extraction and preparation with global coverage and a PyPSA energy modelling framework integration. The data includes electricity demand, generation, and medium to high-voltage networks from open sources, yet additional data can be further integrated. A broad range of clustering and grid meshing strategies help adapt the model to computational and practical needs. The chapter also validates the data for the entire African continent and tests the optimization features with a 2060 net-zero planning study for Nigeria. The demonstration shows that the presented developments can build a highly detailed power system model for energy planning studies to support policy and technical decision-making. The chapter contributes to science by enabling science globally. PyPSA-Earth is expected to represent an open reference model for system planning, and it is hoped that the challenges of the energy transition can be addressed collaboratively. The introduction of the new model demonstrates the potential of open models to provide a competitive alternative to closed-source models for decision-makers, promoting science, collaboration, and transparent policy decision-making.

Chapter 4 - Removing Unintended Storage Cycling Modelling Artefacts [3] (**Part I**), presents an approach to avoid unintended errors appearing in energy system models that consider energy storage. Energy system models are used for policy decisions and technology designs. If not carefully used, models give implausible outputs and mislead decision-making. One implausible effect is 'unintended storage cycling', which is observable as simultaneous storage charging and discharging. Methods to remove such misleading effects exist but are computationally inefficient and sometimes ineffective. Through a set of optimizations, the chapter results suggest that determining appropriate levels of variable costs can remove these unwanted effects. However, setting these costs appropriately depends on the allocation to components and the solver accuracy used for the optimization. This chapter contributes to research by providing a list of recommended variable cost model inputs as well as a minimum threshold that can significantly reduce the magnitude and likeliness of unintended storage cycling. Finally, the results suggest that the approach can remove other similar misleading effects, such as unintended line cycling or sector cycling.

Chapter 5 - Technology Evaluation Methods [4] (**Part II**), reviews existing evaluation methods to assess energy storage technologies. The chapter discusses the benefits and limitations of cost analysis, profit analysis and system-value analysis methods. The work finds that especially system-value analysis are suited to evaluate energy storage.

Chapter 6 - Demonstrating the Market Potential Method in Europe [4] (**Part II**), introduces a new method to evaluate the system-value of energy storage. Traditional ways to improve storage technologies are to reduce their costs; however, the cheapest energy storage is not always the most valuable in energy systems. Modern techno-economical evaluation methods try to address the cost and value situation but do not judge the competitiveness of multiple technologies simultaneously. This chapter introduces the 'market potential method' as a new complementary valuation method guiding the innovation of multiple energy storage. The market potential method derives the value of technologies by examining common deployment signals from energy system model outputs in a structured way. The chapter applies and compares this method to cost evaluation approaches in a renewables-based European power system model, covering diverse energy storage technologies. The results suggest that characteristics of high-cost hydrogen storage can be more valuable than low-cost hydrogen storage. Additionally, they show that modifying the freedom of storage sizing and component interactions can make the energy system significantly cheaper and impact the value of technologies. The chapter suggests that looking beyond the pure cost reduction paradigm and focusing on developing technologies with suitable value approaches can lead to cheaper electricity systems in future.

Chapter 7 - The System-Value of Competing Energy Storage in Decarbonized Power Systems (**Part II**), extends the previous chapter by adding uncertainty considerations and investigating for the first time 20 energy storage in energy system models. Here, two unanswered questions are explored: how significant is the system benefit from optimizing energy storage with competition compared to without and which energy storage is optimization relevant, considering uncertainty. The chapter contributes to the body of literature with several new findings. Traditional system-value analysis that considers only single energy storage options in power system models may overlook significant benefits that can be obtained through the design and operation of multiple energy storage options in symbiosis. However, with the new assessment approach, it was found that not all technologies are optimization relevant. By developing a set of extreme cost scenarios, the findings suggest that certain energy storage technologies may not be worth investing in, while others provide good investment opportunities since they consistently provide system benefits even under high-cost uncertainty. Many of the optimization-relevant energy storage technologies can benefit from being heterogeneously sized to exploit the individual system conditions. This also means that energy-to-power ratios can vary significantly between technologies. The results imply that the new system-value approach can help investment decision-makers in industry, research, and governments to better evaluate and prioritise energy storage technologies based on their overall value in the system.

Chapter 8 - Conclusion and Outlook, summarises the key insights from all chapters and highlights their significance. It also discusses potential future research areas to build upon this work and advance the body of literature.

2 Foundations

> *Life is like riding a bicycle. To keep your balance, you must keep moving.*
>
> — **Albert Einstein**
> (Theoretical physicist)

Abstract

This chapter establishes the essential concepts underpinning this thesis, distinct from a classical introduction. It focuses on providing a technical base rather than outlining research gaps or objectives which are discussed for each chapter, respectively. Here the work details critical aspects of power systems, energy storage models, designs, and optimization algorithms necessary for the comprehensive analyses in later chapters. It explores 'system-friendly' technologies and 'technology-friendly' systems, emphasizing the regional adaptability of energy storage solutions. Additionally, it introduces a typical power system planning optimization problem, setting the stage for deeper, focused discussions and research explorations in subsequent parts.

2.1 Energy storage 'n' power systems

When talking about power systems, there are system-friendly technologies and, vice versa, technology-friendly systems. What Hirth and Müller [21] meant by system-friendly technologies is that technologies can be designed in such a way that they fulfil better the power system needs. For instance, seasonal supply mismatches can be more economically supplied by flexible-sizeable energy storages such as hydrogen storages than design-constrained and high-energy specific cost technologies such as Li-batteries. Contrary, technology-friendly systems mean that system sometimes have their given conditions that promote or discourage the economic installation of certain technologies. For instance, some power systems exist that have only little seasonal electricity supply-demand mismatches which don't require big energy storage solutions due to suitable demand profiles and environmental conditions.

One example is Nigeria, with its sunny at the equator located conditions, the power system can be economically supplied with photovoltaic and Li-battery storage without requiring any hydrogen storage solutions [2]. Therefore, its system promotes solar and low-power specific cost storage solutions as well as penalising wind power as its wind yield is less economical than, e.g. it is in Europe [22]. In summary, while power systems can be diverse through the environmental, political and social heterogeneous conditions, specific technologies, including energy storage, are better suited for one region than for another one. This also means that different technology designs are likely required to exploit the value of systems.

2.2 Energy storage design options

Many things can be associated with design options. While people classify energy storage designs according to the physical nature of how energy is stored, for instance, as thermal, mechanical, electrical, electrochemical or chemical energy, or classify along the typical discharge times or typical grid services [23], the section focuses on design options which determine the functional logic. Energy storage can be classified into three functional components: charger, discharger and store. The charger converts one energy form to the storage energy carrier and the discharger the storage energy carrier to another energy form. For example, in the case of Lithium battery storage, the charger converts electric energy to electrochemical energy, and the discharger reverts this process. Noteworthy, these functional components typically have two distinct principles of mathematical formulation. Either the functional components can be sizing constrained or unconstrained. One example of sizing-constrained storage is the Lithium battery. It has a battery stack that is the store component and one inverter that is the charger and discharger at the same time. While the battery stack can be separately scaled from the inverter, the charger and discharger are constrained to be of equal size. An example of non-sizing-constrained storage is the hydrogen energy storage. Its store component can be, for instance, a pressurised hydrogen steel tank, its charger component is an electrolyser and its discharger component a fuel cell. Thereby all components can be independently sized and maximal adapted for the power system needs. Figure 2.1 summarises these two design options and classifies energy storage solutions into either option. With this knowledge of storage design options, an energy system modeller only requires two generic functions to model most of the energy storage technologies.

The thesis focuses on energy storage that only discharge electricity in power system planning problems. The following section will introduce how such problems are typically modelled.

2.3 Power system planning problem

Contents of this chapter are based on

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The following paragraphs introduce a typical power system planning problem by formulating the open-source power system model PyPSA-Earth based on [3, 4, 19, 24, 25].

The objective of PyPSA-Earth is to minimise the total system costs, comprised of annualised capital and operational expenditures. Capital expenditures include capacity-related, long-term investment costs c at location i for generator $G_{i,r}$ of technology r, storage energy capacity $H_{i,s}^{store}$, charging capacity $H_{i,s}^{+}$ and discharging capacity $H_{i,s}^{-}$ of technology s and transmission line F_l. Operational expenditures include energy-related variable cost o for generation $g_{i,r,t}$ and storage charging $h_{i,r,t}^{+}$ and discharging $h_{i,r,t}^{-}$, as well as energy-level related storage cost $e_{i,s,t}$. Thereby, the operation depends on the time steps t that are weighted by duration w_t that sums up to one year $\sum_{t=1}^{T} w_t = 365days * 24h = 8760h$.

$$
\begin{aligned}
\min_{G,H,F,g,h,e} \quad & (\text{Total System Cost}) = \\
\min_{G,H,F,g,h,e} \quad & \Bigg[\sum_{i,r} (c_{i,r} \cdot G_{i,r}) + \sum_{l} (c_l \cdot F_l) \\
& + \sum_{i,s} (c_{i,s}^{store} \cdot H_{i,s}^{store} + c_{i,s}^{-} \cdot H_{i,s}^{-} + c_{i,s}^{+} \cdot H_{i,s}^{+}) \\
& + \sum_{i,r,t} (o_{i,r} \cdot g_{i,r,t} \cdot w_t) + \sum_{i,s,t} ((o_{i,s}^{+} \cdot h_{i,s,t}^{+} + o_{i,s}^{-} \cdot h_{i,s,t}^{-}) \cdot w_t) \\
& + \sum_{i,s,t} (o_{i,s}^{store} \cdot e_{i,s,t} \cdot w_t) \Bigg]
\end{aligned}
\tag{2.1}
$$

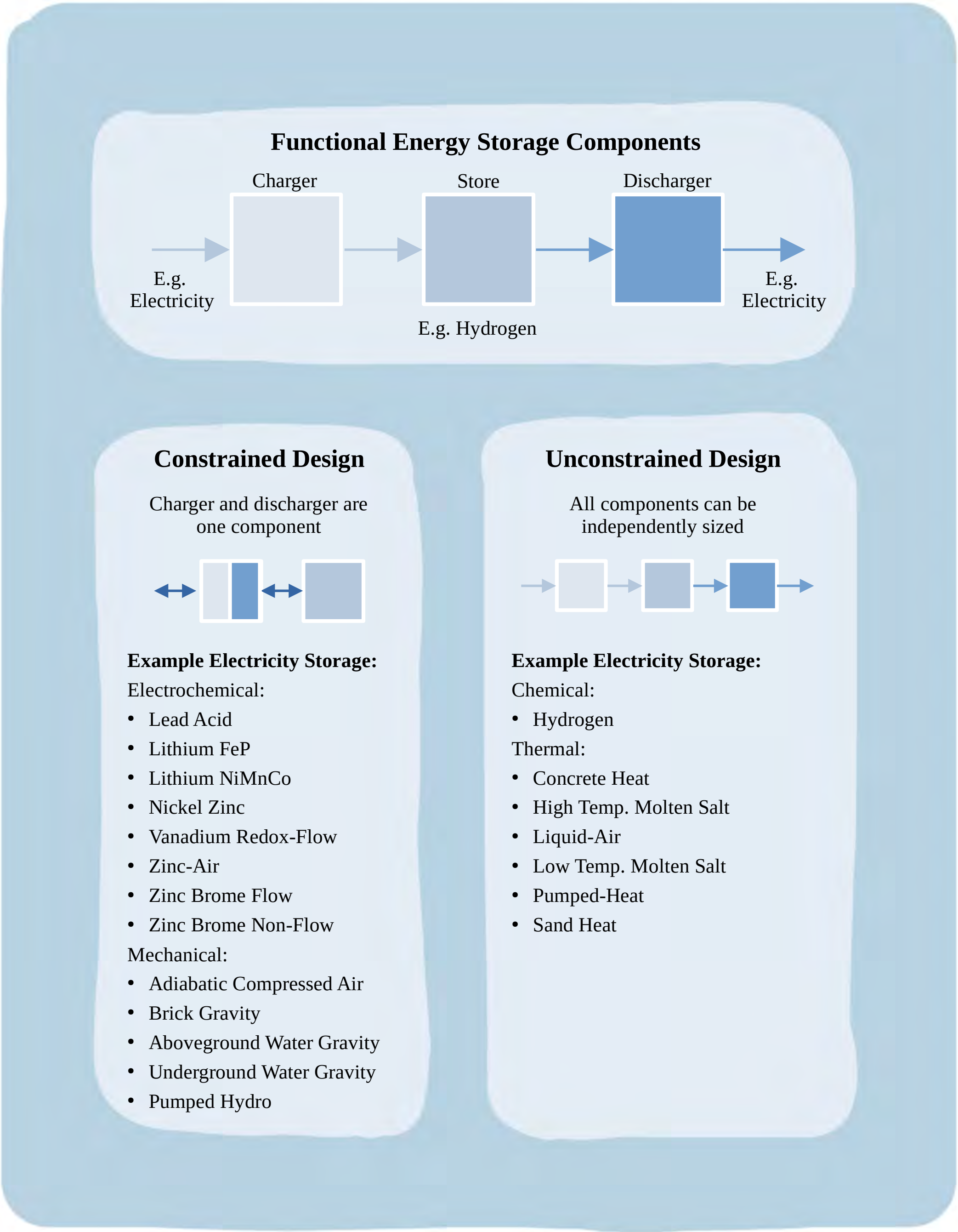

Fig. 2.1.: Illustration of energy storage design options. In power system models, electricity storage can be either modelled as a constrained design or an unconstrained design. These energy storage technologies are later modelled in chapter 7.

The objective function is subject to multiple linear constraints to make scenarios more realistic, leading to a convex linear program with continuous variables. The constraints explained in the following in more detail consist of i) demand equals supply constraint, ii) geophysical and operational constraints for generators, storage units as well as power lines, iii) Kirchhoff's current and voltage law constraints that represent the physics of electric energy flows in the power network, iv) a recovering cyclic energy storage constraint and finally, and v) greenhouse gas emissions reduction constraint. Such linear problems have, in general, one unique objective value with sometimes multiple non-unique operational solutions [3], making complex problems solvable in a reasonable amount of time (sometimes multiple days).

The first constraint requires that for all substations, demand equals supply for all times and locations. This is needed for stable system operation.

$$D_{i,r,t} = S_{i,r,t} \quad \forall i,r,t \tag{2.2}$$

Secondly, since generator and storage units, as well as transmission lines, can experience geographical restriction, PyPSA-Earth can constrain the installed capacities and gives the options for lower as well as upper limits.

$$\underline{G}_{i,r} \leq G_{i,r} \leq \overline{G}_{i,r} \quad \forall i,r \tag{2.3}$$

$$\underline{H}_{i,s} \leq H_{i,s} \leq \overline{H}_{i,s} \quad \forall i,s \tag{2.4}$$

$$\underline{F}_{l} \leq F_{l} \leq \overline{F}_{l} \quad \forall l \tag{2.5}$$

Such constraints help to implement social, environmental or physical based boundary conditions. Atlite is one of the tools implemented in PyPSA to quantify, for instance, the land availability for solar and wind power plants by incorporating protected areas and land cover classification data to reduce the renewable installation potential [26].

Thirdly, while the previous constraint only limits the installations, some components require time-varying operational limits. Examples of such technologies are renewable generators and power lines with dynamic line-rating (DLR) [27] whose operation highly depends on the weather signals. With roughly 20x20km globally rasterized era5 weather data that are available for more than 30 years, again produced by Atlite, PyPSA-Earth can limit the rated power of generators $G_{i,r}$ and lines F_l by a location and time-dependent variable, i.e. temperature, wind speed, humidity and solar irradiation, such that

$$0 \leq g_{i,r,t} \leq \bar{g}_{i,r,t} G_{i,r} \quad \forall i, r \tag{2.6}$$

$$0 \leq f_{l,t} \leq \bar{f}_{l,t} F_l \quad \forall i, r \tag{2.7}$$

Thirdly, the PyPSA-Earth model typically includes a linearised power flow constraint modelling the physicality of the power transmission network. A very distinctive feature compared to most other planning models [25]. This is done by including Kirchhoff's Current Law and Kirchhoff's Voltage Law constraints.

Kirchhoff's Current Law requires local generators and storage units as well as incoming or outgoing flows $f_{l,t}$, of incident transmission lines described by $K_{i,l}$ as the networks' incidence matrix, to balance the inelastic electricity demand $d_{i,t}$ at each location i and time step t

$$\sum_r g_{i,r,t} + \sum_s h_{i,s,t}^{-/+} + \sum_l K_{i,l} \cdot f_{l,t} = d_{i,t} \quad \forall i, s, r, t \tag{2.8}$$

While Kirchhoff's Current Law accounts for both AC and controllable DC lines, Kirchhoff's Voltage Law only additionally constrains AC power lines. Here the voltage angle difference around every closed cycle in the network must add up to zero. PyPSA-Earth formulates this constraint using linearised load flow assumptions, in particular, cycle basis $C_{l,c}$ of the network graph where the independent cycles c are expressed as directed linear combinations of lines [28]. This leads to the constraints

$$\sum_l C_{l,c} \cdot x_l \cdot f_{l,t} = 0 \quad \forall l, t \tag{2.9}$$

where x_l is the series inductive reactance of line l [19]. As might be noted, the linearised power flow assumptions completely disregard the resistance. These assumptions introduce negligible errors when (i) the reactance is much larger than the resistance, such as for high voltage lines, and (ii) the voltage angel differences are small, i.e. $sin(\delta) = \delta$ [28].

Fourth, describing storage constraints, storage charging $h^{+}_{i,s,t}$ and discharging $h^{-}_{i,s,t}$ are both positive variables and limited by the installed capacity $H^{+}_{i,s,t}$ and $H^{-}_{i,s,t}$.

$$0 \leq h^{+}_{i,s,t} \leq H^{+}_{i,s} \quad \forall i, s, t \tag{2.10}$$

$$0 \leq h^{-}_{i,s,t} \leq H^{-}_{i,s} \quad \forall i, s, t \tag{2.11}$$

This formulation keeps the feasible solution space convex, though it does not prevent simultaneous charging and discharging, which is often an unrealistic effect that can heavily distort modelling results in net-zero scenarios. Setting adequate variable cost parameters solves this modelling artefact while keeping the problem formulation linear [3].

The storage energy level $e_{i,s,t}$ is the result of a balance between energy inflow, outflow and self-consumption. Additional to directed charging and discharging with its respective efficiencies $\eta_{i,s,+}$ and $\eta_{i,s,-}$, natural inflow $h^{inflow}_{i,s,t}$, spillage $h^{spillage}_{i,s,t}$ as well as standing storage losses that reduce the storage energy content of the previous time step by a factor of $\eta_{i,s,+}$ are considered.

$$\begin{aligned} e_{i,s,t} \quad &= \eta_{i,s,+} \cdot e_{i,s,t-1} + \eta_{i,s,+} \cdot w_t \cdot h^{+}_{i,s,t} - \eta^{-1}_{i,s,-} \cdot w_t \cdot h^{-}_{i,s,t} \\ &+ w_t \cdot h^{inflow}_{i,s,t} - w_t \cdot h^{spillage}_{i,s,t} \quad \forall i, s, t \end{aligned} \tag{2.12}$$

The amount of energy that can be stored is limited by the energy capacity of the installed store unit $H^{store}_{i,s}$ [MWh], which allows independent storage component scaling.

$$0 \leq e_{i,s,t} \leq H^{store}_{i,s} \quad \forall i, s, t \tag{2.13}$$

To fix the storage technology design, technology-specific energy to discharging power ratio $\overline{T}_s$ can be multiplied by the capacity of the discharging unit $H^{-}_{i,s}$

$$0 \leq e_{i,s,t} \leq \overline{T}_s \cdot H^{-}_{i,s} \quad \forall i, s, t \tag{2.14}$$

to define the upper energy limit per installed storage.

Further, the energy storage units are assumed to be cyclic, i.e., the state of charge at the first and last period of the optimization period T (i.e. 1 year) must be equal:

$$e_{i,s,0} = e_{i,s,T} \quad \forall i, s \tag{2.15}$$

This cyclic definition is not mandatory but helps with the comparability of model results. It further avoids the free use of storage energy endowment, meaning that the model could prefer to start with a higher and end with a lower storage level to save costs.

Finally, PyPSA-Earth can constrain the total emissions. These emissions are tracked by a variable at each generator unit, which depends on the supply source or carrier q. Allowing to constrain the total emission by a limiting parameter $\overline{GHG}$ by

$$g_{i,r,t,q} \leq \overline{GHG} \quad \forall i, r, t, q \tag{2.16}$$

With slight modifications in the problem formulation this model support also unit commitment and quadratic cost functions as available in the PyPSA model framework [29].

As the foundational knowledge is conveyed, the next chapter - "Modelling Power Systems with High Resolution Data - PyPSA-Earth" will take us further into the realm of global energy system modeling. Here, the work introduces PyPSA-Earth, an advanced tool providing high spatial and temporal resolution data for comprehensive energy system analysis, focusing on customization and integration capabilities. This chapter is a step forward from the basic concepts, moving into practical applications and demonstrations of how these foundational elements are employed in real-world scenarios.

Part I

Improving Energy System Modelling With Energy Storage

3

Modelling Power Systems with High Resolution Data - PyPSA-Earth

> *If I have seen further it is by standing on the shoulders of Giants.*
>
> — **Isaac Newton**
> Mathematician and physicist

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Maximilian Parzen et al. "PyPSA-Earth. A new global open energy system optimization model demonstrated in Africa". In: *Applied Energy* 341 (2023), p. 121096. DOI: https://doi.org/10.1016/j.apenergy.2023.121096. URL: https://www.sciencedirect.com/science/article/pii/S0306261923004609. GitHub: https://github.com/pz-max/pypsa-earth-paper

Declaration

I carried out all study elements, authored the initial draft and co-authored the final publication. Other authors reviewed, co-edited, and carried out parts of the computational implementation. In particular, Johannes Hampp created the electricity time-series, Hazem Abdel-Khalek implemented alternative administrative zones data, and Dr. Davide Fioriti was significantly involved in any parts of the publication. Figures not produced by me are explicitly marked in the text.

Infobox

A thesis outline is given in section 1.3 that contextualise the chapters.

Abstract

Macro-energy system modelling is used by decision-makers to steer the global energy transition toward an affordable, sustainable and reliable future. Closed-source models are the current standard for most policy and industry decisions. However, open models have proven to be competitive alternatives that promote science, robust technical analysis, collaboration and transparent policy decision making. Yet, two issues slow the adoption: open models are often designed with particular geographic scope in mind, thus hindering synergies to collaborate, or are based on low spatially resolved data, limiting their use. Here the thesis introduces PyPSA-Earth, an open-source global energy system model with data in high spatial and temporal resolution. It enables large-scale collaboration by providing a tool that can model the world's energy system or any subset of it. The model is suitable for operational as well as combined generation, storage, transmission expansion studies. In this chapter, the novel power system capabilities of PyPSA-Earth are highlighted and demonstrated. The model provides two main features: (1) customizable data extraction and preparation with global coverage and (2) a PyPSA energy modelling framework integration. The data includes electricity demand, generation and medium to high-voltage networks from open sources, yet additional data can be further integrated. A broad range of clustering and grid meshing strategies help adapt the model to computational and practical needs. As novel demonstration, a data validation for the entire African continent is performed and the optimization features are tested with a 2060 net-zero planning study for Nigeria - the highest populated country in Africa. The demonstration shows that the presented developments can build a highly detailed power system model for energy planning studies to support policy and technical decision-making. It is anticipated that PyPSA-Earth can represent an open reference model for system planning, and the PyPSA model community welcomes to join forces to address the challenges of the energy transition together.

3.1 Introduction

3.1.1 Motivation

Energy system planning models are broadly adopted around the world. They are used as instruments to inform policy and investment decision-making, such as operational, supply diversification, and long-term infrastructure planning studies. Inscrutable 'black-box' models, despite being criticised in academia [20], are still the standard for high-impact modelling, such as the African Continental Power System Plan [30]. One of the most popular commercially adopted 'black-box' tools is PLEXOS. Using such tools prevents transparent decision-making while having other major drawbacks, as described in [20]. Open-source models evolved to overcome these typical black-box model problems and can perform equivalent or even more tasks, but at no charge, while additionally supporting transparent and robust analyses [25]. This also motivated popular tools from the International Energy Agency (IEA) such as the TIMES model [31], the successor of MARKAL, to become open-source in 2023. Further, in many examples, the European Commission applies open tools and requests their use in funded projects, proving its belief in the benefits of openness and transparency [32]. Now with the encouraging rise of more than 31 open models in 2019 [33], simultaneously, concerns of failed collaboration and duplication are arising that cost taxpayer money [34]. As a result, it becomes increasingly important to avoid duplication and provide modelling solutions that allow global united efforts. For these reasons, this study proposes an open-source community-backed flexible energy system model able to represent any arbitrarily large region of the world power system in a high spatial and temporal resolution that leverages other existing open-source projects to serve industry, policymakers, and researchers.

3.1.2 Literature analysis

In general, models are idealised representations of real physical systems. To ease building idealised systems, 'frameworks' have been developed to provide pre-compiled equations, algorithms, solver interfaces and/or input/output features. A framework becomes a 'model' only when data is added that describes real physical systems [35]. In this view, PyPSA is a framework and PyPSA-Eur and PyPSA-Earth are models or model-generators for any subset of European and Earth energy systems, respectively. They plug-in realistic data into the PyPSA framework like generators, grid infrastructure and constraints, as well as provide easy scenario building capabilities on top. Nowadays, the open-source community is rich in energy system modelling frameworks that can provide similar functionalities. Table 3.1 compares some available functionalities across selected widely-adopted modelling frameworks [25, 36, 37]. Undoubtedly, each developer team might be capable of filling in missing features, but the functionality of the frameworks is only one important part of models, the other one, often even more relevant, is the integration of data.

Tab. 3.1.: Comparison of selected features for energy system modelling frameworks that are applied in Africa.

Software	Version	Citation	Language	Free and Open	Power Flow	LOPF[d]	SCLOPF[e]	Unit Commitment	Sector-Coupling	Pathway Optimization[f]
Calliope	v0.6.8	[38]	Python	✓				✓	✓	
Dispa-SET	v2.4	[39]	GAMS					✓		
GridPath	v0.14.1	[40]	Python	✓		✓		✓		✓
LEAP	2020.1	[41]	NA[a]						✓	
LUT	2021	[42]	GNU[b]			✓			✓	✓
NEMO	v1.7	[43]	Julia	✓	✓	✓		✓		
OSeMOSYS	2022	[44]	GNU[c]	✓					✓	✓
PLEXOS	9	[45]	NA[a]			✓	✓	✓	✓	✓
PYPOWER	5.15.5	[46]	Python	✓	✓	✓		✓		
PyPSA	v0.20	[25]	Python	✓	✓	✓	✓	✓	✓	✓
SPLAT[g]	2022	[47]	GAMS					✓	✓	
TIMES	2022	[31]	GAMS			✓		✓	✓	✓

[a] NA = no information available.
[b] Mix of GNU-Mathprog and Matlab.
[c] Available in GNU Mathprog, Python and GAMS.
[d] Linearised optimal power flow [25].
[e] Security constrained linearised optimal power flow [25].
[f] Includes myopic and perfect foresight optimizations over multiple years [48].
[g] Also known as SPLAT-MESSAGE.

Existing models are often designed to implement data with limited geographical coverage, such as a specific province, country or continent [49]. Continental models with implemented high-resolution data have proven to be the most maintained and active, possibly by covering many regions of interest and giving the user options for the aggregation level [24, 50]. In contrast, there are several examples where single-country models have soon become outdated, poorly documented or inactive [51, 52, 53]. While global energy system models exist, they currently have several shortcomings. The pioneering global energy system models that impacted policy and research discussions are closed source; for instance, LOADMATCH from Jacobson et al. [54] and LUT model from Breyer et al. [42]. 'GlobalEnergyGIS' [55], an open source tool which can create energy system model data for any arbitrary region, is used in the 'Supergrid' model [56], but misses network data or a workflow management system that are important for flexible and reproducible data processing [57]. Similarly, the GENeSYS-MOD model is a global open-source model; however, it is written in GAMS, preventing free use and offers no data processing workflows [58]. Another promising candidate is the recently released OSeMOSYS Global model, which includes a workflow management system but misses network topology data as well as unit-commitment and power flow constraints that have been shown to affect model results strongly [37, 59].

Similarly, existing PyPSA models are geographically limited. While PyPSA as a framework is adopted worldwide by many companies, non-profit organisations and universities (see example studies in [29]), there is no global model solution available yet. Providing a global energy system model solution has the potential to unlock collaboration potentials that accelerate and improve the energy transition planning.

3.1.3 Contributions

In this chapter, PyPSA-Earth is presented. It is an open-source global energy system model with data in high spatial and temporal resolution. Here, PyPSA-Earth is classified as an energy system model even though the chapter focuses on the electricity sector. This is done for three reasons: i) the underlying model framework allows sector-coupling, meaning modelling not only electricity, but also other sector such as heating and transport; ii) the model can already build hydrogen networks and supply hydrogen demands which are not demonstrated in this study but visible in the source code; and iii) existing work is ongoing to implement the data for the other sectors. Across the chapter, high spatial resolution implies the ability to represent a regional (e.g. country) energy system with a flexible number of subregions, each of them describing an arbitrarily large (e.g. counties) or small (e.g. provinces) proportion of the region under consideration. Similarly, high temporal resolution means that the time series used in dispatch analyses can be hourly, sub-hourly or larger than an hour, in agreement with the needs of the energy model. Details on the data and methods are explained in Section 3.3.

Users can flexibly model the world or any subset of it. Using an automated workflow procedure, they can (a) generate energy system model relevant data and (b) perform planning studies. The novel contributions of PyPSA-Earth are detailed as follows:

1. New model creates arbitrary high spatial and temporal resolution representation of power systems around the world
2. Automated workflow generates national, regional, continental or global model-ready data for planning studies based on open or optionally closed data
3. Integration and linking of multiple data sources and open-source tools to process raw data from multiple sources, e.g. OpenStreetMap
4. Provision of new spatial clustering strategies to simplify the high-resolution model
5. Data and model validation for the African continent and Nigeria
6. Development of 2060 net-zero energy planning study for Nigeria

PyPSA-Earth includes several novel modelling features that make it unique. While the model leverages previous open-source tools, such as PyPSA-Eur [24], the aim of modelling the globe with flexible spatial and time resolution, the filtering methodology, the automatic data fetching by OpenStreetMap, and the data workflow procedures here detailed are a novelty. Accordingly, PyPSA-Earth is not an extension of any previous models, but a novel approach and tool that is first presented here with a focus on the African continent. In the following, PyPSA-Earth is presented and quantitatively validated for the African continent and Nigeria; its optimization features are finally tested for a 2060 net-zero energy planning study for Nigeria's electricity sector.

All code and validation scripts are shared open-source under AGPL 3.0 license. The data, often extracted by python script activation, is available under multiple open licenses. For a detailed license listing, see [60].

3.1.4 Organisation of the chapter

The rest of the chapter is organized as follows. Section 3.2 introduces the novel PyPSA-Earth model that is able to perform large-scale modelling studies. The data processing novelties are described in detail in Section 3.3. Data validation for the African continent is performed in Section 3.4, and a quantitative case study on Nigeria is discussed in Section 3.5. Finally, the limitations of the model are discussed, and the conclusions are drawn.

3.2 PyPSA-Earth model

This section describes the scope of the PyPSA-Earth model, its features as well as the role of the initiative that is facilitating the model developments.

3.2.1 Scope

The PyPSA-Earth model is a novel open-source data management and optimization tool that aims to provide policymakers, companies and researchers with a shared platform for a wide range of macro-energy system analyses needed to achieve the energy transition together. The option to create a tailored country, continental or global model under a unique code repository maximises synergies and wider user-benefits. For instance, one user in Africa can implement new features and data, improve the documentation or implement bug fixes that immediately benefit all other users around the world.

Studies that were already demonstrated in PyPSA [29], and, with the modelling features of PyPSA-Earth described in this chapter, are now globally available include:

1. energy system transition studies
2. power system studies
3. technology evaluation studies (e.g. energy storage, synthetic fuels and hydrogen pipelines)
4. technology phase-out plans (e.g. coal and nuclear)
5. supply diversification studies
6. electricity market simulations

This chapter focuses on the power system modelling features of PyPSA-Earth.

3.2.2 Features

The following features are implemented in PyPSA-Earth:

1. flexible model scope: from Earth to any subregion
2. high temporal and spatial resolution
3. model-ready data creation
4. co-optimization of investment and operation
5. single or multi-year optimization
6. flexible addition of arbitrary optimization constraints, e.g. socio-economic, technical, or economic

Moreover, the PyPSA-Earth model has been developed with the following non-functional requirements:

1. easy to use and learn
2. highly customizable and flexible
3. modular to include new features and data
4. fully reproducible

The proposed features of PyPSA-Earth are a novelty as compared to the literature in Section 3.1. Furthermore, new features can be created in or adopted from other PyPSA-based models that share a similar backbone. Examples are the work on endogenous learning with pathway optimization and multiple investment periods [61], dynamic line rating constraints based on spatially differing environmental conditions [62], the implementation of generic constraint settings that enable equity constraints such as applied in [63] and uncertainty analyses by input parameter sweeps or by exploring the near-optimal solution space [22].

The data and methods Section 3.3 presents more details on the presented features.

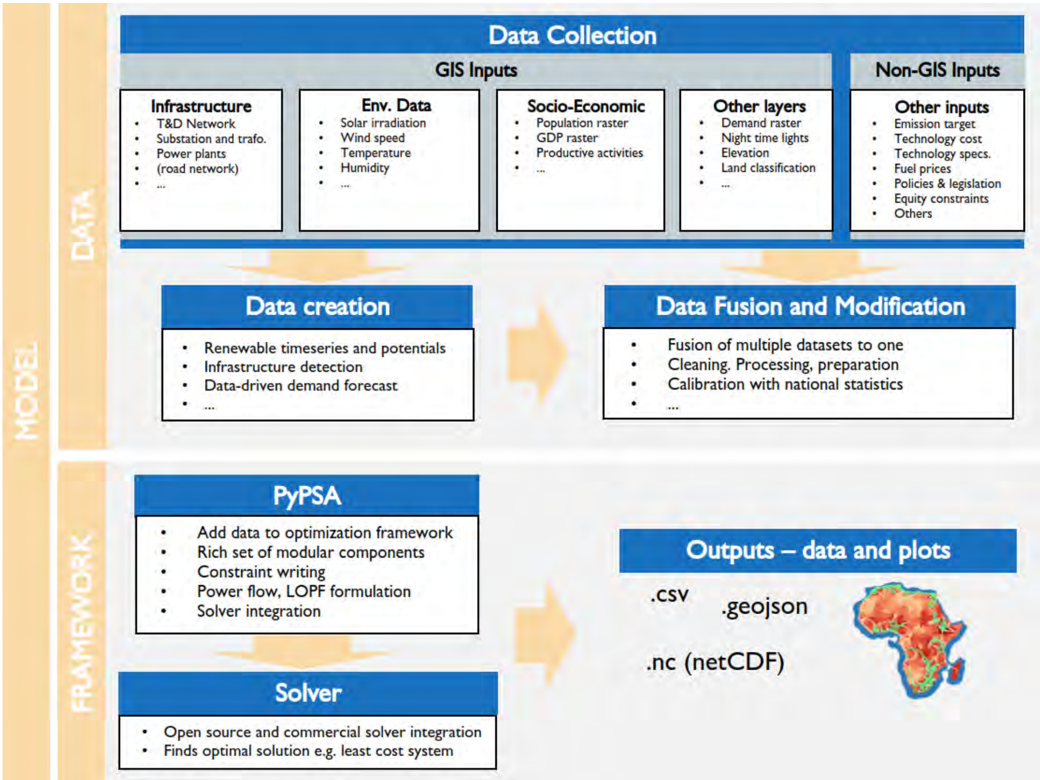


Fig. 3.1.: PyPSA-Earth model design. After providing the configuration parameters and countries of interest, data is collected and processed to be then fed into the PyPSA model framework, which enables to perform the desired optimization studies such as least-cost system transition scenarios.

3.2.3 PyPSA meets Earth initiative

The PyPSA meets Earth initiative is an independent research initiative that aims to improve energy system planning with open solutions. It supports, builds and maintains the PyPSA-Earth model and is therefore briefly introduced. The initiative's vision is to support transparent and debatable decision-making on the energy matter that cannot be achieved with the status quo ruled by commercial inscrutable closed-source "black-box" tools. Current research activities in the initiative can be categorised into three distinct groups:

- open data
- open energy system model and
- open source solver

First, the open data activities focus on open data creation, collection, fusion, modification, prediction and validation for energy system models. These data activities are not limited to aggregated country information but prioritise work on high spatial and temporal resolution data, which is fundamental for scalable and accurate mini-grid and macro-energy system model solutions. Second, the open energy system modelling activities focus on implementing new functions and data streams into the model, such as building a sector-coupled model with multi-horizon optimization that is useful across the globe. Third, open source solver-related activities deal with benchmarks and efficient interfaces that help to adopt and develop open source solvers. For instance, a benchmark was created that became a successful public funding proposal and attracted sufficient funding for the open-source solver HiGHS [7]. This activity pushes breakthroughs in large-scale optimization performance required for energy system models, which were until now reserved only for people that can afford commercial proprietary solvers.

In order to assure a continuous inflow of people that maintain, improve and use the software, as needed by open-source software [64], the initiative supports a free and open community where anyone can contribute. The initiative adopts:

- *GitHub* to publicly record issues, requests, solutions or source code-based discussions
- *Discord* as a voice channel and messaging social platform for regular public meetings and exchanges
- *Google Drive* to publicly store files and meeting notes

Together, these tools provide the backbone of the open community supporting the initiative goals and activities (data, model, solver).

3.3 Data and methods

In this section, the novelties of PyPSA-Earth methodology are highlighted and described in detail. As depicted in Figure 3.1, first, a workflow management tool is introduced that supports the model user experience. Then, data creation and processing approaches are discussed considering the main data blocks used by the PyPSA-Earth model: power grid topology and spatial shapes, electricity demand, renewable potential and power plant locations. Further, a subsection describes some advanced pre-processing techniques such as clustering and line augmentation used to introduce data into the model in a robust and efficient way. The final part describes the energy system modelling and optimization framework with its solver interfaces.

3.3.1 Workflow management tool

First of all, similarly to PyPSA-Eur [24], PyPSA-Earth relies on the 'Snakemake' workflow management [65] that decomposes a large software process into a set of subtasks, or 'rules', that are automatically chained to obtain the desired output. Accordingly, 'Snakemake' helps sustainable software design that enables reproducible, adaptable and transparent science, as described in [66]. The whole PyPSA-Earth workflow was implemented as a new set of 'Snakemake' rules. For more details, Figure 3.2 represents a workflow of PyPSA-Earth automatically created by 'Snakemake' for which the user can execute any part of the workflow with a single line of code. That is expected to improve the user and developer experience, as complex tasks are decomposed into multiple modular smaller problems that are easier to handle and maintain.

3.3.2 Network topology and model

The electricity network topology is one of the main inputs needed to build an energy system model which accounts for realistic power flow approximations across regions. The most comprehensive and accurate data on power grids are curated by the transmission system operator. In practice, the availability of open power grid data

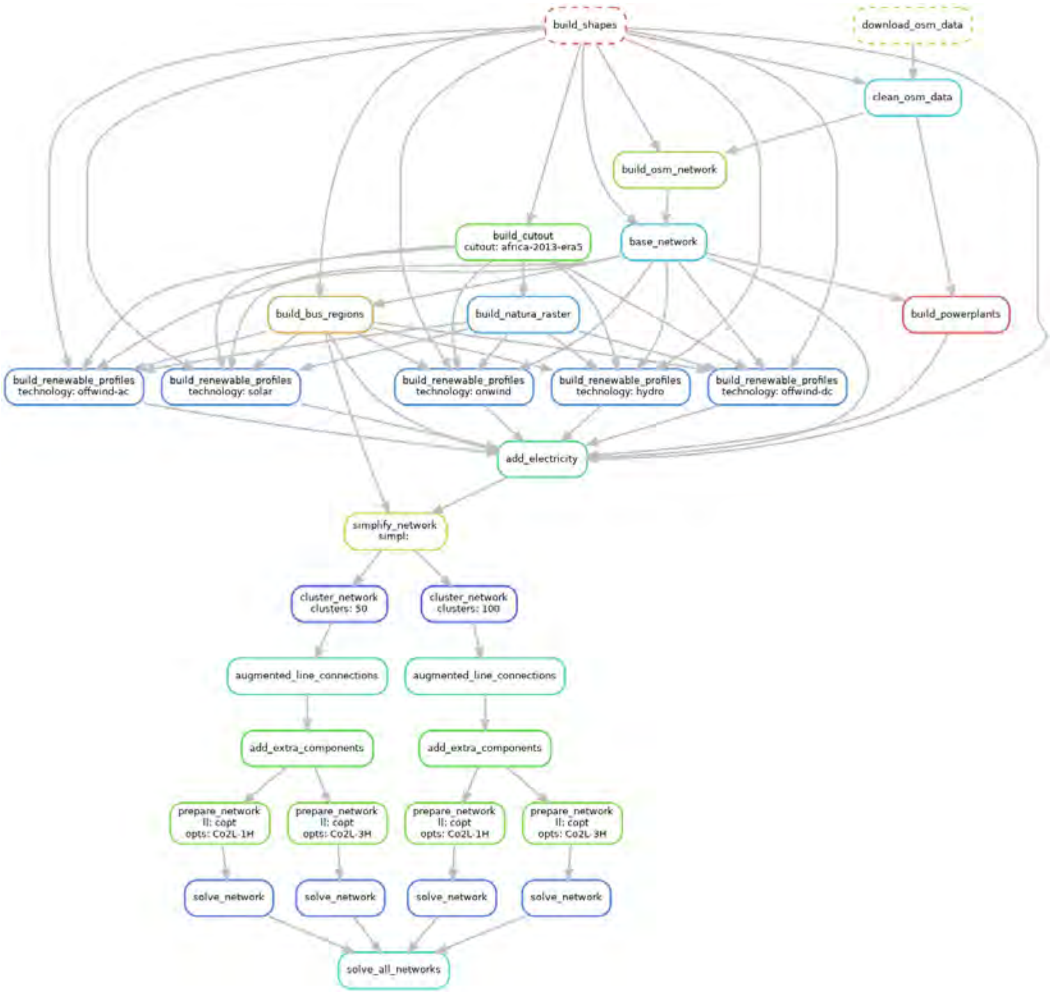


Fig. 3.2.: Directed acyclic graph of a PyPSA-Earth example workflow. Each box represents a rule that modifies or creates the input, resulting in outputs. Already computed rules are shown as boxes with dashed borders, solid bordered rules indicate rules yet to be computed during the workflow execution. The workflow creates here four least-cost scenarios with varying spatial and temporal resolution and is triggered by a single line of code. Wildcards define options for the spatial resolution with 50 and 100 clusters and the temporal resolution with 1 and 3 hours (Co2L-1H and Co2l-3H).

is still relatively low for many parts of the world, with the situation in Africa being extremely sparse.

A natural way to address the lack of power grid data is to utilize open geospatial datasets. Currently, a few open source packages have been published to extract and build networks from such datasets (e.g. Gridkit [67], Transnet [68], SciGrid [67]). However, each of these packages focuses on applications for a particular world region rather than on the global coverage and there is still no ready-to-use solution which could be implemented into a global model. To fill this gap, this work has developed an original approach which reconstructs the network topology by relying solely on open globally-available data. The developed approach is based on the OpenStreetMap (OSM) datasets that are a crowd-sourced collection of geographic information, which is daily updated and includes geolocation references [69].

The electricity network topology is created in three novel steps: i) downloading, ii) filtering and cleaning the data, and iii) building a meshed network dataset with transformer, substation, converter and high voltage alternating current (HVAC) as well as high voltage direct current (HVDC) components. Figure 3.3 shows sample raw and cleaned networks along with the options for clustering and line augmentation that are introduced in Section 3.3.7 and 3.3.8, respectively.

For the download step, the *esy-osm* tool is used to allow fast retrieval of OSM data through multi-threaded processing [70]. Appropriate OSM features are used to extract all necessary network components, including substations, transformers and power lines. Their geospatial description was cleaned in this process and the data structure aligned with the PyPSA framework requirements.

Beyond that, to build the network an approach has been developed to improve the quality of the OSM-extracted grid topology by accounting for a reasonable tolerance of OSM-derived coordinates.

3.3.3 Fundamental shapes

Fundamental shapes represent the smallest defined regions that gather various data types to characterise the energy system, such as in Figure 3.3 or Figure 3.4. Before being ready for the model-framework execution, data is often provided in many different ways, e.g. geo-referenced point locations, raster data, among others. To properly execute the modelling, such information is gathered and aggregated at the level of the fundamental shapes. These shapes can represent either administrative

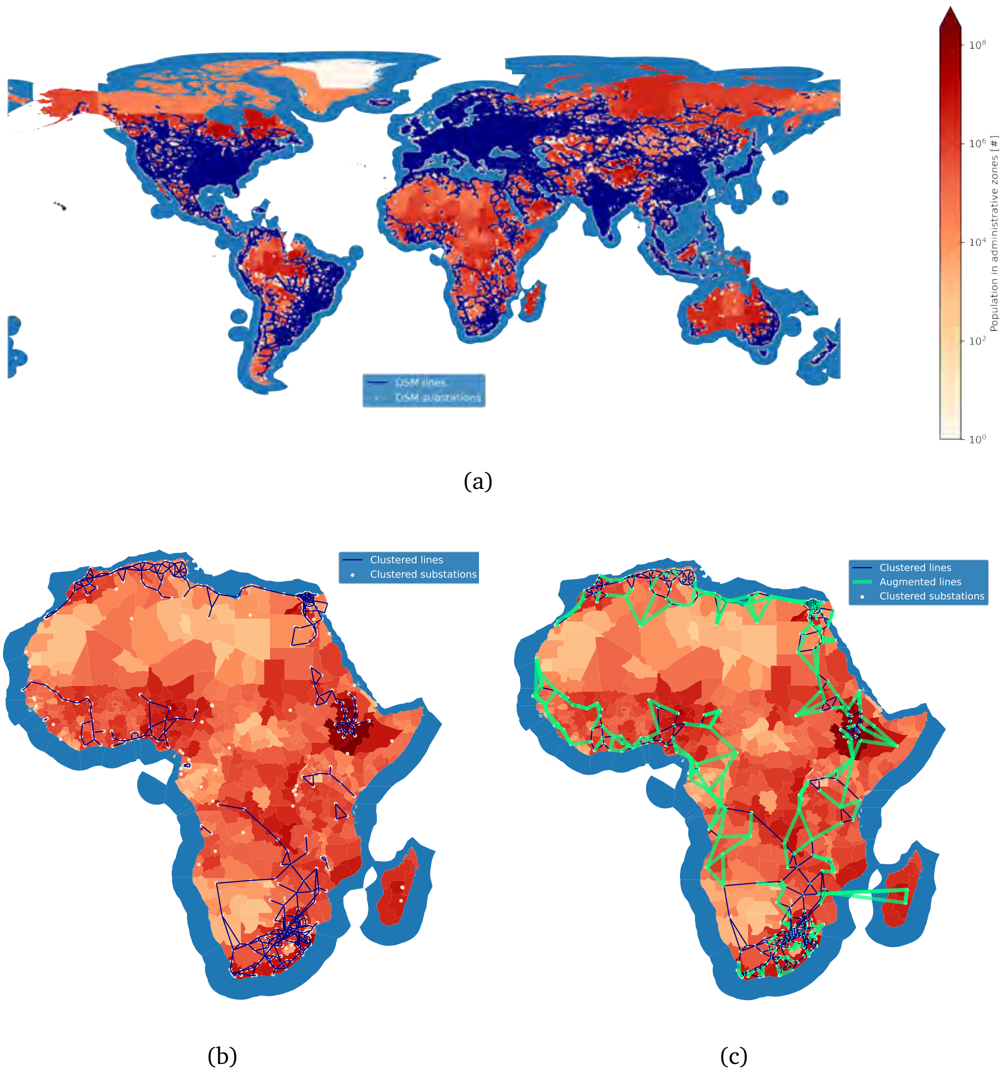


Fig. 3.3.: Representation of transmission networks and shapes produced by PyPSA-Earth show: (a) a sample Open Street Map transmission network, (b) a clustered 420 node African transmission network and (c) its augmented version with additional line connections to test the benefits of additional interconnections. In case of c), the applied k-edge augmentation guarantees that every node has at least a certain number of connections, three in the case of the figure. The augmented lines are connected by a minimum spanning tree algorithm to the nearest neighbour.

zones or spatial zones generated from the grid structure as shown in Figure 3.4 which is in the following discussed in more detail for onshore and offshore shapes.

For onshore regions, the model provides two ways to build fundamental data shapes. The first retrieves the so-called GADM that represents administrative zones at various levels of detail (e.g. national, regional, province, municipality) [71]. The second one uses the substation GIS location to create Voronoi partitioned areas for each substation, which boundary is defined as equidistant to the centroid of the nearest sites [72]. The latter approach is beneficial to replicating the network accurately, while the former helps communicate results.

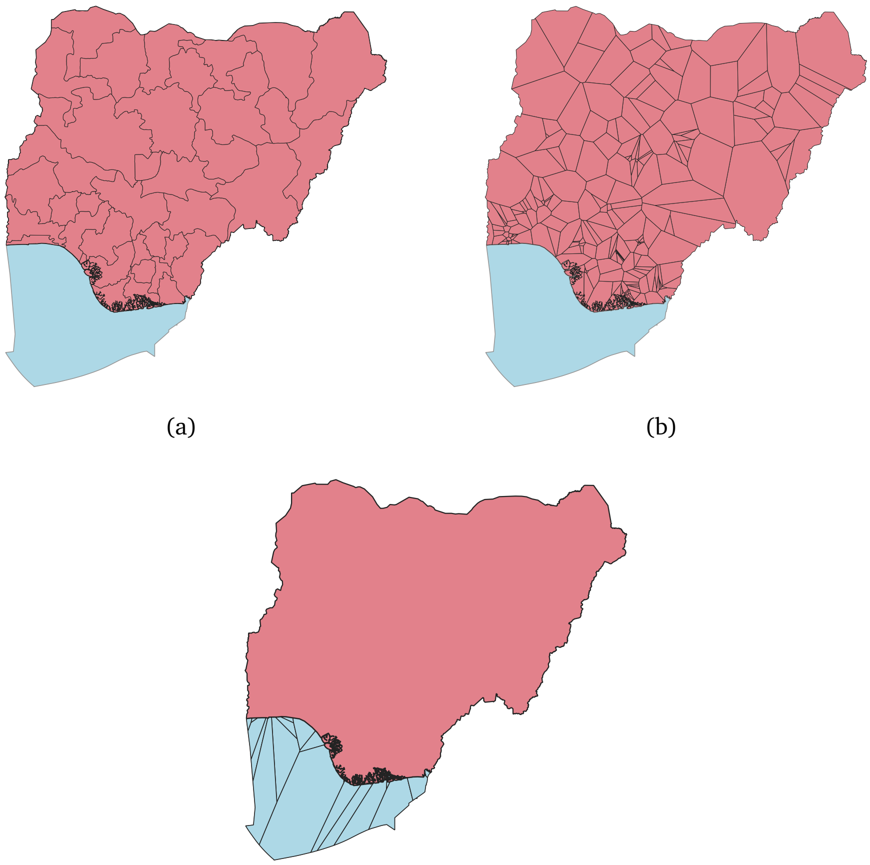
For offshore regions, the model uses only Voronoi partitioned areas to create fundamental shapes. These Voronoi areas are built from high voltage onshore nodes and are limited to the offshore extent by the Maritime Boundaries and Exclusive Economic Zones (EEZ) data for each country [73].

3.3.4 Electricity consumption and prediction

The model currently provides globally hourly demand predictions considering 'Shared Socioeconomic Pathways' [74] scenarios for 2030, 2040, 2050 and 2100 and weather years of 2011, 2013 and 2018. The demand time series is created using the new contributed *synde* package [75] which implements a workflow management system to extract the demand data created with the open source Global-Energy GIS (GEGIS) package [55].

In principle, GEGIS produces hourly demand time series by applying machine learning methods [55] using as predictors temperature, population, Gross Domestic Product (GDP), industrial structure, heating and cooling technologies etc. This approach is not new as it was already applied and tested in [76]. The observed absolute error of GEGIS in the validation test is considered acceptable for energy studies as it is 8% across 44 countries, yet with generally worse performance in low-income countries [55].

The coverage of the *synde* package is currently limited. Figure 3.5 shows that there are no data outputs for especially low-demand countries. A heuristic creates data for the countries with missing data by scaling the Nigerian demand time series proportionally to population and GDP. This approach is validated in Section 3.4.2.



(a)

(b)

(c)

Fig. 3.4.: Fundamental shapes of Nigeria in PyPSA-Earth: (a) shows the onshore regions represented by the GADM zones at level 1, (b) shows the onshore regions represented by Voronoi cells that are derived from the network structure, and (c) shows the offshore regions also represented by Voronoi cells based on the closest onshore nodes. Image produced by Hazem Abdel-Khalek.

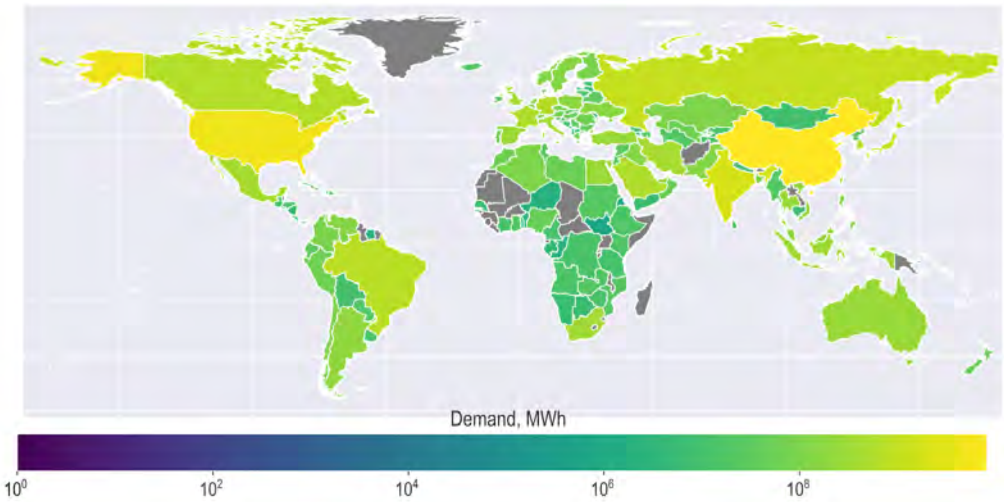


Fig. 3.5.: Demand predictions created per country using the *synde* workflow based on *GEGIS*. For grey-coloured countries, synde does not provide data, however, a heuristic creates representative time series as described in Section 3.3.4. Image produced by Johannes Hampp, Ekaterina Fedotova and Maximilian Parzen.

3.3.5 Renewable Energy Sources

Renewable energy sources such as solar, wind and hydro time series are modelled with the open-source package *Atlite* [26]. *Atlite* i) creates cutouts that define spatio-temporal boundaries, ii) prepares cutouts, which means that environmental and weather data is added to geospatial boundaries by matching various datasets (ERA5 reanalysis data [77], SARAH-2 satellite data [78], and GEBCO bathymetry [79]), and finally, iii) applies conversion functions to produce technology-specific spatially resolved time series and potentials [26]. Currently, the *PyPSA-Earth* model framework implements solar photovoltaic, on- and offshore wind turbines, hydro-runoff, reservoir and dam power resources. In the case of hydro, the runoff time series are obtained by *Atlite* for each powerplant location, as described in Section 3.3.6. As our new contribution, the hydropower output is thereby proportionally rescaled to match the reported total energy production of existing plants as reported per country by [80]. At the time of writing, available in *Atlite* but not yet implemented in PyPSA-Earth are potentials and time series for concentrated solar power, solar thermal collectors, heat demand and dynamic line rating with a wide range of technology options. For details on the model implementation for each technology, the reader is referred to the *PyPSA-Eur* publication which the presented model mostly builds-upon [24]. A brief concept demonstration of *Atlite* is provided in Figure 3.6.

3.3.6 Generators

Given the limitation of reliable datasets for power plants for the African region, the existing powerplantmatching tool [81] has been extended to include additional datasets, such as OpenStreetMap, to fine-tune the African model and validate the results with the final goal of maximizing accuracy and quality of the result.

Powerplantmatching has been successfully proposed to estimate the location and capacity of power plants in Europe. The validation performed with respect to the commercial World Electric Power Plants Database (WEPP) by Platts and the dataset by the Association of European Transmission System Operators (ENTSO-E) reaches an accuracy of around 90% using only open data [81]. By default various open data sources are included such as [82], ENTSO-E [83], GEO [84], and renewable statistics by IRENA [85] among others. The approach applied for *powerplantmatching* is based on the procedure depicted in Figure 3.7, where the raw datasets are first downloaded, then filtered to remove missing or damaged data, and aggregated. Once the refined data are obtained, the datasets are pairwise compared to identify duplicated entries. Finally, non-duplicated data are merged into a unique dataset and used as a source for PyPSA-Earth. Only a few of these datasets have global scope (GEO, GPD and IRENA) and have been validated for Africa. In particular for Africa, where data is lacking, including all available open data can be critical to maximizing the accuracy of the results. Therefore, inspired by future work suggested in [86], the *powerplantmatching* tool was extended to optionally include and process OpenStreetMap data to improve the quality of outputs.

3.3.7 Spatial clustering approach

In order to tackle the computational complexity of solving a co-optimisation problem of transmission and generation capacity expansion, the model offers state-of-the-art spatial clustering methods which are adapted from the PyPSA package and PyPSA-Eur model [25, 87]. Spatial clustering allows aggregating the nodes of the system to reduce the complexity of the model, which is essential for reducing computational needs.

The available clustering methods provide a focus on (i) conserving the representation of renewable potentials as well as the topology of the transmission grid, (ii) accurately representing the electrical parameters to improve estimates of electrical power flows in an aggregated model, (iii) aggregating spatially close nodes disregarding other a-priori information of the network, or (iv) according to their location

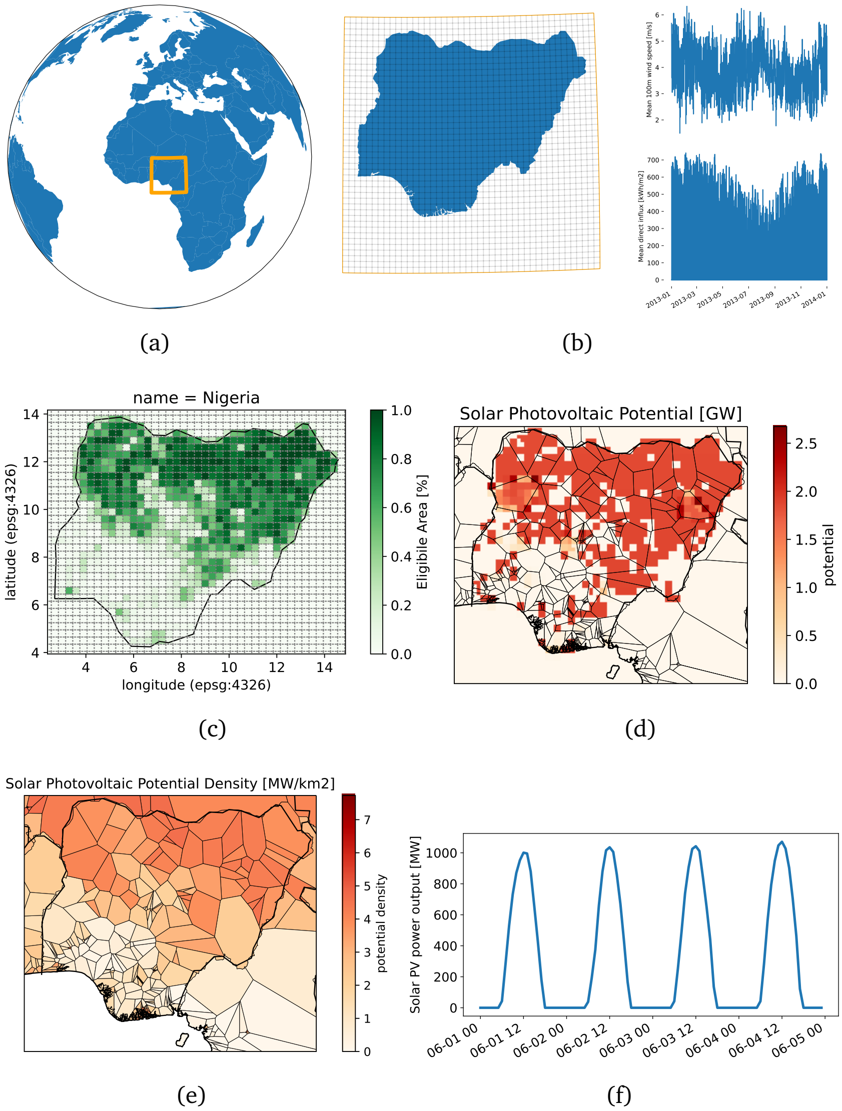


Fig. 3.6.: A concept demonstration of Atlite for Nigeria. (a) Shows that environmental and weather data is extracted in a *cutout* for the region of interest. (b) The cutout is split in a raster of $(0.25°)^2$ or roughly $(27.5km)^2$ (length varies along latitude), whereby each cell contains static or hourly time series data. The example wind speed and direct irradiation influx time series are shown for one cutout cell that contains an *ERA5* extract of the Copernicus Data Store [77]. (c) Shows the eligible area raster, which is built by excluding protected and reserved areas recorded in *protectedplanet.net* and excluding specific land-cover types from *Copernicus Global Land Service* whose eligibility can vary depending on the technology. (d) Illustrates the maximal installable power raster, which is calculated by the eligible area and the socio-technical power density of a technology e.g. $4.6MW/km^2$ for solar photovoltaic. (e) The raster is then downsampled to the region of interest or fundamental shape by averaging the proportion of the overlapping areas. (f) Finally, by applying a PV technology model to (b) and combining it with (e) one can define per region the upper expansion limit and the maximal hourly availability constraint for a given technology.

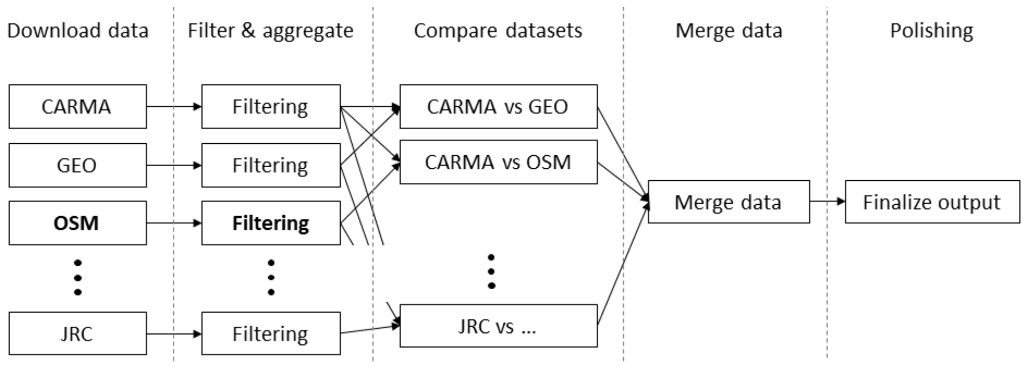


Fig. 3.7.: Flowchart of the *powerplantmatching* procedure, including the novel OSM input (in bold) which was developed for PyPSA-Earth. Image produced by Davide Fioriti.

with regards to the country's subdivisions facilitating results interpretation for policy recommendations. An analysis of suitable clustering methods that depend on the modelling application is provided in [88].

In summary, (i) the clustering approach that focuses on a better representation of variable sources or sinks of the model is inspired by [89]. It includes variable potentials, i.e. capacity factors or full load hours for solar and wind, or the variable electricity demand as a distance metric between nodes. This is combined with a hierarchical clustering approach, similar to the suggestions provided in [90]. However, nodes can be only aggregated when a physical transmission line connects them instead of assuming a synthesised grid in contrast with [90]. (ii) The clustering method that focuses on a better representation of the transmission grid was initially suggested by [91] to be applied to the case of electricity system modelling. It is a density-based hierarchical clustering operating on the line impedance. (iii) The network can also be reduced using a weighted k-means algorithm on the locations of the network nodes as explained in detail in [72]. (iv) Finally, using the GADM shapes allows aggregating all nodes in the same shape.

Any of these methods can be applied in single or two distinct iterations, as displayed in Figure 3.8 for Nigeria. In each of these two iterations, a different method can be applied, choosing from (i)-(iv). In the first iteration, all nodes are clustered to a desired number of representative nodes, aggregating generators, flexibility options (electricity storage and transmission lines) and electrical demand. The second iteration is optional and allows the remaining nodes to be clustered again. However, now only the transmission network is effectively reduced such that the representation of renewable resources is fixed to the resolution of the previous iteration (compare the first row and second row of Figure 3.8). The spatial resolution of the transmission network must always be larger or equal to the resource resolution, i.e. the clustering of the first iteration sets an upper bound.

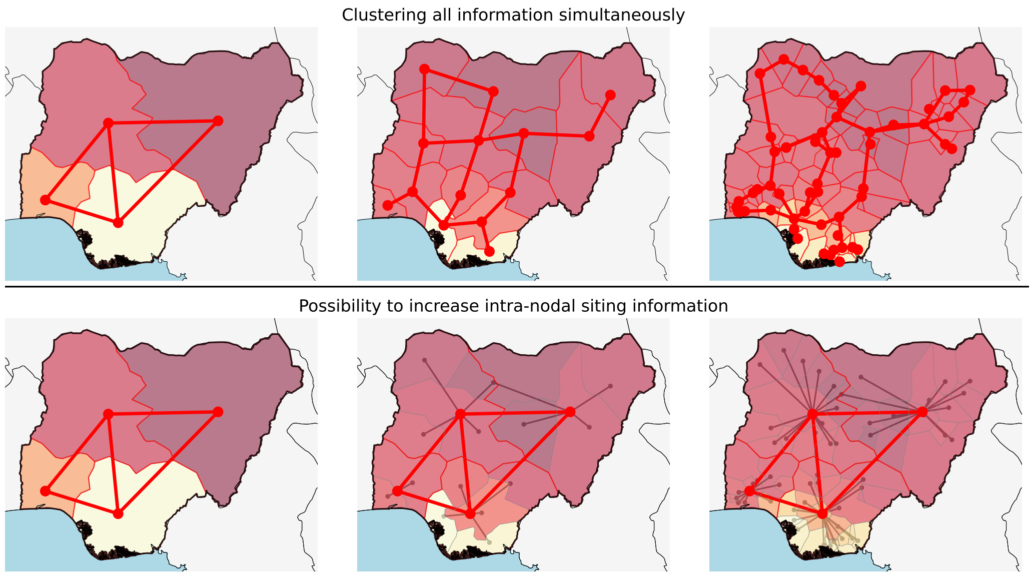


Fig. 3.8.: Illustration of the clustering methodology applied for the transmission network (red nodes and edges) and resource resolution (grey nodes and edges). The first row shows how nodal data (i.e. generators, storage units, electrical loads etc.) is aggregated in tandem with the resolution of the transmission network. Three exemplary resolutions of the network for Nigeria are displayed here: 4, 14 and 54 nodes from left to right. The second row shows how the clustering also allows modelling the transmission grid at a different resolution than the resources. In this example, the transmission network contains 4 nodes connected by 4 lines (all in red) at every resolution, while 4, 14 and 54 generation sites become available (left to right). The background colour represents exemplary capacity factors in shades of red, for an arbitrary technology. The darker the colour, the higher the capacity factor. Image produced by Martha Maria Frysztacki and Maximilian Parzen.

3.3.8 Augmented line connection

The African network is often not well interconnected. This is due to isolated national planning data or the presence of isolated mini-grids that are popular electrification measures [92]. Therefore, an algorithm to mesh a given network and assess different grades of connectivity is proposed. To investigate the benefits of meshed networks, PyPSA-Earth can perform a k-edge augmentation algorithm that guarantees every node has a modifiable number of connections to other nodes. Only if nodes do not already fulfil the connectivity condition, the algorithm will create new lines to the nearest neighbour by a minimum spanning tree. The new 'augmented' lines can be set to an insignificant size (e.g. 1 MW) to create new options for line expansion in the investment optimization. For example, Figure 3.3 shows the comparison between the standard clustered network with 420 nodes and its augmented version. Only the model that includes augmented line connections can explore an interconnected continent.

3.3.9 Model framework and solver interface

The PyPSA-Earth model integrates the PyPSA model framework with its solver interfaces to perform planning studies; details on the mathematical modelling are provided in 2.3 for the sake of brevity. Using PyPSA has several benefits compared to other tools that are briefly introduced in the following. First, PyPSA enables large-scale optimization in Python. Python is well known for being user-friendly, but when analysing the memory consumption and speed for building optimization problems it was considered non-competitive compared to tools based on the programming language 'Julia' or 'C++' [93] – a bottleneck which also hinders large-scale optimization required for PyPSA-Earth. As a reaction, developers in the PyPSA ecosystem built *nomopyomo* overcoming the bottlenecks [33]. More recently, the same group is working on a general package called *Linopy* that promises a 4-6 runtime speed up and a 50% improvement in memory consumption compared to the optimization problem formulator Pyomo, possibly making it also more memory efficient than the Julia alternative *JuMP* as indicated in [93]. Another point making the PyPSA dependency attractive is that it is one of the most popular tools, as suggested by GitHub stars in the GPST benchmark [94], possibly due to its standard component objects and the continuously maintained documentation [29]. Finally, the framework offers several solver interfaces (HiGHS, Cbc, GLPK, Gurobi, among others) providing flexibility in solving various optimization problems with open-source and proprietary solutions.

3.4 Validation

The data validation section aims to assess the data quality with publicly available data: at a continental level in Africa and a country level in Nigeria.

3.4.1 Network topology and length

Validating the African power grid is challenging. Unlike in Europe, where ENTSO-E [95] provides reliable open data with continental scope, such a transparent data source is lacking in Africa, and only a few utilities release open data. The self-proclaimed most complete and up-to-date open map of Africa's electricity network is offered by the World Bank Group, which implements Open Street Map data, as well as indicative maps data from multiple sources [96]. However, the World Bank data should not be used as a single validation set, because it may report outdated data, given that it has not been updated after 2020, and is partially based on indicative maps rather than on geo-referenced data, making the post-validation time-consuming. Conversely, PyPSA-Earth builds its grid topology directly from daily updated Open Street Map data. Finally, the World Bank data also provide less detailed information than Open Street Map; for instance, it does not give any information on the frequency, circuit or cable number, limiting the information that can be used for validation. In the following, grid statistics and topology are compared on a Nigerian and African scale. This also includes nationally reported data from the Nigerian energy commission.

First, the transmission lines are validated by comparing the total circuit lengths at different alternate current (AC) voltage levels. Transmission lines can carry one or more 3-phase circuits, whereby each circuit has at least three cables. Instead of looking only at the line length, which is the distance between high voltage towers, it is common to report the total circuit length, which multiplies each line length, e.g. distance from the tower to tower, with the number of circuits [24]. Table 3.2 indicates that the Nigerian network length reported at the World Bank aligns approximately with the official transmission company statistics [97], suggesting that the World Bank data is either accurate in Nigeria or used as a reference by the transmission system operator. This official reported total circuit length is approximately 35% longer than the original Open Street Map data or the modified and cleaned PyPSA-Earth derivative. Conversely, on a continental scale, Open Street Map provides approximately a 117% longer total circuit length than the reported World Bank data. To summarise, while Open Street Map data is qualitatively less available in Nigeria by looking at the statistics, it offers significantly more data on a continental scale.

To further compare and validate the data, Figure 3.10 highlights good agreement between the network topology in Nigeria and Africa of OpenStreetMap and World Bank sources. However, in central and south Nigeria, the World Bank covers more

Tab. 3.2.: HVAC and HVDC circuit line lengths of Nigeria and Africa from different sources

Circuit lengths in 1000km	Nigeria			Africa			Ref
	110-220kV	220-380kV	>380kV	110-220kV	220-380kV	>380kV	
World Bank Group[a]	9.3	12.1	0.0	59.4	63.5	41.0	[96]
Open Street Map (OSM)	6.3	9.1	0.0	87.9	180.7	76.7	[69]
Transmission Company of Nigeria	More than 20			-	-	-	[97]
PyPSA-Earth (cleaned OSM)	6.7	9.1	0.0	88.3	183.7	82.9	

[a] Information about circuits is missing.

power lines. On the African scale, the opposite is observed. Open Street Map covers more network structures in East and North Africa.

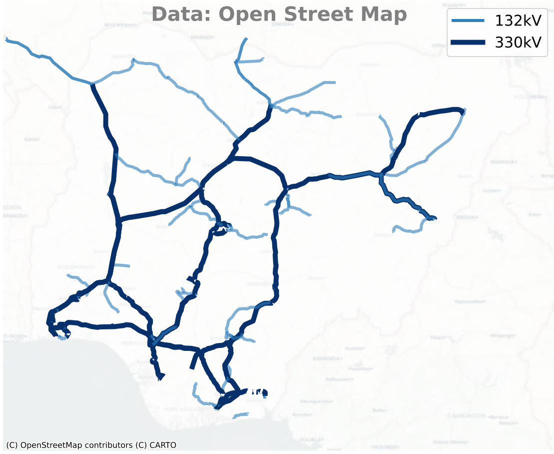
3.4.2 Electricity consumption

This subsection validates the demand prediction on the example year 2030 for every country in Africa by comparing the individual country consumption for 2020 and 2030 with official continental annual electricity consumption used in PyPSA-Earth. Figure 3.11 shows 2020 reported electricity consumption data per country, published from *Our World in Data* that is additionally refined by data from the global energy think-tank Ember and BP's statistical review of world energy [98]. The used electricity demand data in PyPSA-Earth roughly doubles from 2020 to 2030, indicating demand growth. While national demand predictions are often not available, the demand prediction is further validated by comparing it to other - more common - continental demand predictions. In Africa, *Our World in Data* reported an electricity consumption in 2020 of 782 TWh/a. For 2030, [99] predicted 1924TWh/a, [100] 1877 TWh/a and the PyPSA-Earth model data 1866 TWh/a, predicting more than a doubling of Africa's electricity consumption by 2030. In summary, looking at the total African electricity consumption suggests that the data used in the global PyPSA model is in the range of others.

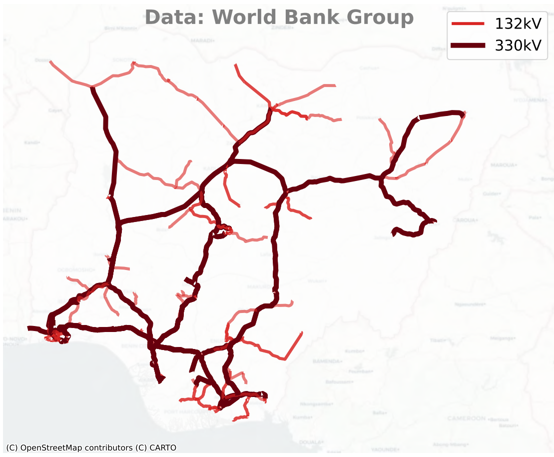
3.4.3 Solar and wind power potentials

The validation of solar and wind potential is performed by comparing statistics by international organizations, such as IRENA, with the outputs of the PyPSA-Earth model, both including total generation capabilities and the specific power densities per unit of available land.

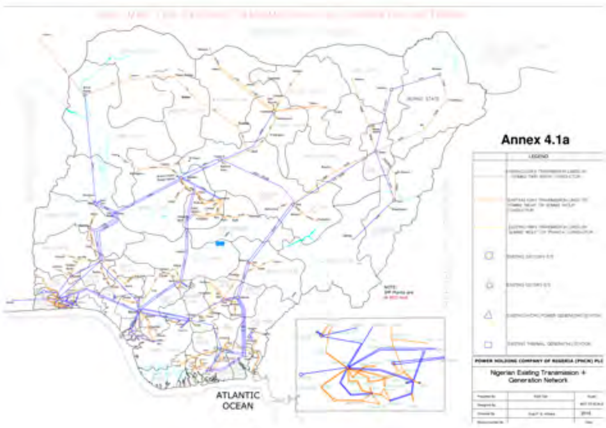
Solar and wind potentials are well-reported across the African continent. In 2021, the Global Wind Energy Council estimated for Africa a technical potential for wind generation of $180.000TWh$ (PyPSA-Earth: $108.700TWh$), which is sufficient to



(a)



(b)



(c)

Fig. 3.9.: Network topology of open available transmission network data (above 110kV) from (a) OpenStreetMap and (b) World Bank Group. The Nigerian Transmission Company also publishes a map (c) however without sharing the underlying data.

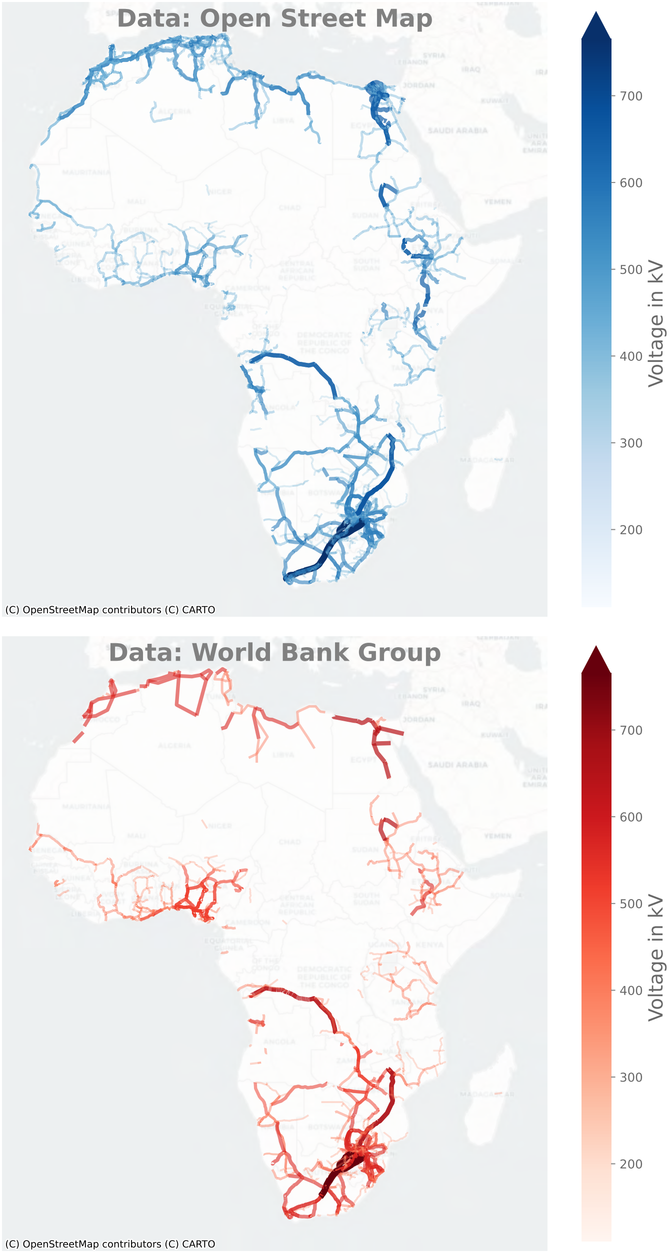


Fig. 3.10.: Continental network topology of open available transmission network data (above 110kV) from OpenStreetMap and the World Bank Group. The voltage ranges from 110-765 kV in both data sets. The line visualisation varies with the voltage level and includes transparency, thickness and colour.

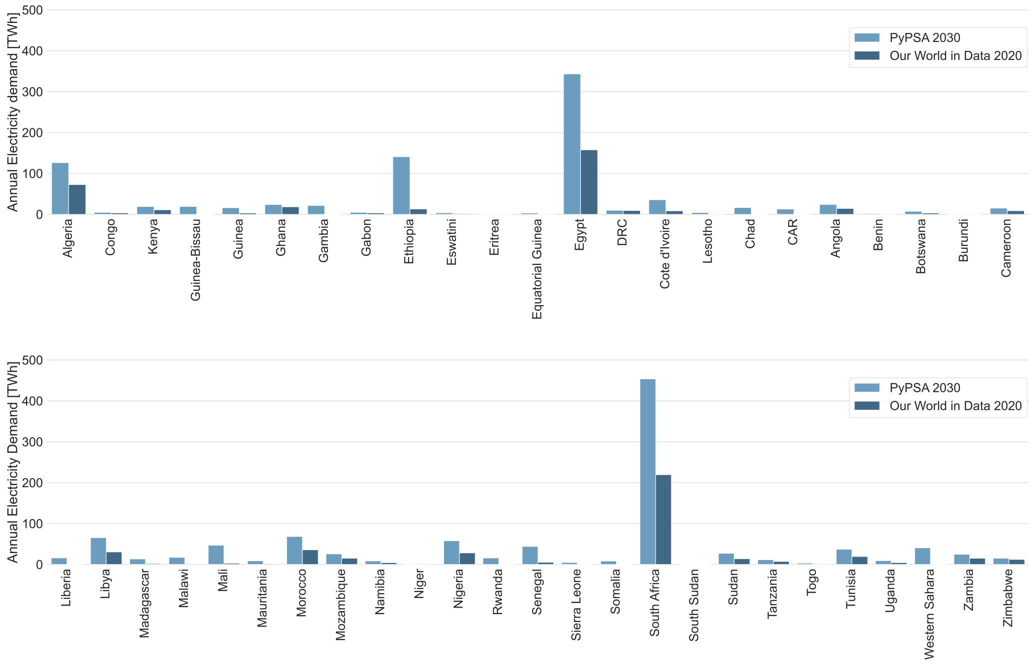


Fig. 3.11.: Comparison of reported [98] and predicted annual electricity consumption data across African countries indicate in every country demand growth. For 2030, the African total electricity consumption of PyPSA aligns with other predictions from [99] and [100].

electrify the continent 250 times relative to the 2019 demand [101]. Similarly, the International Renewable Energy Agency estimated in 2014 that the technical potential in Africa is $660.000 TWh$ (PyPSA-Earth: $122.200 TWh$), which is sufficient to electrify the continent 916 times [102]. The discrepancy between the technical potentials observed in the PyPSA-Earth model and the institutional reports is due to the underlying assumptions. In fact, how many renewables can be installed in a region depends on two main assumptions: the excluded areas $[km^2]$ and the power density per technology $[MW/km^2]$, both discussed in the following.

While available areas are defined in a data-driven way similar to [102] and [24] (see details in Section 3.3.5), the remaining eligible area quantifies the technical potential per technology through the technical power density factor. However, this density applies only to land specifically and uniquely allocated to renewable production, yet this cannot easily be generalized to all non-protected land areas at the country level. In fact, land areas are also necessary for non-technical activities such as economic activities, industries, farming, well-being, and housing, among others. Accordingly, PyPSA-Earth considers a more conservative power density coefficient to account for such socio-economic considerations.

Focusing on solar photovoltaic power plants, the power density of the 41 largest installations in the world [103, 104] is assessed: the average power density is $46.4\ MW/km^2$, the minimum $10.41\ MW/km^2$, and the maximum $150.0\ MW/km^2$. The type of solar module and the solar photovoltaic plant design are driving factors for this extensive range of values. For instance, the Cestas Solar Park in France uses high-performing solar modules and additionally contains a compact east-west orientation solar field design leading to the $150.0\ MW/km^2$ extreme. Similarly to [24], the technical power density is reduced to 10% of the average power plant density to represent the socio-technical limit: $4.6\ MW/km^2$ for solar photovoltaic.

For onshore and offshore wind farm technologies, this paragraph verifies power density assumptions by analysing seven existing utility-scale wind farms. The observed average technically feasible power density for onshore wind farms is 6.2 MW/km^2, and for offshore wind farms, 4 MW/km^2 [105]. Using the same approach as [24], by default PyPSA-Earth reduces these values from 6.2 to 3 MW/km^2 and from 4 to 2 MW/km^2 for onshore and offshore wind farms, respectively, to represent socio-technical power densities and give wind farms space to lower generation reducing wake-effects.

Currently, the same socio-technical power density is applied irrespective of the land cover type. However, roughly about 43% of the continent is characterised as extreme deserts [106], giving the opportunity in these regions to be less conservative about the social-technical power density.

3.4.4 Power plant database

This subsection compares the site-specific power plant database used in PyPSA-Earth to national statistics.

Data on existing power plants is critical for accurate energy simulations as they affect long-term investments, dispatch, and stability of the energy systems. For validation purposes, relevant country statistics are provided by IRENA [107] and USAID [108]. While the PyPSA-Earth data is geo-referenced, hence including the location, type and nominal capacities of each power plant, the other sources only provide country statistics. Therefore, data used in PyPSA-Earth is of higher quality, especially for energy system modelling in high spatial resolution that would be impossible to perform with the IRENA and USAID sources only.

Figure 3.12(b) shows that the PyPSA-Earth model matches the largest fraction of the installed capacity of existing databases, with 165 GW out of the 229 GW reported by

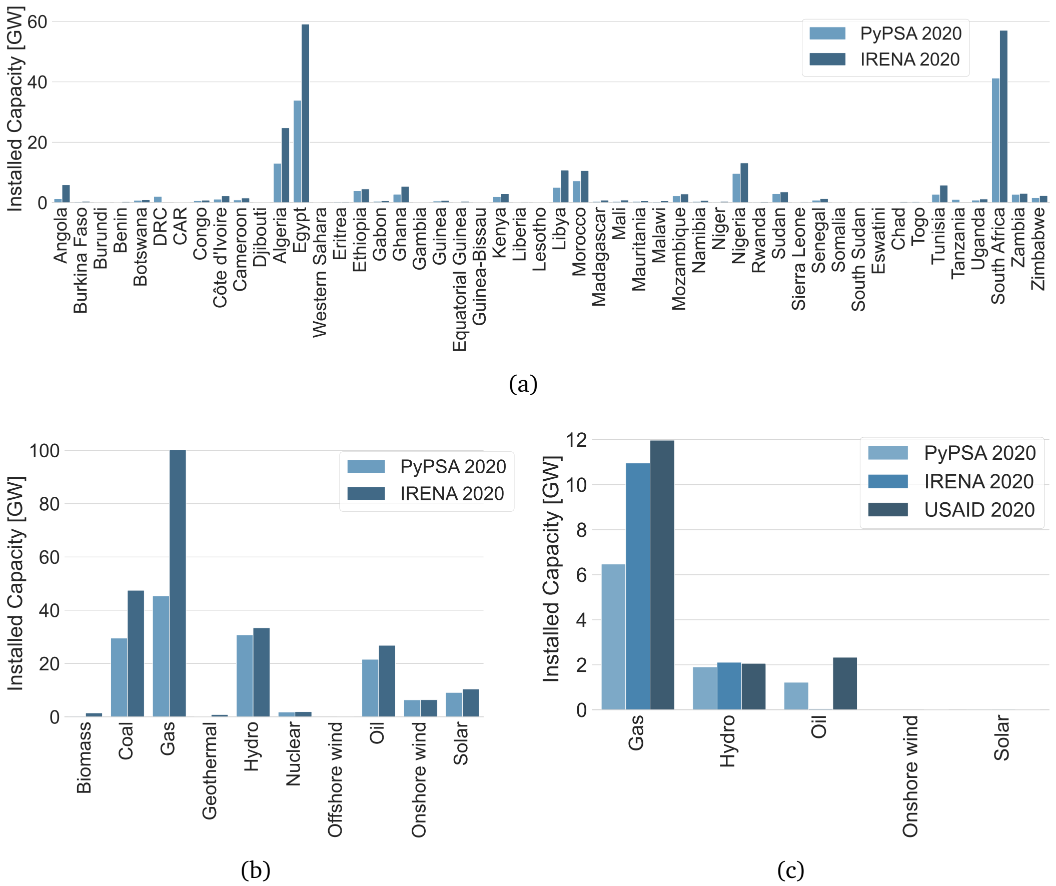


Fig. 3.12.: Total installed generation capacity in Africa by (a) country and (b) technology, including a focus on (c) the installed capacities in Nigeria.

IRENA. Most technologies are matched with adequate accuracy (2–15% error), yet larger differences occur especially for coal and gas power plants, partially due to the recent installation of power plants over the last 3-4 years, whose data has not been updated by the sources described in Section 3.3.6. In future work, adding more recent data sources may improve the data situation [109]. Furthermore, it is noted that, although the current PyPSA-Earth procedure does not include geothermal and Concentrated Solar Power (CSP) technologies, their capacity can be relevant for certain countries (e.g. Kenya, Morrocco and South Africa), but at an African scope, these technologies still represent a small fraction of the installed capacity. Therefore, the proposed validation is considered of good accuracy, supporting the appropriateness of the PyPSA-Earth model.

3.5 Demonstration of optimization capabilities in Nigeria

At COP26, Nigeria's president Buhari committed to net zero emissions by 2060 [110]. To demonstrate that the presented model can be useful for Nigeria's energy planning activities, this chapter showcases the optimization capabilities of PyPSA-Earth. In particular, this section covers two least-cost power system optimizations, one for 2020 to reproduce the historical system behaviour and one representing a decarbonised 2060 scenario (see Figure 3.14 and 3.15).

3.5.1 Nigeria 2020 - Dispatch validation

The 2020 scenario applies a dispatch optimization with linear optimal power flow constraints to simulate and validate the optimization results for Nigeria. Accordingly, only the operation of existing infrastructure is optimized for the lowest system cost, excluding any infrastructure expansion e.g. generation or transmission line expansion (see Figure 3.14).

Starting with the scenario design. The power grid retrieved from OpenStreetMap is clustered into 54 nodes, representing the aggregation zones for the demand and supply. Since the existing network is more meshed than the OpenStreetMap based PyPSA-Earth network (see Figure 3.10), a few augmented line connections with a negligible minimal capacity of 1 MW are added such that every node has at least two line connections, see (b) in Figure 3.14, and overcome short missing network data.A total demand of 29.5 TWh is considered for 2020 using the national demand profiles provided in PyPSA-Earth. The magnitude aligns with reports from *Our World in Data* (28.2 TWh) [98]. The demand profiles are distributed across all nodes proportional to GDP and population. With the available hourly electricity demand time series and the existing 2020 power plant fleet (validated in Section 3.4.4), the model calculates the optimal generator dispatch considering power flow constraints.

The dispatch validation shown in Table 3.3 compares the generation shares of the PyPSA-Earth results to those reported at *Our World in Data* [98]. The comparison highlights that PyPSA-Earth adequately represents the total electricity production shares by source in Nigeria with acceptable accuracy. Model results for the solar generation have a 100% accuracy compared to data provided by *Our World in Data*, gas generation is $2TWh$ (10%) higher than the benchmark, while hydro generation is $0.3\ TWh$ (5%) lower. These deviations could be explained by the $1.3\ TWh$ (4%) higher assumption of total electricity demand and differences in the specific marginal costs of resources. Using the cost assumptions from [50], an average marginal price for electricity of $59 \text{€}/MWh$ is derived, which aligns with reported production costs in the range of $45 - 70 \text{€}/MWh$ [111].

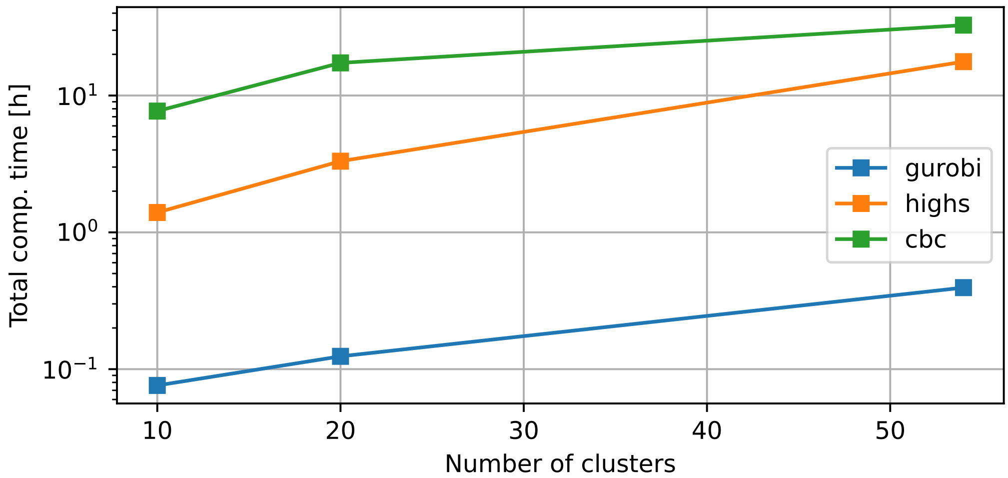
Tab. 3.3.: Nigeria 2020 dispatch comparison

	Total	Hydro	Coal	Gas	Wind	Solar
PyPSA-Earth [TWh]	29.5	5.8	-	23.6	0	0.04
Our World in Data [TWh]	28.2	6.1	0.6	21.4	0	0.04

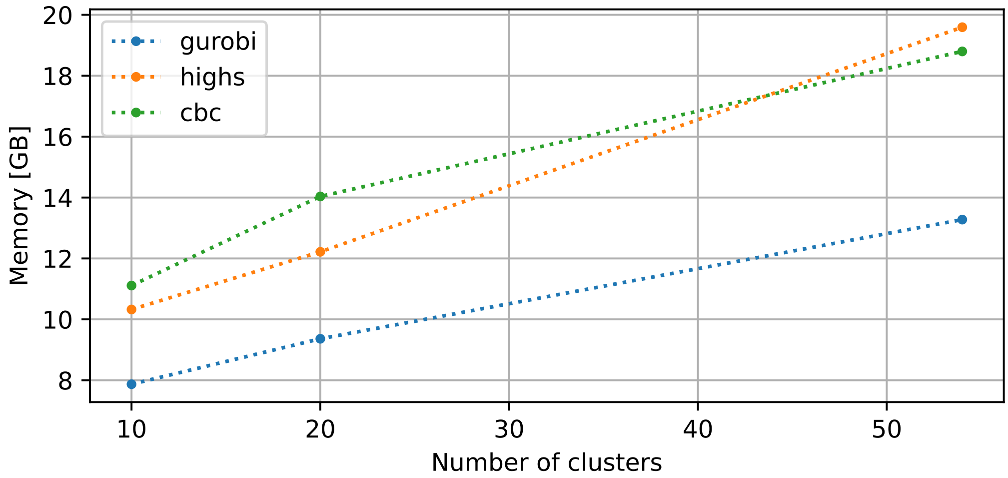
The computational needs for this scenario in terms of total solving time (computational time times the average load of the processors) and memory, are shown in Figure 3.13. The scenario computations used 4 threads with Gurobi 9.5.1 solver while only a single-core with HiGHS 1.2.1 and CBC 2.10.8, since their parallel solving capabilities are currently limited. While the commercial Gurobi solver is very efficient, the results in Figure 3.13 confirm that the open-source HiGHS solver can also optimize the network below one day with memory requirements that are available for laptops. One must note that this performance benchmark does not include other possible PyPSA cases with integer variables, e.g. as used for unit commitment, or quadratic cost functions which would increase the solving times. Given the expected improvements for open-source solvers, the computational requirements are likely to decrease significantly [7].

3.5.2 Nigeria 2060 - Net-zero study

The 2060 net-zero scenario performs a brownfield capacity expansion optimization. This means that new renewable energy and transmission capacity can be built on top of existing infrastructure. Simultaneously, a dispatch optimisation is performed subject to linear optimal power flow constraints. To explore new transmission grid structures, the meshing strategy is increased such that each node connects HVAC lines to at least three nearest neighbouring nodes and that a random selection of far distance nodes above $600km$ connects HVDC lines, see b) in Figure 3.15). Using a random selection for long-distance HVDC can help identify valuable line connections before applying any heuristic that might not find these. Additional to the net-zero emission constraint, the 2060 total demand has been calibrated in agreement to [112] to about 250 TWh by linear interpolation of the Stated Energy Policies of IEA for Nigeria [85]. Observing the optimized infrastructure in Figure 3.14, the overall optimal least-cost power system can be mostly supplied with solar energy and a mix of battery energy storage. Hydrogen energy storage with steel tanks is included as an expansion option. However, hydrogen solutions are not significantly optimized, probably because fuel and energy trade with other countries is ignored. Also, Nigeria



(a)



(b)

Fig. 3.13.: Solution time (a) and memory requirements (b) for the 2020 Nigeria dispatch optimization for Gurobi 9.5.1, HiGHS 1.2.1 and CBC 2.10.8 solvers at different spatial resolution; solution time is weighted by threads. Images produced by Davide Fioriti.

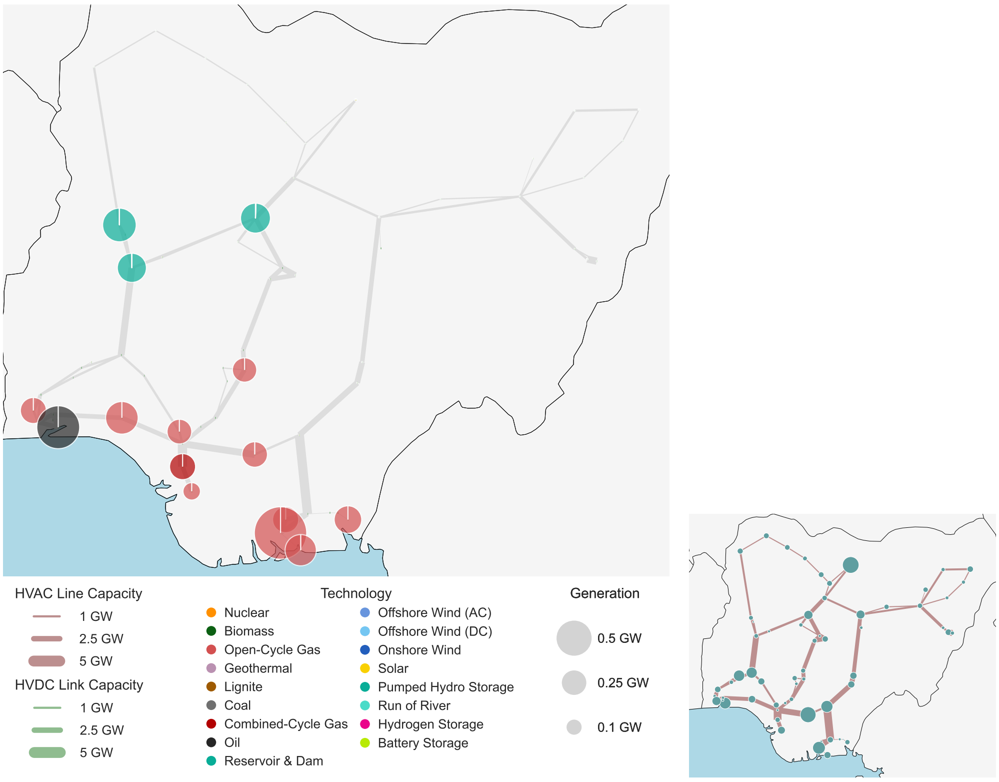
lies close to the equator, where solar irradiation is homogeneous across the year, requiring less seasonal hydrogen energy storage. The battery storage that consists of an inverter component [$€/MW$] and a Li-Ion battery stack [$€/MWh$], can be independently scaled by the model such as applied in [4]. The energy-to-power ratio (EP) indicating the sizing between these storage components is optimized in the range $4.5\ h$ – $15.0\ h$ with an average of $6.75\ h$. The total optimized Li-Ion battery storage discharging capacity and energy capacity is $67.9GW$ and $459.7GWh$, respectively. The optimal solar capacity distribution is spatially uneven. Most solar is expanded in the country's north, where the solar potential is significantly higher [113]. It is also cost-optimal to build new transmission routes in the north and east of Nigeria, enabling the spatial distribution of electricity. The total optimized solar PV capacity is $256.9GW$, whereas about 20% of the solar energy is curtailed on an annual average. The HVDC options are not used significantly, indicating it is not cost-optimal in the scenario. Figure 3.16 shows the dispatch profiles outputs of the optimization, which illustrates that most batteries charge during the day and discharge at night. Notably, to be conservative, with cost assumptions for 2050 [114], the average marginal prices reach only $51\ €/MWh$, compared to $59\ €/MWh$ in the 2020 scenario. As a result, the optimized renewable electricity future for Nigeria could be cheaper than today.

3.6 Limitations and future opportunities

3.6.1 Missing network topology data

Modelling can only be as good as underlying data – the same applies to PyPSA-Earth. By relying on open sources to model energy systems, their data quality is a concern that needs to be acknowledged in the presented work. Yet, this subsection also describes possible procedures based on image recognition to not only improve the data situation in PyPSA-Earth but potentially all energy models. This effort may complement the traditional effort by public institutions that disclose data of public relevance, such as installed network infrastructure, as performed by ENTSO-E [83].

Compared to Europe or North America, institutions that provide infrastructure data with geolocation for modelling have no analogues in Africa. The missing network data situation is limiting the use of energy system models. However, other types of data from which energy system components can be inferred exist on a much larger scale. Satellite imagery is one such data type. As part of the PyPSA meets



(a) (b)

Fig. 3.14.: Optimization results of Nigeria's (a) 2020 power system. The coloured points represent installed capacities. (b) Shows all network options on a different scale as (a) with the total electricity consumption per node.

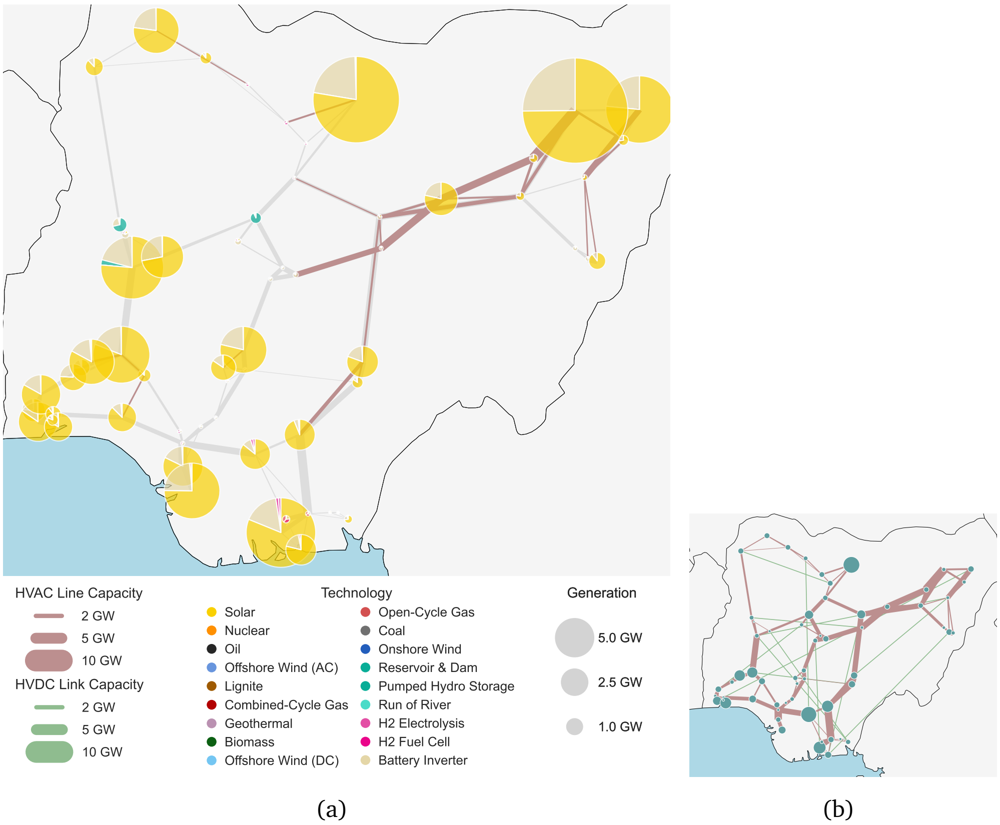


Fig. 3.15.: Optimization result represents Nigeria's (a) 2060 power system. The coloured points represent installed capacities. Light grey and dark grey lines are existing and newly optimized transmission lines, respectively. (b) Shows all network options on a different scale as (a) with the total electricity consumption per node.

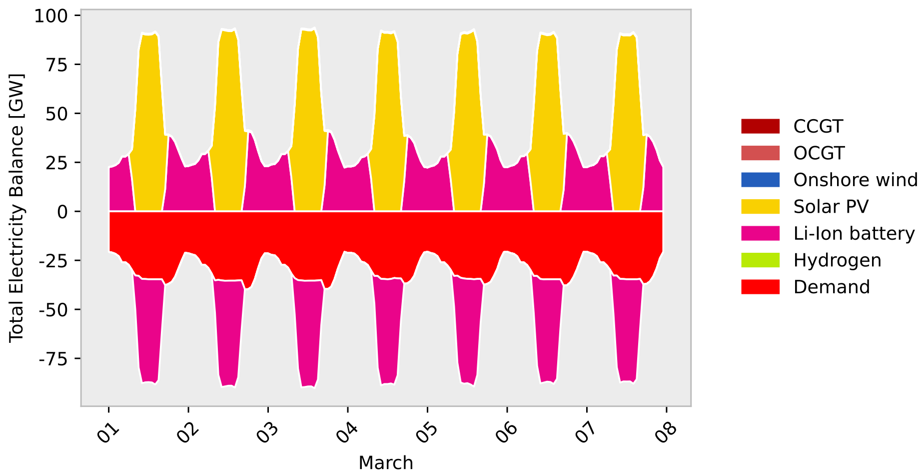


Fig. 3.16.: Total electricity balance for the 2060 scenario. The time-series is hourly sampled for selected days in March including electricity supply (above zero) and consumption (below zero). CCGT and OCGT stands for closed and open cycle gas turbines, respectively.

Earth initiative, researchers are exploring opportunities to use neural network-based object detection applied to satellite imagery to enrich the existing datasets on energy infrastructure. In the past, such efforts have either been hard to apply on larger scales due to high requirements on manual input [115] or are coarse approximations to the true grid structure [116]. Under the umbrella of this initiative, one aim is to develop precise and scalable methods and base our efforts on recent advances in the field.

3.6.2 Missing demand time series and prediction biases

Demand is a significant uncertainty factor in Africa due to the growth in magnitudes over the following decades that has implications on results created by PyPSA-Earth. Therefore, improving demand predictions is essential. This is also a limitation in the data fed into the presented model and highlights research opportunities to address this challenge. PyPSA-Earth demand data is limited, as indicated in Section 3.3.4, by poor prediction performance for low-income countries due to input data biases and by missing machine learning output data for some low-demand countries due to software bugs. Additionally, while the open-source *synde* package [75] used in PyPSA-Earth extended the original GEGIS package for demand prediction by a workflow, there are opportunities to create a package focusing only on demand prediction substituting the GEGIS design that provides all energy model data in one package [55].

Developing a package focusing on sector-coupled energy demand forecast for macro-energy system modelling worldwide is an opportunity to improve the status quo of existing tools, not limited to the power sector. Further, instead of validating the demand with annual means, one should validate with hourly officially reported time-series, since the data quality is better indicated by the latter.

3.6.3 Imprecise global data

PyPSA-Earth relies on open data with global scope. This means that sometimes data is used that approximate country-specific details needed for national energy planning studies. While improving the global open data situation is one opportunity [117], another is to enable the integration of national and regional more precise data that can also be used as a source for validation. Therefore, PyPSA-Earth does not only use global data as default but will allow the integration of national or regional more precise data with specialized functions here named "linkers".

3.6.4 Additional technologies

PyPSA-Earth includes the major transmission, generation and storage technologies, however, some are not yet included. Examples of not implemented generation technologies are CSP, location-based geothermal, and other secondary technologies such as wave/tidal energy harvesting. While at a global scale, these technologies represent a minor fraction, for country-specific analyses, they may have substantial implications, such as in the case of Kenya for geothermal or Morocco for CSP. Moreover, while currently only lithium-ion batteries and hydrogen energy storage are considered, additional technologies may be considered and tested, such as the well-known Redox Flow batteries, Compressed-Air Energy Storage (CAES), Liquified-Air Energy Storage (LAES), that can have a large market in the future. Moreover, the dynamic calculation of the transmission capacity as a function of weather conditions [24], also known as Dynamic Line Rating (DLR) [118], is not yet included.

These limitations, at the time of writing, represent future opportunities to improve the model and capture relevant technologies to perform detailed energy studies for all countries.

3.7 Conclusion

This chapter presents the PyPSA-Earth model, which is an open-source global energy system model in high spatial and temporal resolution. It is making high-resolution modelling accessible to countries which so far had not detailed energy planning scenarios developed. Using a novel comprehensive workflow procedure PyPSA-Earth automatically downloads open data, provides model-ready data and integrates optimization features to address large-scale energy system planning. In agreement with the open-source spirit, the model is not built from scratch but derived from the European-focused PyPSA-Eur model adding global data as well as several new features.

The methodology is confirmed to be flexible and accommodate a high temporal and spatial resolution power model for national and regional energy planning with global scope. The validation performed for the African continent highlighted that PyPSA-Earth successfully provides power network and installed generation data that match trustworthy third-party national data with adequate accuracy, hence suggesting PyPSA-Earth to be a reliable model for energy planning. The 2020 and 2060 planning studies for Nigeria have further confirmed that net-zero emission scenarios for the electricity sector can be performed using PyPSA-Earth, leading to realistic results comparable with similar studies but in higher spatial detail. That further stresses the robustness of the approach and the flexibility of the methodology to be used in practical projects.

Given the need for reliable tools to foster the energy transition and the need for the efficient use of resources, PyPSA-Earth can successfully support policymakers, utilities, and scholars in providing reliable, transparent, and efficient decision-making on energy studies. While several open source projects are developed but discontinued, PyPSA-Earth developers aim to foster collaborative energy system modelling on the same code-base to provide a well-maintained and robust tool, rather than disperse resources across multiple models that get easily outdated. Given the flexibility of the approach, additional improvements can be integrated, and scholars interested in contributing are invited to contact the PyPSA-Earth team to join forces. Accordingly, this chapter and the proposed tool can serve as a backbone for further research and business activities built on top of PyPSA-Earth, to meet various energy transition planning needs that must be cheap and fast to develop for every nation and community on Earth.

Further studies, may address the sector-coupled version of PyPSA-Earth. In addition to power and hydrogen data, this requires various electric as well as non-electric demand and supply side data from other sectors including heat, industry and/or transport. Other future work may interface energy modelling with economics modelling for better energy policy decisions, the improvement of the demand forecasts also in alignment with climate change scenarios, the improvement of imprecise global network data using object detection on satellite images or the validation of the model in other regions. To construct also reliable power systems in Africa with less load shedding, one should dedicate future studies on frequency response measures, black start, n-1 security constraints and similar which can be also addressed in PyPSA. Lastly, one could also explore instead of ideal market as often modelled in PyPSA, different market configuration for Africa.

Building on the global modeling perspective of this chapter, the next chapter - "Removing Unintended Storage Cycling Modelling Artefacts" addresses a critical issue in energy system models: unintended storage cycling. This chapter shifts the focus from broad modeling capabilities to specific challenges within the modeling process, presenting solutions to enhance accuracy and reliability in energy models with energy storage integration.

4 Removing Unintended Storage Cycling Modelling Artefacts

> *Given enough eyeballs, all bugs are shallow.*
>
> — **Linus Torvalds**
> Software engineer

Contents of this chapter are based on

Maximilian Parzen et al. "Reducing energy system model distortions from unintended storage cycling through variable costs". In: *iScience* 26.1 (2023), p. 105729. DOI: https://doi.org/10.1016/j.isci.2022.105729. URL: https://www.sciencedirect.com/science/article/pii/S2589004222020028. GitHub: https://github.com/pz-max/unintended-storage-cycling

Declaration

I carried out all study elements and authored the initial draft. Co-author Martin Kittel co-edited and reviewed paragraphs, and validated some results. Other authors were involved in the review.

Infobox

A thesis outline is given in section 1.3 that contextualise the chapters.

Abstract

Energy system models are used for policy decisions and technology designs. If not carefully used, models give implausible outputs and mislead decision-making. One implausible effect is 'unintended storage cycling', which is observable as simultaneous storage charging and discharging. Methods to remove such misleading effects exist, but are computationally inefficient and sometimes ineffective. Through 124 simulations, the chapter shows that determining appropriate levels of variable costs depends on the variable cost allocation to certain components and the solver accuracy used for the optimization. For the latter, if the accuracy is set too loosely, the solver prevents the removal of unintended storage cycling. Further, this chapter provides a list of recommended variable cost model inputs as well as a minimum threshold that can significantly reduce the magnitude and likeliness of unintended storage cycling. Finally, the results suggest that the new approach can remove other similar misleading effects such as unintended line cycling or sector cycling.

4.1 Introduction

Energy system models are mathematical models used to investigate possible pathways for decarbonising our energy systems; in many cases, minimising total system costs [49]. They provide insights on optimal dispatch and investment patterns in the short- and long-term, thus guiding energy technology design decisions [4] and supporting the decision-making of governments, grid operators, energy system planners, manufacturers, and researchers. However, if not carefully used, such models can mislead decision-making.

One model artifact distorting optimal model results is USC [119], which is observed in 12 of 18 well-established energy system models, as reviewed by Kittel and Schill (2022) [119]. The effect impacts storage use. Instead of curtailing Variable Renewable Energy (VRE) surplus, the excess electricity is converted, among others, into unintended storage losses by simultaneous charging and discharging of the same storage capacity. The consequence of this behaviour are distortions in optimal model outcomes. For example, energy storage or renewable generators may have significantly more FLH in a scenario with, compared to one without USC (Figure 4.1), signalling deceptively more intensive operation. Further, USC is technically infeasible for some storage technologies, e.g. single lithium-ion batteries, that can either charge or discharge but not both simultaneously. Hence, the effect urges its removal. USC may also manifest across space and time (Figure 4.2). For instance, USC across space may occur in multi-regional model settings through simultaneous charging in one region and discharging in another region for the sole purpose of dissipating surplus renewable energy instead of curtailing it, notably in the absence of transmission costs. Similarly, USC across time represents unintended simultaneous charging and discharging cycles across multiple periods [119]. The fact that USC is not limited to one point in space and time aligns with the non-guaranteed operational uniqueness in scenarios with multiple storage assets [120].

USC is not the only such misleading effect. There is a group of related effects classified under the term unintended energy losses, which arise in a cyclic manner [119]. Unintended, because they distort optimization results. Cyclic, as they occur in the energy systems wherever efficiency losses are present between energy components that cycle energy by charging and discharging, sending and receiving, or converting and re-converting operations.

The literature on unintended energy losses is limited. State-of-the-art guidance on best-practice energy system modelling probably unintentionally ignores these artefacts [17, 18], while others do this intentionally [121]. Attempts to remove unintended energy losses exist. For instance, an intuitive approach is to prohibit simultaneous charging and discharging by introducing a binary variable. This binary variable can then represent two mutually exclusive storage operational modes: charging or discharging, with only one being possible at the time. Introducing a binary variable requires reformulating the optimization from a linear to a mixed-integer problem [122]. This reformulated problem is not only harder to solve and require more computations, but also does not guarantee the full USC removal due to its occurrence across space and time. Differently, [123] penalises active power losses in the objective, however, as described in [122], this approach can distort model outputs under heavy load conditions. This is probably the case because one uniform penalty applied to all technologies that experience losses does not recognise any operational order.

While the above literature provides solutions on USC arising in models that abstain from binding renewable energy targets, Kittel and Schill (2022) [119] investigate USC arising in models that are constrained by a binding renewable energy target. In these models, USC causes an increase of VRE generation, which can be realised without additional renewable capacity installations. Thus, the renewable energy target can be achieved with less VRE capacity at lower costs. Yet, it does not serve demand, which requires additional generation from other dispatchable technologies. Here, USC flaws

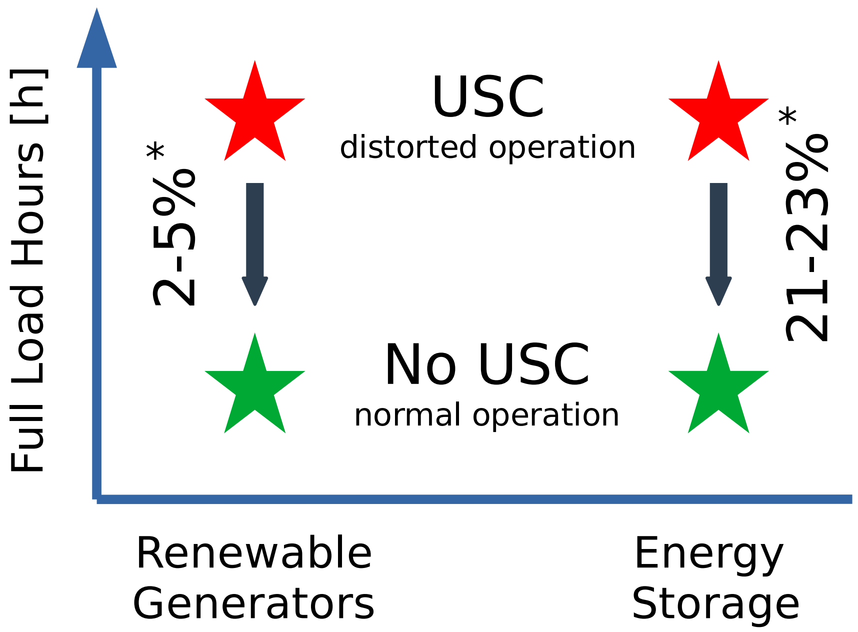


Fig. 4.1.: Impact of USC on model outputs. Exemplary impact of scenarios with and without USC on storage and renewable generation. The USC effect increases the operation of close to zero variable cost assets. Results from a numerical analysis conducted in this study, marked with an asterisk (*), show FLH differences of up to 23% for energy storage and 5% for renewable assets in a 100% renewable energy system scenario.

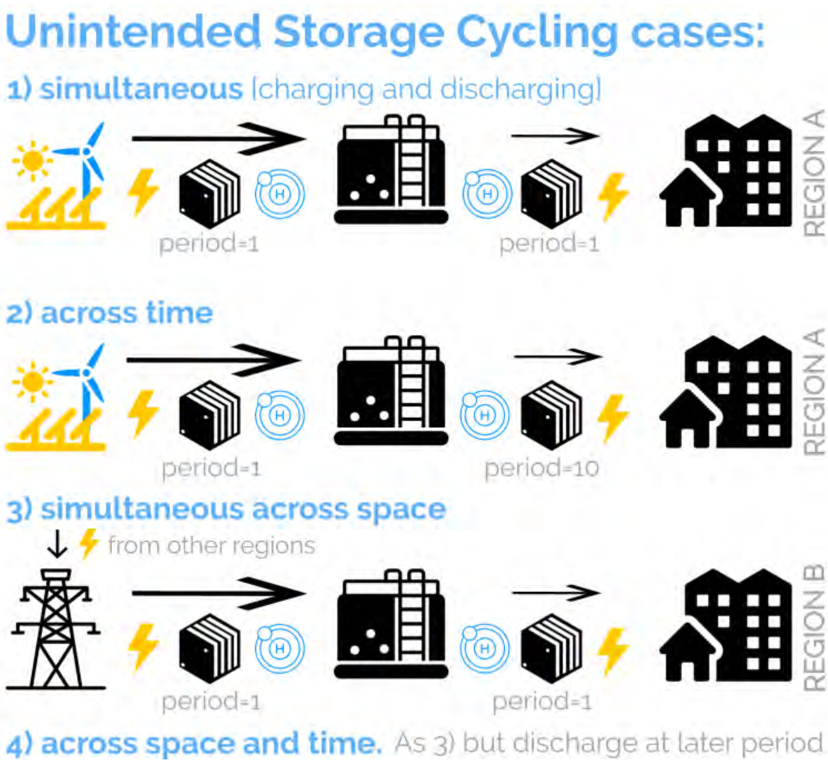


Fig. 4.2.: Unintended storage cycling cases for a hydrogen storage example. The left stack represents the electrolyser, while the right stack reflects the fuel cell which converts electricity to hydrogen and vice versa. The arrow size above the storage components reduces to indicate an efficiency drop. Under renewable energy surplus (variable cost = 0), excess energy is removed from the system by USC instead of renewable curtailment. Thereby, USC may occur over space and time if no constraint prohibits this artifact.

both optimal dispatch and investment decisions. To remove USC, the renewable energy constraint must include these unintended energy losses, preventing the cost-minimizing conversion of intended VRE curtailment into unintended energy losses.

However, the novel solution presented in Kittel and Schill [119] is not applicable to model formulations *without* binding renewable targets [25, 36, 124, 125], which are more frequently used than models with binding renewable targets [119]. In models without binding renewable targets, USC is caused by a different mechanism: It may arise if one or multiple options to dissipate unused energy from the system are available and come at e.g. zero cost. Given such a parameterization, the optimization becomes indifferent with regard to the use of any energy dissipation options. VRE surplus energy can either be curtailed or erased from the system via unintended energy losses from USC, distorting optimal dispatch results (see Section 4.2.1 and 4.3.1). Thus far, the removal of unintended storage cycling in energy models without binding renewable constraint is unexplored.

This chapter addresses this gap by contributing to the existing literature in several aspects: Firstly, it provides a method for removing USC in linear models *without* binding renewable energy targets. The analysis shows that the removal can be achieved by a deliberate setting of variable costs of affected system components. Since variable costs penalise not only USC but also the operation of affected system components, these must be carefully chosen. Unlike Mixed Integer Linear Program (MILP)-based approaches, this solution keeps the problem formulation linear, making it more effective and efficient. Secondly, it mathematically formalises how the simultaneous charging and discharging case of USC occurs. Thirdly, it explores the impact of USC and its removal on operational and investment decisions as well as total system cost in a decarbonised German energy system model. To this end, here it is demonstrated how variable costs, their magnitude and allocation, can remove USC, while also giving new insights on the role of the solver accuracy. Finally, the chapter provides a reviewed list of variable cost inputs, which may guide the removal of USC in other energy models.

4.2 Methodology

Model formulation

The occurrence of USC depends on the model formulation [119]. This chapter builds on top of the previously introduced general power model formulation from the Foundation chapter, Section 2.3, which abstain from binding renewable energy target constraints. The specific model use and formulation for the demonstration are described in Section 4.2.2.

4.2.1 Detecting unintended storage cycling occurrence

USC can be caused by charging and discharging at the same time or across space and time. This chapter focuses on the detection of USC in form of simultaneous charging and discharging that can be identified by analysing the storage operation patterns.

A straightforward approach to detect USC is to count the occurrence of simultaneous charging and discharging over the optimization horizon, which is used in later parts of this study. Here, USC may occur under three cases in energy systems with energy storage [119]: During effective charging, effective discharging, or in an idle energy state with effective net-zero charging.

The storage charging power $h^+_{i,s,t}$ describes the power provision from the grid to the charging component. If reduced by the charging efficiency $\eta_{i,s,+}$, it results in storage charging power $h^+_{i,s,t,store}$ that increases the storage energy level over time.

$$h^+_{i,s,t,store} = \eta_{i,s,+} \cdot h^+_{i,s,t} \tag{4.1}$$

Likewise, store discharging power $h^-_{i,s,t,store}$ describes the power provision from the storage that reduces the storage energy level over time. If reduced by the discharging efficiency $\eta_{i,s,-}$, it results in the storage discharging power $h^-_{i,s,t}$ that provides power to the grid.

$$h^-_{i,s,t,store} = \frac{h^-_{i,s,t}}{\eta_{i,s,-}} \tag{4.2}$$

The first case USC occurs under effective charging $USC^+_{i,s,t}$, which increases the storage energy level over time:

$$
\begin{aligned}
if \quad & h^{+}_{i,s,t,store} > h^{-}_{i,s,t,store} \quad \text{and} \quad h^{-}_{i,s,t,store} > 0: \\
& \text{USC}^{+}_{i,s,t} = \text{true}
\end{aligned}
\tag{4.3}
$$

The second case occurs under effective discharging $USC^{-}_{i,s,t}$, which decreases the storage energy level over time:

$$
\begin{aligned}
if \quad & h^{+}_{i,s,t,store} < h^{-}_{i,s,t,store} \quad \text{and} \quad h^{+}_{i,s,t,store} > 0: \\
& \text{USC}^{-}_{i,s,t} = \text{true}
\end{aligned}
\tag{4.4}
$$

The third case appears under non-zero equal charging and discharging $USC^{=}_{i,s,t}$, or idle energy state, which keeps the storage energy level over time constant (neglecting standing losses):

$$
\begin{aligned}
if \quad & h^{+}_{i,s,t,store} = h^{-}_{i,s,t,store} \quad \text{and} \quad h^{+}_{i,s,t,store} > 0: \\
& \text{USC}^{=}_{i,s,t} = \text{true}
\end{aligned}
\tag{4.5}
$$

4.2.2 Numerical implementation and data

A stylized parameterization of PyPSA-Eur [24] is used as a numerical implementation for the model to explore the occurrence and amplitude of USC, as defined in Section 4.2. A complete model formulation of PyPSA-Eur is provided in the Appendix of [4]. PyPSA-Eur is a European power system model, representative of energy models that abstain from binding renewable energy targets. The analysis applies the model to a stylised setting parameterised to the German power sector for a 100% GHG emission reduction scenario (see Figure 4.3). It limits the available set of technologies to solar Photovoltaic (PV), onshore wind, offshore wind, as well as an H2 storage system consisting of an electrolyser, a tank, and a fuel cell. Also, it sets the spatial resolution to 16 nodes within Germany. Offshore wind power plants may be connected via High Voltage Alternative Current (HVAC) or, in the case of sites far offshore, more costly High Voltage Direct Current (HVDC) transmission lines. The model has perfect foresight and optimizes with an hourly temporal resolution. Weather and load data stem from 2013. Hourly load data originates from the ENTSO-E Transparency platform and are distributed across the regions depending on NUTS3 based GDP data (see more in [24]). All renewables and energy storage technologies are greenfield optimized, i.e., without considering the existing capital stock. State of charge of energy storage capacities is constrained to start and end with 100%. The self-consumption of the H2 storage tank is assumed to be zero. The

Tab. 4.1.: Model input assumptions.

Technology [a]	Investment [€/kW]	Fixed O&M [€/kW/a]	Variable cost [€/MWh]	Lifetime [a]	Eff. [-]	Source
onshore wind	1040	25	variable[b]	30	1	DEA [127]
offshore wind (HVAC[c])	1890	44	variable[b]	30	1	DEA [127]
offshore wind (HVDC[c])	2040	47	variable[b]	30	1	DEA [127]
PV	600	25	variable[b]	25	1	Schröder et al. [128]
hydrogen electrolyser[d]	350	14	variable[b]	25	0.8	Budischak et al. [129]
hydrogen storage tank[d]	8.44 / €MWh	-	variable[b]	20	1	Budischak et al. [129]
hydrogen fuel cell[d]	339	10	variable[b]	20	0.58	Budischak et al. [129]
transmission (submarine)	2000 / €MWkm	2%/a	0	40	1	Hagspiel et al. [130]
transmission (overhead)	400 / €MWkm	2%/a	0	40	1	Hagspiel et al. [130]

[a] All technologies include a discount rate of 7%.
[b] 'Variable' means set according to scenarios.
[c] Offshore wind power plants can be connected by high voltage alternating current of direct current
[d] Unconstrained energy storage sizing and not fixed to specific energy to power ratio.

transmission network is based on the network topology from 2020, considering also planned lines until 2030 from the ENTSO-E Ten Year Network Development Plan (TYNDP) 2018 [126]. Grid expansion is endogenous but limited to additional 25% newly built lines for the modelled target year to represent political hurdles of transmission expansion [19]. Table 4.1 lists relevant techno-economic assumptions. This stylised setting allows for demonstrating USC in the context of energy models without binding renewable energy targets and how it can be removed by a deliberate setting of variable costs.

4.2.3 Experimental setup

To investigate the suggested method for removing USC, in the base case scenario the analysis sets the variable cost (EUR/MWh) of the renewable generators, H2 electrolysers, H2 tanks, and H2 fuel cells to zero. Further scenarios are then defined varying *ceteris paribus* the variable cost of one of these system components in the range $e \in \{0, 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 10^{0}, 10^{1}, 10^{2}, 10^{3}\}$. That is, in each scenario, the variable cost of one system component changes according to range e, while the others are kept constant at zero. Note that, in the respective scenarios, variable costs of all renewable generators are varied at once. Cost additives of 100 or 1000 €/MWh (10 or 100 ct/kWh) represent a demonstrative, non-realistic value for all included technologies that could be interpreted as falsely set variable costs.

The double-precision arithmetic limits the amount of numbers a computer can recognise. While optimization solvers are also influenced by double-precision arithmetic, they additionally include tolerances to solve problems faster, which comes at the

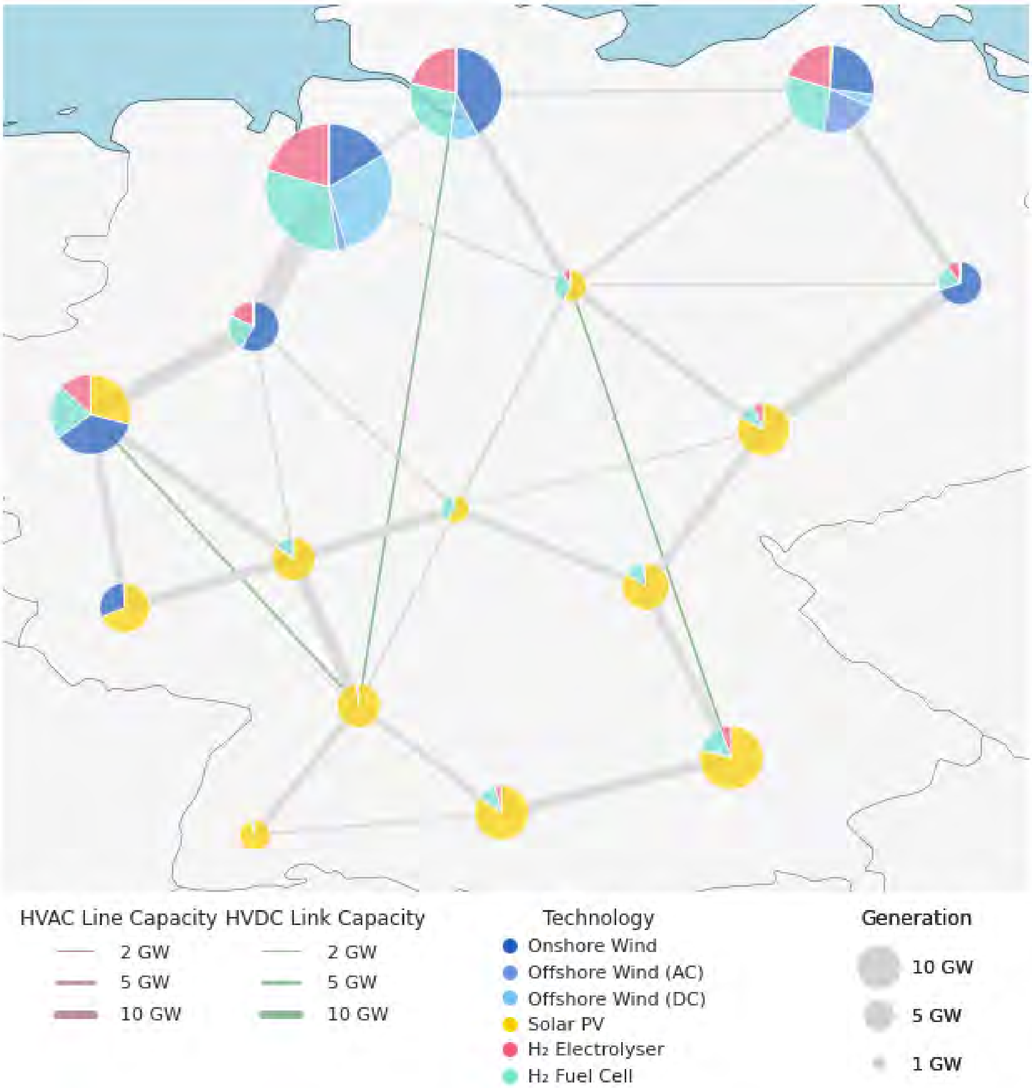


Fig. 4.3.: Illustration of model output. It shows an example model scenario with optimized generation and storage capacities in Germany for a 100% GHG emission reduction case.

cost of accuracy. The analysis varies the precision of two Gurobi solver parameters simultaneously yielding three scenarios: low, medium, and high accuracy. The first modified Gurobi parameter that impacts the precision is the $FeasibilityTol$ or primal feasibility tolerance, which requires all constraints to satisfy a specific tolerance to be feasible [131]. For instance, constraints such as $(a * x) <= b$ require to hold $(a * x) - b <= FeasibilityTol$, thus expanding the solution space. This value is varied by $e \in \{10^{-5}, 10^{-6}, 10^{-7}\}$ from low to high accuracy. Simultaneously, the Gurobi parameter $BarConvTol$ is varied, which describes the barrier solver (also known as Interior Point Method (IPM)) termination tolerance as a relative difference between the primal and dual objective values [131]. Given one solution space for an optimization problem, this relative difference is also known as duality gap [132], which IPM reduce iteratively toward zero before the termination tolerance is reached. Again, this value is varied by $e \in \{10^{-4}, 10^{-5}, 10^{-6}\}$ from low to high accuracy.

The computations to generate all results ($10 * 4 * 3 = 120$ scenarios) required 25.5 h for 1 CPU core with 8GB memory.

4.3 Results and Discussion

In the following subsections, the analysis introduces how to remove USC as well as investigate the impact of USC and its removal on model outcomes such as optimal dispatch, installed capacity, and total system cost. The stylised model formulation, its numerical implementation and the experimental setup are described in the Section 4.2.

4.3.1 Removing unintended storage cycling by variable cost additives

Variable cost additives are defined as not necessarily true observed variable costs, but more generally as assumed additional costs components.

Suppose an optimization problem, such as provided in the model formulation Section 4.2, finds a least-cost total system architecture. Then the system operation may adapt any value as long as it does not lead to more cost (left side of Equation (4.6) and (4.7)) and does not break constraints such as demand is equal to supply (described in 4.2).

Further, suppose the energy system contains a renewable energy surplus at a time step, while variable operational cost $o_{i,s/r}$ of storage and renewables are assumed to be zero, then:

$$0 \quad = \underbrace{o_{i,r}}_{0} \cdot g^*_{i,r,t} + \underbrace{o^+_{i,s}}_{0} \cdot h^{*,+}_{i,s,t} + \underbrace{o^-_{i,s}}_{0} \cdot h^{*,-}_{i,s,t} + \underbrace{o^{store}_{i,s}}_{0} \cdot \triangle e^*_{i,s,t} \tag{4.6}$$

These zero costs may lead to a situation where surplus generation is fed into the grid rather than curtailed. However, to guarantee the energy balance, extra surplus generation needs to be dissipated by USC (indicated by *), which leads to higher storage usage.

In contrast, in case costs exist for either generation or storage operation,

$$0 \quad = o_{i,r} \cdot \underbrace{g_{i,r,t}}_{0} + o^+_{i,s} \cdot \underbrace{h^+_{i,s,t}}_{0} + o^-_{i,s} \cdot \underbrace{h^-_{i,s,t}}_{0} + o^{store}_{i,s} \cdot \underbrace{\triangle e_{i,s,t}}_{0} \tag{4.7}$$

every additional operation of variable renewable generators or storage is prevented in the first place, thus avoiding USC.

Equations (4.6) and (4.7) illustrate that a system with USC (indicated by *) has components with higher operating hours than one without,

$$\sum_{t=1}^{T} g^*_{i,r,t} \geq \sum_{t=1}^{T} g_{i,r,t} \tag{4.8}$$

$$\sum_{t=1}^{T} h^{*,+/-}_{i,s,t} \geq \sum_{t=1}^{T} h^{+/-}_{i,s,t} \tag{4.9}$$

$$\sum_{t=1}^{T} e^*_{i,s,t} \geq \sum_{t=1}^{T} e_{i,s,t} \tag{4.10}$$

caused by energy dissipation through excessive storage use rather than curtailing renewable surplus.

In summary, to remove USC, a situation with USC must become more expensive than one without because, fundamentally, the objective function aims to minimise cost. One approach is to add variable cost $o_{i,r} > 0$ to the generation dispatch. Another is to add variable costs $o_{i,s} > 0$ to any or all energy storage components, such as charger, store or discharger. All such variable cost additives penalise any extra operation of generators or storage units caused by USC energy dissipation, even across space and time. Nevertheless, since variable costs penalise not only USC but also the operation of these units, these must be carefully chosen.

4.3.2 Effects on operational optimization

Figure 4.4 illustrates the number of hours with USC in the system (scatter plots, right y-axis). It further shows FLH of the H2 fuel cell for varying variable costs of the renewable generators or H2 storage components (lines, left y-axis). The approach to count the USC occurrence is given in Section 4.2.1.

Adding variable cost to any class of storage components or all renewables can successfully remove USC beyond a certain threshold that depends on the solver accuracy. The observed occurrence of USC spatially averaged over all modelled nodes with variable cost below 10^{-3} is roughly 5200, regardless the level of solver accuracy. Note that for the determination of the USC occurrences, any simultaneous charging and discharging below the energy value of 1 MWh is not counted as USC to ensure that only significant USC energy volumes are considered. Otherwise, USC would occur in almost every time step of every scenario with marginal energy volumes, which may be caused by the solver tolerance and the non-uniqueness of the optimal operation of storage assets [120].

More importantly, the USC energy volume decreases for increasing cost additives, irrespective of the USC occurrence counting method. This decrease is illustrated by the FLH curves in Figure 4.4. In general, the FLH curves reveal that adding variable costs affects the operation of the storage system. The decline in FLH as the variable cost increase is due to two overlapping effects, indicating a trade-off between the removal of USC and an undistorted operation of the storage system. For the lower range of the investigated variable cost additive scenarios, the reduction of the USC energy volume is the prime driver of the FLH decline. In contrast, very high cost additives render the storage system's operation less economically viable, strongly decreasing its optimal use. In the medium-to-high range of the cost additives, both USC is prevented and storage operation remains largely constant and undistorted, indicated by the plateau of the FLH curves.

In our stylised setting at medium solver accuracy – which refers to the PyPSA-Eur default values [50] – USC is fully removed in any considered scenario with a variable cost threshold of at least 10 €/MWh or 1 ct/kWh. While for scenarios with a variable cost additive of 1 €/MWh USC still occurs, the USC energy distortions are only marginal with a slight increase of the fuel cell's FLH of 21h compared to a cost additive scenario with 10 €/MWh (1265h - 1244h). Hence, a variable cost additive of slightly above 1 €/MWh (or 0.1 ct/kWh) is likely to prevent USC distortions in our case study.

The very cost additive threshold that removes USC depends on the level of solver accuracy. In the case of low solver accuracy, the threshold is relatively high at 100 €/MWh. However, FLH curves hardly stabilise in a plateau, which would indicate that storage operation remains unaffected. This makes it difficult to identify the optimal cost additives that prevent USC. Further, such a high variable cost additive level is implausible for VRE or storage components. For medium and high solver accuracy, FLH curves form a plateau, with the lower end at 10 and 1 €/MWh, respectively. Note that this work discretely increments the variable cost additives by one order of magnitude. The true underlying thresholds, defined by the minimum variable costs that remove all USC, can be in between these increments.

The observed impacts of USC on the operation are extreme by design of this study. The operational distortions are amplified through the exclusion of dispatchable renewable and conventional generators, such as biomass, nuclear, or green gas. Including such dispatchable generators may decrease the USC energy distortions in many energy models, as this would introduce additional variable costs that reduce the impact of USC (see Section 4.3.1). Nevertheless, this study also reveals that assuming no variable cost for generators or storage technologies, as done in multiple if not most energy system modelling studies [13, 119, 133, 134, 135], risks unintended operational distortions. The analysis investigates if these distortions, as well as variable cost additives, also impact the investment optimization in the next section.

4.3.3 Effects on investment optimization

Figure 4.5 illustrates the optimized generation and storage capacity of all modelled scenarios. The optimal installed capacity is much more robust to cost additives than optimal operation. At additives of 1 €/MWh, which is sufficient to avoid USC occurrence, optimal capacity results remain unaffected. Only for very high additives of 10 to 100 €/MWh the optimal installation is affected.

In scenarios with very high VRE variable cost additives, wind power is used more, while both PV and storage are used less. This is due to the more stable generation pattern of wind power compared to solar PV which requires more storage to smooth

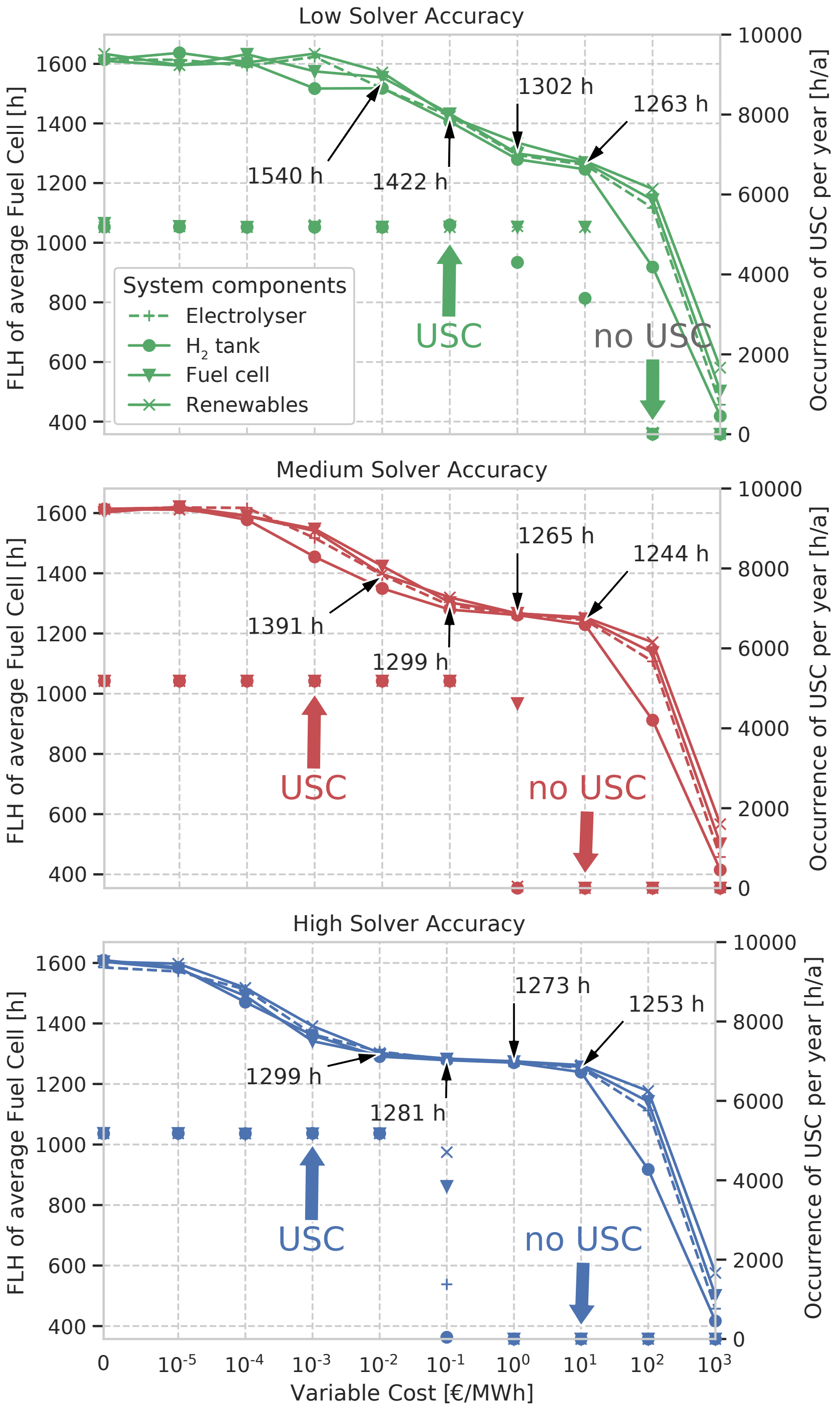


Fig. 4.4.: Analysis of USC for different model scenarios. FLH of the H2 fuel cell (lines, left y-axis) and occurrences of USC (scatter plots, right y-axis) for three levels of solver accuracy (low, medium, high from top to bottom) across different levels of variable cost additives for renewable generators or H2 storage components (x-axis). FLH are averaged across all nodes in Germany. Per scenario, the variable cost additives are added to only one component, while no variable costs accrue for all others.

its diurnal generation profile. Additionally, even though variable costs are added only to generator operations, the use of storage becomes more expensive as storage efficiency losses multiplies VRE generation cost. For instance, at an electricity price of 100 €/MWh and a round-trip efficiency of 25%, discharging 1 MWh comes at energy procurement costs of 4 MWh $\times$ 100 €/MWh (4 MWh must be charged to generate 1 MWh of storage output). This multiplication effect of generation costs in energy storage components would be less of an issue if generation had lower costs. For instance, consider variable generation costs of 0 €/MWh for the same efficiency as before. The effective operation costs of charging and discharging were zero - yet, causing USC.

For plausible variable cost additives, USC does not impact optimal investment decisions. This is one major difference to USC arising in energy models with a renewable energy constraint, where the artifact causes complex distortions of optimal investments [119].

4.3.4 Effects on total system costs

The total system costs consist of operational and investment cost and is a key parameter to assess the wider energy system. Figure 4.6 shows the total system cost results for all optimization runs stacked by system components. It reveals that scenarios with USC and applied USC removal strategies have only negligible impact on the total system costs unless the variable costs are set too high (above or equal to 10 €/MWh). Depending on the technology for which the variable costs are added, a significant cost increase can be detected due to the extra operational cost that needs to be covered. Again, the assumed values, for instance, of 100 €/MWh for the dispatch of all included renewables, might not be realistic but illustrate the impact of mistakenly choosing the wrong values.

4.3.5 Variable costs suggestions to alleviate unintended storage cycling

Our results suggest that variable costs should be carefully set for all assets to guarantee the removal of USC while avoiding any distortion of optimal investment and dispatch decisions. In our stylised setting, the lower end of the plateau of the FLH curves in Figure 4.4 indicates the optimal threshold for an appropriate cost

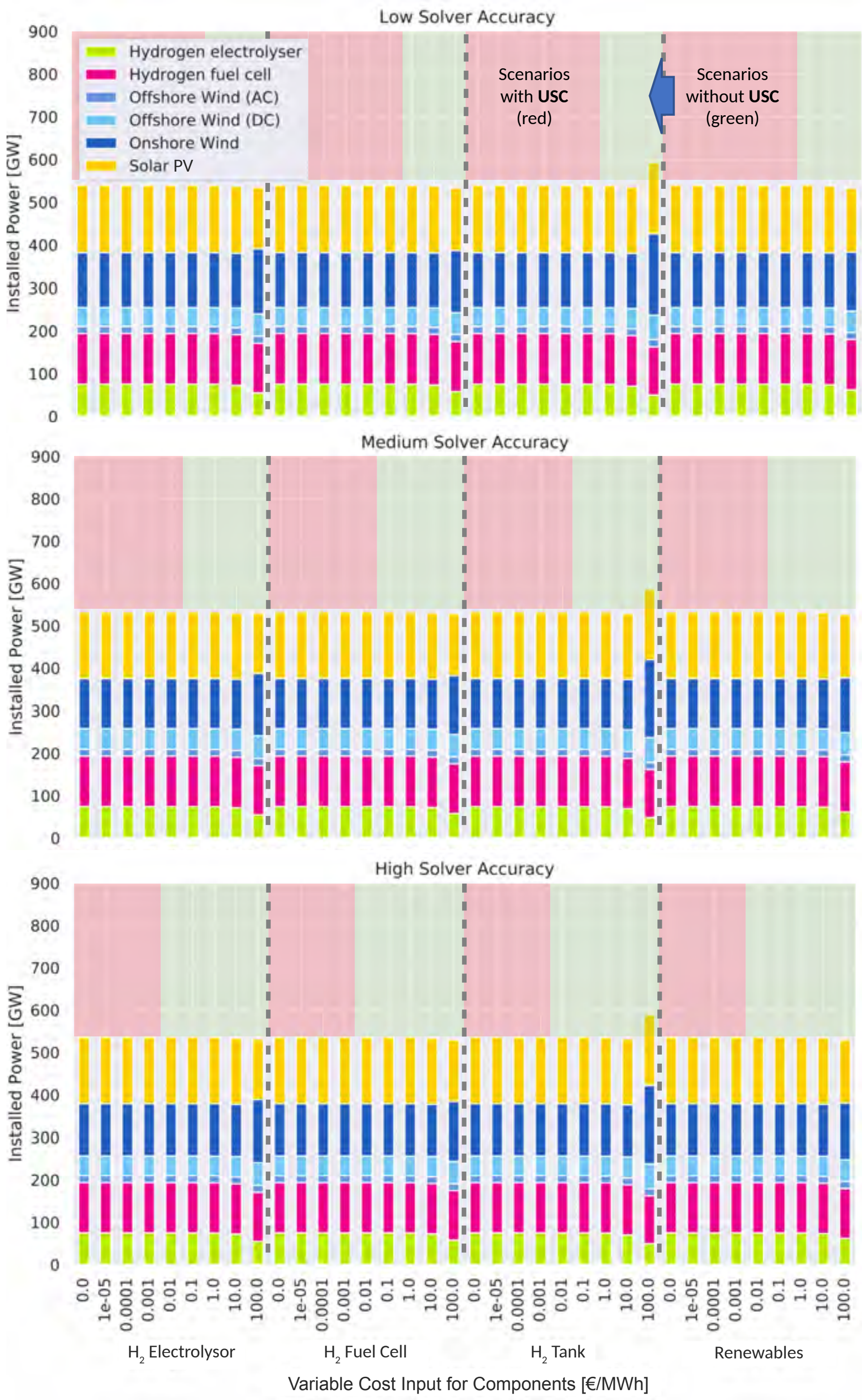


Fig. 4.5.: Installed capacity of all generation and storage assets for different variable cost additive scenarios. In scenarios in red USC arises, while in the green the effect is prevented. This figure omits illustrating results from the scenarios using variable costs additives of 1000 €/MWh to keep Figure 4.5 and 4.6 consistent and readable.

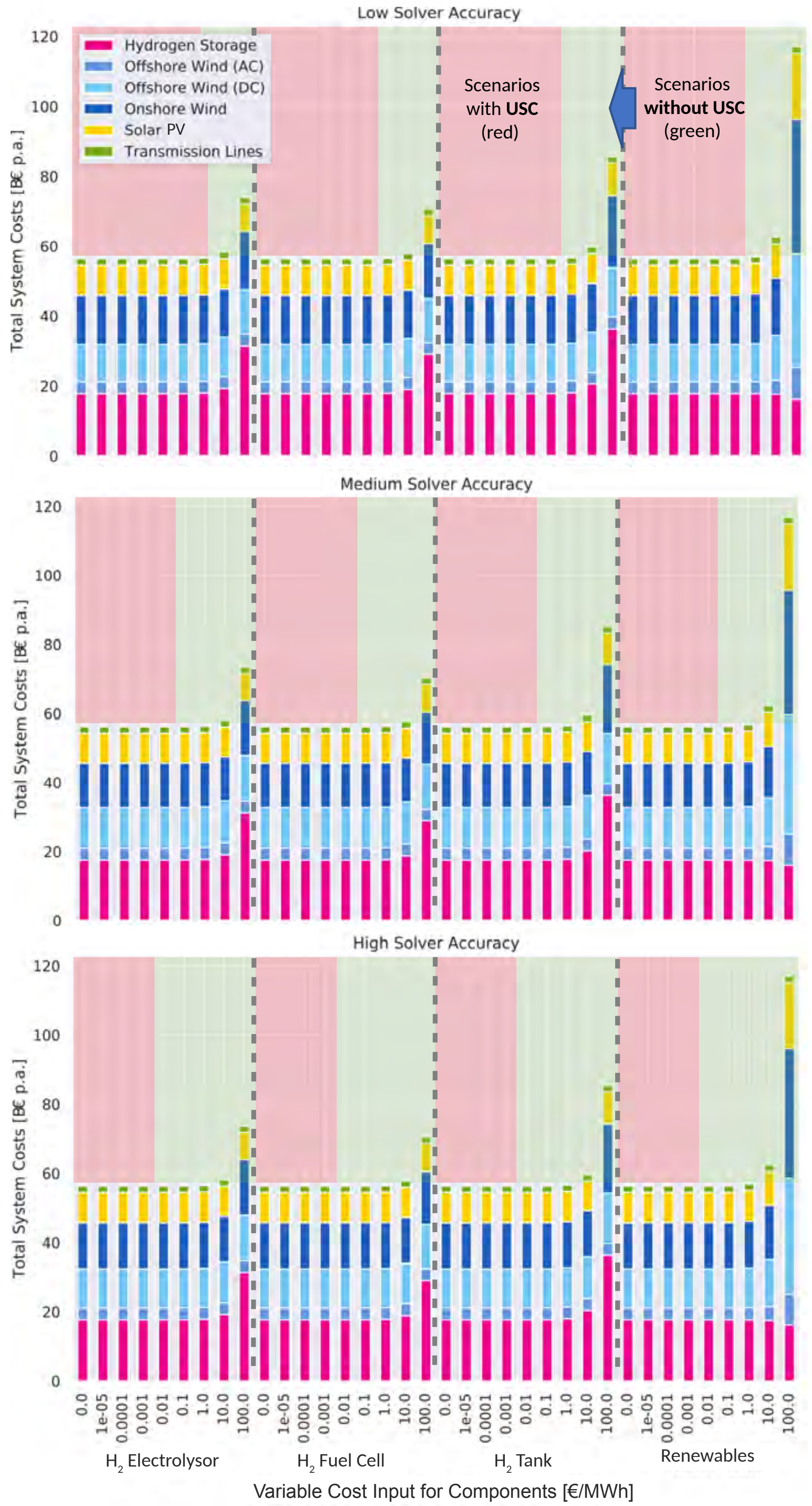


Fig. 4.6.: Total system costs for different variable cost additive scenarios. In scenarios in red USC arises, while in the green the effect is prevented. Costs of the hydrogen storage consist of electrolyser, fuel cell, and H2 storage tank. This figure omits illustrating total system costs from the scenarios using variable costs additives of 1000 €/MWh for readability.

additive. Values below this threshold do not prevent USC, while values above this threshold can lead to investment and operational distortions.

Providing variable costs above a minimum threshold is key to avoid USC in models without binding renewable targets, even for technologies with zero or near-zero variable costs. For instance, if a solar PV plant is given no or too small variable costs, then solvers cannot recognise them. Consequently, these values should be replaced by the minimum value depending on the solver accuracy and used solver. In our stylised setting of PyPSA-Eur, this minimum value is 1 €/MWh at the used default Gurobi solver settings of ($BarConvTol$ = $1e^{-5}$, $FeasibilityTol$ = $1e^{-6}$), which remove most USC effects. While 1 €/MWh or 0.1 ct/kWh may be considered as relatively high, our results in Figures 4.4, 4.5, and 4.6 show that these little variable costs neither affect the investment nor the operational costs significantly, making it a threshold candidate to alleviate large USC distortions.

From Figure 4.4, it is observed that there are multiple options to remove USC. First, setting minimal variable cost only for one storage component, such as charger, store, or discharger for all storage technologies in all regions across the network. Second, imposing minimal variable costs to all VRE generation types at all locations (see Equations 4.6 and 4.7). Third, one can also combine the first and second point and impose minimal variable costs to all storage and generator assets. With likely negligible affects on computational time and total system cost distortion, the third option is recommended because it is most consistent and provides additional redundancy to remove USC.

The fact that some technologies are assumed with zero costs for energy dispatch (see 4.2) could be reconsidered. The concept of *variable cost for lifetime reductions* may justify cost assumptions for non-zero dispatch generators or storage components. Suppose a wind turbine operates 100% and another one only 50% of all hours of a year. Further, both turbines are equally maintained by contract-based operation and maintenance service providers (often annualised as fix-costs). However, the twice as much operating turbine is likely to experience, on average, earlier signs of fatigue in the mechanical structures and power electronics [136, 137]. As a result, the turbine with more operating hours was indeed experiencing costs, namely variable costs for lifetime reductions that are associated with the reduced technical lifetime or extra required operation and maintenance. Such variable cost for lifetime reductions cost may be not trivial and vary across technologies. For instance, in the case of thermal-based processes like steam turbines in concentrated solar power plants, a steady rather than fluctuating operation is preferred. This reduces thermal stresses that otherwise shorten the plant lifetime [138]. In summary, even though associating variable cost to the technical lifetime is not trivial, these costs are likely to appear in the energy systems often in addition to other variable costs e.g. parasitic loads, water consumption. These variable costs makes it likely to argue for variable costs greater than zero that might even reach the minimum variable cost of $1e/MWh$ required to significantly remove the risk of unintended storage cycling.

In Table 4.2, a comprehensive list of variable costs suggestions is provided, including a minimum threshold for technologies that are considered near-zero or zero variable cost devices [139, 140]. Replacing the zero or near-zero variable costs by the threshold often insignificantly increase computations since relatively few additional variables need to be optimized. In general, these tabulated values contain large uncertainties since they are not provided in great detail in the literature [141]. The suggested threshold of 1 €/MWh has to be taken with caution as it may not apply to all energy models. The threshold is recommended for a specific modelling tool, namely PyPSA-Eur, while using the Gurobi solver with default accuracy of $BarConvTol = 1e^{-5}$, $FeasibilityTol = 1e^{-6}$. If the model formulation, the solver, or the solver parameters differ, then this suggestion may no longer be valid. So while the ideal threshold may require quantification for each model parameterization separately, the values in Table 4.2 could serve as a default starting point for the identification of an appropriate cost additive.

4.4 Limitations

In our case study, the minimum variable cost threshold of 1 €/MWh (or 0.1 ct/kWh) removes all significant USC effects at default Gurobi solver accuracy settings without impacting the overall optimization significantly. However, this threshold cannot be generalised to all other energy models. Instead, the efficacy needs to be tested for each model, solver and parameterization. This can be done by checking for simultaneous charging and discharging while maintaining an appropriate level of solver accuracy.

4.5 Conclusion

Reliable energy model results are essential for planning optimal pathways for the energy transition. However, in energy models without binding renewable energy targets, USC can distort operational results of optimized energy systems, while it

Tab. 4.2.: Variable O&M cost suggestions. The variable O&M cost are for a set of renewable generators and storage technologies in energy models based on 2030 data. The O&M costs exclude fuel cost, e.g. for biomass.

Technology	variable cost [€/MWh]	Source
onshore wind	1.4	DEA [127]
offshore wind	2.7	DEA [127]
PV	$0 \rightarrow 1^*$	Clauser & Ewert [142]
CSP[a]	2.9	Clauser & Ewert [142]
CSP + Storage	4	Clauser & Ewert [142]
biomass	6.7^a	Clauser & Ewert [142]
tidal	3.1^d	[-]
wave	3.0^d	[-]
geothermal	5.6	Clauser & Ewert [142]
run of river	$3.6^{a,b}$	EIA [143]
hydroelectric dams	$3.6^{a,b}$	EIA [143]
pump-hydro storage	$3.6^{a,b}$	EIA [143]
battery inverter	$6.8^{a,c}$	EIA [143]
battery storage	$13.5^{a,c}$	EIA [143]
hydrogen electrolyser	3^e	Glenk & Reichelstein [144]
hydrogen storage tank	$0^f \rightarrow 1^*$	DEA [127]
hydrogen fuel cell	$0^f \rightarrow 1^*$	DEA [127]

[*] Reported below 1 €/MWh, but set to 1 €/MWh to avoid USC
[a] Interpolated between 2020 and 2035
[b] Aggregated as hydroelectric devices by EIA
[c] Assumption of cost split: 2/3 store and 1/3 inverter
[d] Assumed similar to offshore wind. Lack of alternative data [145]
[e] Required conversion with hydrogen energy density of $33.3 kg/MWh$
[f] DEA reports the value for the whole hydrogen storage system

keeps investment results unaffected. This means that policy questions related to optimal capacity expansion can be answered while disregarding the occurrence of USC. However, when any operational signals are discussed such for technology evaluations, then assessing USC is important. In our case study, the modelling artifact significantly increased the FLH of storage and renewable assets of up to 23%, potentially misleading decision-makers. Since USC is technically infeasible for some storage technologies, e.g. single lithium-ion batteries, and can lead to significant operational distortions, it should be removed.

This chapter shows that setting an appropriate level of variable costs is capable of removing USC, while keeping the problem formulation linear and convex. However, determining this level is not trivial. The optimization solver may not recognise too low variable costs, which then does not guarantee the removal of USC. Hence, it is recommended to set minimum variable costs at a certain threshold that depends on the solver's accuracy and tolerance. Very high variable cost, on the other side, may prevent USC but can also significantly distort the relative cost ratio of available generation and balancing technologies. As a consequence, optimal investment and dispatch decisions may be flawed. To avoid such model distortions, it is essential to set the variable cost carefully and as accurately as possible.

Additionally, this chapter provides a selection of recommended variable costs for a set of storage and renewable generation technologies extracted from the literature. These values include the identified threshold of 1 €/MWh (or 0.1 ct/kWh) as a minimum level to remove all significant USC. While the analysis did not apply the minimum threshold to all storage and renewable generation technologies at the same time, the results in Figures 4.4, 4.5, and 4.6 already prove that the threshold sufficiently reduces USC distortions without changing the optimization result much when applied for either one of the storage components or all generators. Thus, the values in Table 4.2 should be taken as baseline. The suggestions may also serve as a starting point for USC tests in other model applications following the rule-of-thumb: near-zero variable costs additives lower the risk of significant USC distortions compared to assuming no variable costs at all.

Future work should analyse the removal of other forms of unintended energy losses beyond USC by setting appropriate variable costs. For instance, unintended line cycling manifests by simultaneous sending and receiving of electricity through power lines in the distribution and transmission grid [37, 119]; and sector-coupled cycling, e.g., by electric energy that is converted to heat by boilers and re-electrified at the same time with organic Rankine Cycle plants. These unintended energy losses may originate from the same issue, namely that missing operational costs make a cost-minimising energy model indifferent between possible options to lose unused energy either by cyclic dissipation or VRE curtailment. Further, while this study investigates USC in energy models triggered by insufficiently specified cost assumptions, USC also arises when using additional constraints, e.g., binding renewable energy targets [119]. Constraint-based unintended energy losses are not yet fully explored and merit future research. Finally, USC can be caused by charging and discharging at the same time or across space and time. Throughout the chapter, the focus is set to only detect USC caused by simultaneous charging and discharging. This is accomplished by being aware that variable cost additives penalise any extra operation of generators or storage units caused by USC energy dissipation, even across space and time. However, to prove this, future work should explore USC detection methods across space and time.

Other future work can also investigate alternative methods to remove USC. A two-step optimization approach, which has yet to be discussed in the literature, may be able to remove USC while not risking to distort the optimization results. The first step minimises the total system costs in an investment and dispatch co-optimization, which results in a solution with unintended storage losses. The second step adds the objective value from the first step as a side constraint in a dispatch optimization which minimises the operational losses or maximises the generator curtailments in the system to eliminate unintended storage losses. While solutions times between the variable cost and the two-step optimization approach are likely to be in the similar range, future work can compare these methods in more detail.

Transitioning from the storage modeling details presented in this chapter, the next chapter - "Technology Evaluation Methods" broadens the scope to the evaluation process of energy storage technologies. This chapter reviews existing assessment methods, discussing their benefits and limitations. It's a bridge from the technical specifics of modeling to the broader context of how we understand and value energy storage in power systems.

Part II

Applied Energy Storage System-Value Optimization

5 Review of Technology Evaluation Methods

Innovation distinguishes between a leader and a follower.

— **Steve Jobs**
CEO Apple Inc.

Contents of this chapter are based on

Maximilian Parzen et al. "Beyond cost reduction: improving the value of energy storage in electricity systems". In: *Carbon Neutrality* 1.1 (July 2022), p. 26. DOI: 10.1007/s43979-022-00027-3. URL: https://doi.org/10.1007/s43979-022-00027-3

Declaration

I carried out all study elements. Co-authors mainly provided reviews and suggestions.

Infobox

A thesis outline is given in section 1.3 that contextualise the chapters.

Abstract

This chapter provides a comprehensive classification and evaluation of techno-economic analysis methods for energy storage technologies, addressing their value in both current and future market contexts. The chapter categorizes the literature into three main approaches: cost analysis, profit analysis, and system-value analysis, each varying in objectives and metrics. Cost analysis focuses on the component and system costs, employing methodologies like the levelized cost of storage (LCOS). Profit analysis, from an investor's perspective, incorporates real-world market dynamics and revenue streams, using metrics like Net Present Value (NPV) and Internal Rate of Return (IRR). System-value analysis, on the other hand, delves into the broader impacts on the energy system, considering 'visible' and 'hidden' values and employing energy system models to predict future market changes. The review suggest that while current methods are vital for industry decision-making and policy regulation, they often overlook the complex interactions within energy systems. Therefore, the chapter emphasizes the need for integrated approaches that consider both individual technology improvements and system-wide impacts to fully understand and enhance the value of energy storage technologies.

5.1 Introduction

Energy storage technologies create value today. This is why the UK has nowadays up to 14 potential revenue streams for energy storage technologies [146]. However, with higher shares of VRE and the need for more long-term energy storage solutions, the future markets might change.

This section reviews and classifies currently applied storage valuation methods, or in other words, techno-economic analysis approaches that appraise the competitiveness of energy storage including both, technicalities and economic measures.

This study classifies the literature into three groups: cost analysis, profit analysis and system-value analysis, which mainly differ in the objective of the metrics. Figure 5.1 summarises what components will be discussed. These methods are broadly employed for industry decision making, research focus consolidations, and policy regulation [10, 147, 148], which underlines their importance and the impact of any improvement.

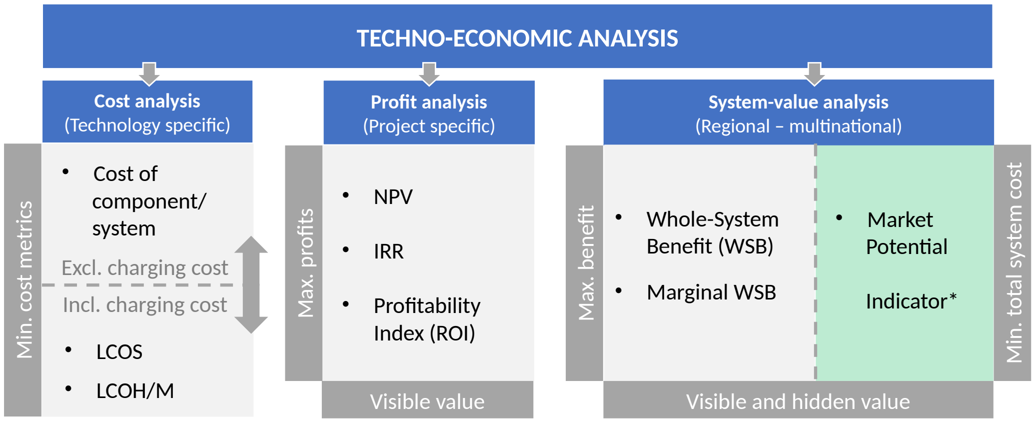


Fig. 5.1.: Classification of current techno-economic analysis methods in the context of energy storage. *Market potential indicator is a suggested decision metric and part of the newly introduced market potential method. The abbreviations mean the following: LCOS, levelised cost of hydrogen or methane (LCOH/M), NPV, IRR, ROI.

5.2 Visible vs. hidden value

To understand the 'visible' and 'hidden' value terminology chosen to classify the literature, one should acknowledge that current markets can be considered imperfect and incomplete for multiple reasons:

- Markets are not temporally or spatially resolved. For instance, spot prices are settled over larger spatial areas and not in real-time, leading to not perfect spatial dissolved socialised grid fees [149].
- Market power can be exploited. Dominant market participants act for their profit while damaging the average participant [149].
- Forecast information is imperfect. Forecasts of demand, wind and solar generation underlie uncertainties leading to imperfect operation and planning [149].
- Other negative and positive externalities exist related to incomplete markets, which distort the price. Negative externalities are, for instance, non-priced costs for carbon emission, air pollution and biodiversity losses; positive externalities are non-priced benefits such as non-tracked carbon reduction benefits [149].

In this context, system-value analysis generally analyses markets by partially or entirely reducing these market flaws. For instance, energy system models can cover higher spatial and temporal resolution, exclude market power, assume perfect foresight and account for externalities. However, not all models idealise. Some can also incorporate effects of imperfect and incomplete markets by adding cost and benefits related to uncertainty and non-optimal operation and investment [33, 49, 150].

’Visible values’ are benefits that can be priced or accounted for in real-world imperfect and incomplete markets as used for profit analysis. In contrast, ’hidden values’ are benefits that are not yet priced or accounted for in real world markets. An example are hidden energy storage benefits for network or peak plant deferral or reduced solar and wind power plant curtailments [151]. To track both hidden and visible values, system-value approaches use idealised models assuming perfect and complete markets.

The following subsections will clarify for each techno-economic analysis class their objectives, methods and users, and further analyse the grade of technical detail and how the approaches handle the role of competition in uncertain future markets.

5.3 Cost analysis

Here the cost analysis of energy storage is categorised into two groups based on the used methodology: while one solely estimates the cost of storage components or systems, the other additionally considers the charging cost, such as the levelised cost approaches. Their general objective is to minimise the cost metric for a particular technology or application.

An example of the first approach is represented in [152]. The energy weighted cost of a storage system (€/kWh) is minimised, without any electricity price signal, by a cost optimisation model that simultaneously maximises the round-trip efficiency of the storage. In [153, 154], instead of assuming the cost of components, they break down storage components or systems into materials and manufacturing processes. This methodology, known as process-based cost analysis, allows a deeper understanding of cost reductions by mass production or switching to different manufacturing methods. While both approaches do not mention competitiveness or the value of energy storage, their outputs combined with cost and benefit analysis allows finding the value of energy storage solutions.

The levelised cost approaches for energy storage include metrics such as the levelised cost of storage when electricity is discharged (LCOS) and LCOH or LCOM when hydrogen or methane are discharged, respectively [147, 155]. All the levelised cost metrics above are similarly structured. They divide the total cost of the considered system by the discharged energy. Both parameters must be discounted to represent the time value of money [156]. Because all levelised cost metrics work similarly, this section uses as generalised form the levelised cost of X (LCOX), where 'X' indicates that the equation holds for various discharged energy carriers:

$$\text{LCOX} = \frac{(\sum_0^T \text{Total cost})_{Discounted}}{(\sum_0^T \text{Total discharged energy})_{Discounted}} \tag{5.1}$$

Thereby, the total cost typically consists of capital expenditures, operational expenditures and charging expenditures [157, 158, 159]. Sometimes additional factors are included that can impact total cost and total discharged energy, such as degradation rates, taxes, or self-discharging [147]. While the next chapter demonstrates that one can also use price signals from energy system models and calculate nodal LCOS, this is not commonly applied in the LCOS literature [4].

Levelised cost metrics are used to evaluate many applications, such as energy arbitrage, frequency regulation, voltage regulation, system restoration and operational management (i.e. redispatch). For this purpose, the levelised cost metric assumptions must be categorised for the specific application, such as charging price, operational time and power to energy ratio [147, 159].

While the 'cost of component' or 'cost of system' approach is widely used for design decisions with high technological detail [152, 153, 154], the levelised approaches forego some technical detail to inform project developers and policy about their projected competitiveness in the market [147].

Cost of component or system metrics are excellent for exploring cost reduction opportunities in great technical detail. On the other hand, LCOS-like metrics differ by being a good first indicator for the competitiveness between various technologies for a particular application.

A technology improvement should lead to total system cost reductions. However, the main limitation of cost-analysis methods is that cost reductions for one energy technology can be only a clear signal for technology improvement under the condition that its other techno-economic characteristics do not degrade. For example, an energy store only clearly improves if the cost reduces at least for one component such as charger, store or discharger, while the other component costs and efficiencies are not negatively influenced. If this is not the case, a complex solution space exists for which a more costly energy storage can lead to lower total system cost, and hence, being more valuable, see Section 4.3.

5.4 Profit analysis

The profit analysis describes methods from the investor's perspective. They tend to choose profitable energy storage projects at current energy market designs [160, 161]. Thereby, the general objective for the investor is to maximise the profit indicator for a given investment.

The inclusion of discharging behaviour and revenue streams are distinctive for profit analysis. Depending on the market design, several different revenue streams for energy storage exist. In the UK, for instance, 14 potential revenue streams exist, such as frequency response provision or wholesale market arbitrage, which can be power (€/kW) or energy (€/kWh) related [146]. In general, not every storage has access to the same revenue streams due to specific characteristics and requirements [147]. Most studies include only the energy arbitrage service from energy storage, which means buying cheap electricity and selling it later more expensive [162]. Other studies co-optimise multiple energy services, which result in higher benefits [162, 163, 164].

The profit analysis typically evaluates energy storage projects with capital budgeting techniques based on discounted cash flow methods to acknowledge the time value of money [156]. The energy storage literature uses multiple project assessment metrics: present value (PV) is employed to calculate the feasible cost of a storage project [160], NPV to evaluate the profitability of a project [144, 151], and IRR to determine at which discount rate or opportunity cost a project is viable [162, 165]. NPV and IRR are good investor signals when investment capital can be accessed easily. However, when investment capital is limited, projects should be evaluated by a profitability index, which relates the discounted benefits to the cost [156]. Many energy storage studies, therefore, investigate energy storage by the profitability index [156], which is also termed cost-benefit ratio [166, 167], NPV-ratio [168], ROI [169], return on equity (ROE) [161], all giving the signal of how much money can be achieved per investment. Another common metric in the context of energy storage is the payback period [165, 170, 171], which [156] judges to be an illustrative but not useful factor for investment decisions. Finally, when multiple energy storage technologies with different lifetimes are evaluated and compared, such as in [144, 167, 171], an equivalent annual annuity metric is recommended [156]. For instance, one could break down the NPV to an equivalent annual annuity where the highest annuity is the preferable project.

The main limitation of the profit analysis is that it misses the 'hidden' or broader power system cost and benefits of energy storage. Because it only focuses on the 'visible' cost and benefits at the current market design. Future energy markets might internalise 'hidden' benefits, such as shown in market design efforts to address the previously hidden greenhouse gas emission costs. Hidden costs and benefits are, for instance, savings due to investment deferral of network upgrades or peak plants, or when fewer curtailments increase the value of renewable generators [172]. Employing a hybrid method of profit and system-value analysis, the authors in [151] added social or 'hidden' benefits to the NPV metrics, which are not directly accounted for in the market design. This lead to a higher value of energy storage solutions. The drawback of the approach is that many assumptions are made and added exogenously to the NPV characteristics ignoring the spatial and temporal heterogeneity of the hidden cost and benefits. What may be a reasonable assumption at one location at a specific time must not be the case at another location at the same or another time. Including these variables endogenously, as some energy system models do, can help anticipate better infrastructural changes and reduce risks.

As a result, the profit analysis is a useful method to investigate a storage project's value and competitiveness at present for a specific location at current market designs. This might be sufficient for investors to assess short-term projects at specific locations. However, when one looks at the value of energy storage in the long term or across many regions, the following system-value approach can give some extra insights.

5.5 System-value analysis

As previously stated, the system-value analysis estimates the value of energy storage which are 'visible' and 'hidden' at existing markets, for longer time horizon and large spatial regions by considering perfect and complete markets in the analysis. Energy system models are used for the system view, which optimises investment and operation of generators, networks and storage or demand response units at the same time to accomplish the objective of minimising total system cost. The results of such analysis are nowadays mainly applied for policy recommendations. However, they also reveal insights for technology design. For instance, it was found that high capacity factor wind turbines can be equally desired in an optimal energy system as their less capital intensive alternative technology with lower capacity factors – having smaller hub heights and shorter blade lengths [21, 173].

The system-value approaches are important to identify the benefits of energy storage. Which benefits are considered depends on the energy system model design. For instance, [13] neglects network expansion, missing significant network expansion cost savings from storage deployment [10]. On the contrary, the authors in [10, 174] use a model that incorporates generation, network, and system operations savings from energy storage in the UK.

The WSB given in €/year and the marginal WSB given in €/kW or €/kWh are two inspiring concepts how to attach a system-value to the energy storage in power systems [10, 13, 175, 176]. Both concepts share a comparison of a none or existing storage scenario with one that includes an energy storage expansion. Such approaches are also known as counterfactual scenarios [17]. Thereby, the total system cost difference between the scenarios is the WSB that the energy storage creates [174]. When the marginal WSB curve, given in €/kW or €/kWh, is integrated by the respective storage unit (in kW or kWh), then the WSB is obtained. The marginal WSB is described as vital since it provides the upper-cost limit for energy storage for a given amount of installed storage [177]. Only if the marginal value is above its marginal cost, the storage is an economically viable option and should be installed. Additionally, to the WSB and its marginal value, the authors in [177] extended the concept by the differentiation of the benefits in net and gross benefit. The gross benefit excludes the investment cost of energy storage, while the net benefit includes them. Thereby, the gross value method is used to benchmark how much the cost can rise for a given technology. The net benefit analyses the holistic value for a specific storage case.

Both WSB methods above lead to insightful results. For instance, (i) that every additional installed energy storage capacity decreases its marginal value; (ii) that the value of energy storage can suffer from competition with other flexibility providers, such as demand response or bi-directional charging of electric vehicle; and finally (iii) that energy storage benefits can be decomposed into its origins such as network and peak capacity savings [10, 174].

The drawback of the WSB approaches is that they are unsuitable as evaluation metrics to signal between multiple storage alternatives what technology is more competitive. The WSB approaches seem to work correctly only for a single energy storage design. When multiple energy storage units are included in the WSB analysis at the same scenario and with variable sizing for each location, it becomes difficult with counterfactual approaches to allocate benefits. Or, in other words, it becomes unclear which energy storage at what location is responsible for certain energy storage benefits at a specific time. As a result, WSB approaches cannot assign a value to one particular storage or compare multiple storage technology candidates.

5.6 Conclusion

This study observed that most energy storage technologies are designed with the aim to reduce their component or storage system costs, however this approaches ignore energy system interactions. Similar, the profit analysis is excellent to explore the value of single storage projects under existing market condition, but is limited when exploring future market potentials with larger system interactions. Lastly, system-value approaches aim to acknowledge wider energy system interactions, however, existing approaches are not practical for technology evaluation as they can only evaluate single storage technologies.

In the next chapter "Demonstrating the Market Potential Method in Europe", a new method is introduced that extends existing system-value literature to also enable the system-value assessment for multiple energy storage. This novel approach is compared with traditional cost evaluation methods in a European power system model.

6 Demonstrating the Market Potential Method in Europe

> *Sharing is good, and with digital technology, sharing is easy.*
>
> — **Richard Stallman**
> Software engineer

Contents of this chapter are based on

Maximilian Parzen et al. “Beyond cost reduction: improving the value of energy storage in electricity systems”. In: *Carbon Neutrality* 1.1 (July 2022), p. 26. DOI: 10.1007/s43979-022-00027-3. URL: https://doi.org/10.1007/s43979-022-00027-3. GitHub: https://github.com/pz-max/unintended-storage-cycling

Declaration

I carried out all study elements. Co-authors mainly provided reviews and suggestions.

Infobox

A thesis outline is given in section 1.3 that contextualise the chapters.

Abstract

From a macro-energy system perspective, an energy storage is valuable if it contributes to meeting system objectives, including increasing economic value, reliability and sustainability. In most energy systems models, reliability and sustainability are forced by constraints, and if energy demand is exogenous, this leaves cost as the main metric for economic value. Traditional ways to improve storage technologies are to reduce their costs; however, the cheapest energy storage is not always the most valuable in energy systems. Modern techno-economical evaluation methods try to address the cost and value situation but do not judge the competitiveness of multiple technologies simultaneously. This chapter introduces the 'market potential method' as a new complementary valuation method guiding innovation of multiple energy storage. The market potential method derives the value of technologies by examining common deployment signals from energy system model outputs in a structured way. This work applies and compares the new method to cost evaluation approaches in a renewables-based European power system model, covering diverse energy storage technologies. The chapter shows that characteristics of high-cost hydrogen storage can be more valuable than low-cost hydrogen storage. Additionally, it reveals that modifying the freedom of storage sizing and component interactions can make the energy system 10% cheaper and impact the value of technologies. The results suggest looking beyond the pure cost reduction paradigm and focus on developing technologies with suitable value approaches that can lead to cheaper electricity systems in future.

6.1 Introduction

In the face of global ambitions to reduce greenhouse gas emissions, the energy transition characterised by increasing shares of wind and solar power will benefit from more energy storage in the future electricity system [10, 13, 178]. How many benefits can be delivered by energy storage depends, among others, on how future technology will be designed. Consequently, research and development (R&D) must evaluate the techno-economic design of energy storage systems to be most beneficial.

A traditional technology evaluation approach is to reduce the cost of its devices [179]. For energy storage, these costs can be defined as absolute costs (€), or relative to energy (€/kWh) or power (€/kW) quantities. In particular, in the material science and chemistry literature, cost reductions of energy storage are a pivotal element, alongside maintaining other storage characteristics such as a 'sufficient' high efficiency, power and energy density, and safety [180, 181]. Though, what is 'sufficient' high is often unclear. Only if one energy storage outperforms the other in all characteristics it represents a superior technology; otherwise, more expensive energy storage with suitable technical characteristics can compete as well (as will be demonstrated in Section 6.3). Similar, evaluation techniques exist that aim to maximise the profit, however, these are mostly suitable to evaluate single projects (see review in Section 5.1). Fortunately, material science literature has recognised one of the key challenges that energy storage depends on different applications and the interaction with the energy system [182].

Alternative technology evaluation approaches use energy system models. These tools describe energy systems mathematically and capture system-values arising from storage interactions with the wider energy system (see Section 5.1 for more details). Some studies applying energy system models focus on storage technology evaluation and guidance. For instance, [176] explores the design spaces for long-duration energy storage, [10, 13, 175] explore the system-value of generic storage technologies and [174] explores technology specific system-values of liquid-air energy storage and pumped-thermal electricity storage. A limitation of these studies is that counterfactual scenarios constrain this analysis type to single generic or rigid storage examples making the evaluation results questionable.

This study introduces as technology evaluation approach the 'market potential method' which can be described as systematic deployment assessment. Different to classical market potentials that are derived from energy system models which quantify mainly system effects [183], this work focuses on the systematic assessment of market potentials to evaluate energy storage technologies (see Section 6.2.1). This approach overcomes the previously described limitations and simultaneously analyses multiple and more-flexibly sized energy storage. As discovered later in Section 6.3, reflecting competitive situations and unique constraint demand and supply mismatches in macro-energy systems are important factors that can affect the system-value of energy storage.

The contribution of this work to existing literature is as follows:

- It reviews and discusses techno-economic approaches that are currently used to evaluate and compare energy storage technology in Section 5.1. It includes cost, profit and system-values analysis.

- It shows that current cost metrics can be misleading for technology design decisions. Section 6.3.2 and 6.3.3 show that a high LCOS hydrogen storage can be equally or even more valuable than a low LCOS one from the system perspective. The conclusion is drawn by observing the deployment of low and high LCOS hydrogen storage systems in a least-cost power system investment planning model.

- It extends system-value approaches by the newly developed 'market potential method' in Section 6.2.1. It is further applied and discussed in Section 6.3. The market potential method systematically evaluates deployment estimations from energy models by looking at a set of probable scenarios in high spatial-temporal resolution over large regions such as Europe. Compared to existing alternatives that are described in Section 5.1, the new approach could be potentially more useful and overcomes many limitations. Research and industry could apply the new approach as a complementary tool to guide energy storage innovation.

- It shows that modifying the freedom of storage sizing and component interactions can lead to significant energy system benefits (Section 6.3.1) and impact the system-value of a technology (Section 6.3.3). It underlines the impact of developing and offering adaptive components, such as charger, storage and discharger, separately instead of complete storage systems.

In this study, not all energy values are included. In general, energy storage systems can provide value to the energy system by reducing its total system cost; and reducing risk for any investment and operation. This chapter discusses total system cost reduction in an idealised model without considering risks. Reducing risk in power systems can be seen as option value [10] leading to a more beneficial investment and operation. Furthermore, only energy balance benefits within a European power system model are included, ignoring other energy sectors apart from the electricity sector. This study neglects sub-hourly signals relevant to address grid stability benefits, but includes hourly up to seasonal arbitrage based scarcity signals relevant to address short and long-term balancing benefits (described in Section 6.2.3).

Our findings suggest that a narrow cost focus on designing energy storage is not enough. Future R&D design decisions should additionally use system-value insights from energy system models. The presented market potential method could be one approach to accomplish this.

6.2 Methodology

The methodology section is built up as follows. First, the new system value assessment method, the 'market potential method' is defined in theory. Second, an experimental model setup for hydrogen and battery storage is described that compares cost and system-value analysis approaches. Finally, to carry out the experiment, the power system model PyPSA-Eur is introduced with its problem formulation, set of scenarios and model input data.

6.2.1 Market potential method

The 'market potential method' attempts to expand the existing system-value methods to give more useful signals of which storage technology is valuable in existing or future energy systems. Figure 6.1 illustrates that the 'market potential method' consists of: first, the 'market potential indicator', which corresponds to the expanded power or energy capacities of a storage component such as charger, discharger or capacity unit; second, the 'market potential criteria' which seek to support design-decision making of storage technologies.

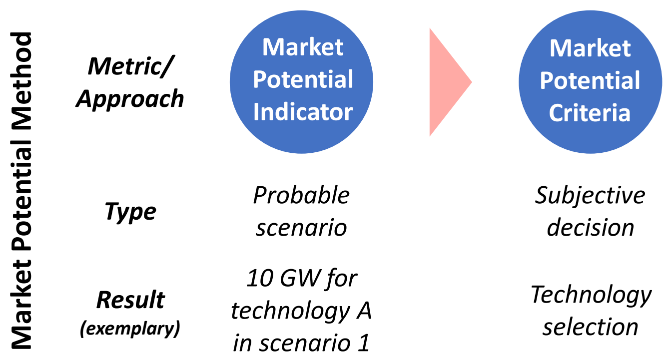


Fig. 6.1.: High-level description of the Market Potential Method. First a market potential indicator is derived for a single or multiple possible scenarios. The market potential indicator is then used by an entity through a market potential criteria to support design-decisions making on energy storage technology.

Market potential indicator

The foundation of the introduced method is the MPI. The MPI is not a new metric. It is a result of energy system models that analyse scenarios in future energy systems and describes the total quantity of a particular storage technology in a cost minimised electricity system [13, 184, 185]. However, the MPI has never been a central metric to improve, compare and explore storage designs in detail; it was rather used to inform policymakers and market participants about probable energy futures to reduce investors' risk [185]. The work utilises the MPI to guide technology innovation with probable scenarios and market potential criteria.

The market potential can be either aggregated or disaggregated. In the context of energy system models, this thesis defines the disaggregated MPI of a storage unit as optimised (or expanded $t - t_0$) power or energy-related size at a region. Thereby, the market potential focuses on the storage component c, representing a charger, discharger or store unit. The over a region i aggregated MPI is determined by:

$$\mathrm{MPI}_{t-t_0,c} = \sum_{i \in \mathbb{N}} (\mathrm{MPI})_{t-t_0,c,i} \qquad [MW \ or \ MWh] \tag{6.1}$$

It is crucial to consider the MPI by components rather than by a fixed-sized storage system for mainly two reasons. First, grid-scale energy storage can be highly scalable and adaptable [14, 186]. For instance, electrolysers (MW), steel tanks (MWh) and fuel cells (MW) composing hydrogen storage systems can be freely scaled and combined. Moreover, in a H_2-hub operation, two different electrolysers could feed the same H_2-storage tank. Second, energy storage system components–for instance, hydrogen–are not required to be at one location. Indicated by [155], hydrogen pipelines can become an economically viable option when large amounts of hydrogen need to be transported. Its integration means that hydrogen electrolyser and fuel cell are not required to be located in one place. Consequently, because storage components can be independently scaled, adaptable in operation and do not require co-location, it seems advisable to optimise them separately.

Scenario selection and dealing with uncertainty

The use of energy system models is subject to uncertainty as predicting the future with certainty is impossible. It is impossible because one can make decisions that impact the future, such as done by agreeing on multilateral CO_2 targets, which improved renewable energy deployment and led to learning by doing cost reductions effects [179]. Nevertheless, analysing a broad range of future scenarios can reduce uncertainty [15].

The market potential method in linear programming models relies on possible and probable scenarios. Many different ways exist to create 'possible' scenarios which differ in the set of deterministic input assumption and constraints [15, 187]. However, a possible future does not necessarily mean that it is a probable one. A good approach to develop scenarios that can be expected in future is to follow the ones which are provided and encouraged by either national or multinational institutions - and engage in public consultations if they require changes [185]. An example of the latter one is the European Network of Transmission System Operator for Electricity (ENTSO-E) which provides updates on multiple pathway scenarios every two years based on storylines towards the European agreed targets - known as Ten-Year Network Development Plan (TYNDP) [185]. Transparency in energy modelling, also from trusted institutions, is a key requirement to lower uncertainty [35].

Scenarios can be additionally selected to investigate multiple technology designs. For instance, technology manufacturers might be interested in such analysis to guide energy storage innovation.

This study includes three different hydrogen design constraints and two different charger and discharger technologies for technology assessment, which are described in more detail in Section 6.2.3. While this study uses an exemplary 100% GHG emission reduction scenario that is sufficient for the research purpose, future work should include probable scenarios such given by national or multinational institutions like ENTSO-E.

Market potential criteria

The 'market potential criteria' give the market potential indicator its meaning and can help with decision-making. The criterion includes two simple rules. In an optimised energy system model with many if not all technological alternatives, the technology with:

- $MPI = 0$, for one scenario is probably not valuable.
- $MPI > 0$, for one scenario is probably valuable.

Additionally, the positive MPI magnitude can be used as supportive decision criteria to deal with uncertainty. This can be, for instance, the 'threshold' or the 'bigger is better' rule described below:

- $MPI > X$ or 'threshold rule'. Where a company or institution decides what minimum market potential X must be achieved. For instance, an alkaline electrolyser needs to have a market size of 1 GW to be an attractive technology for a company.

- $MPI_A > MPI_B$ or 'bigger is better' rule. If two technologies A and B are compared, the one with higher market potential is more likely to be valuable.

In particular, when the evaluation condition appears in multiple scenarios, it reduces the uncertainty of the statements. For instance, when hydrogen storage is significantly optimized in all scenarios it is a clear indicator that it is likely that the technology is valuable in many different probable futures.

Figure 6.2 illustrates how the market potential criteria could be applied as a decision support tool. The illustrative example could lead to the anticipative decision of a technology manufacturer or research institution to focus rather on the first two technologies than the latter ones.

Only with the criteria one can systematically analyse the market potential indicators and reduce risk. Together, the market potential indicator and criteria build the market potential method.

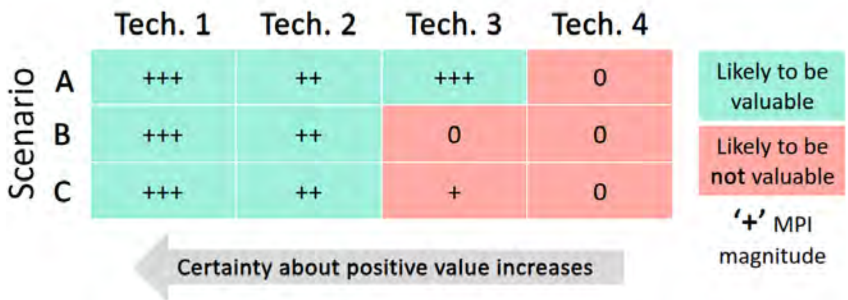


Fig. 6.2.: Qualitative illustration of market potential criteria applied to a set of scenarios and technology options. The "+" indicates the MPI magnitude. Additionally, the threshold rule is set to a single plus, meaning that a company requires at least two plus to consider a technology as a potential candidate to manufacture or start R&D activities.

6.2.2 PyPSA-Eur. Model structure and data

The open European transmission system model PyPSA-Eur is adopted to determine the value of various energy storage systems in a European electricity system. PyPSA-Eur is an adaptable investment and dispatch model built on the core model PyPSA

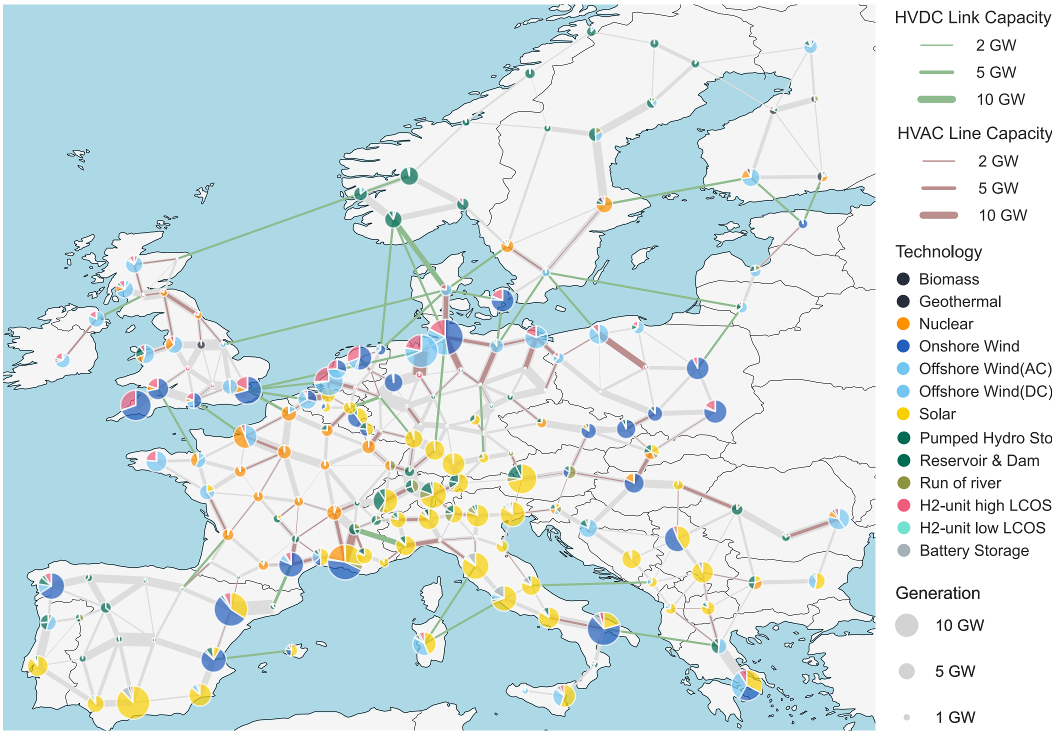


Fig. 6.3.: Optimal generation, storage and network expansion under a 100% emission reduction scenario and technology data for 2030. Light grey lines showing the existing installed network capacity, dark grey lines the additional expanded capacity. Plot produced with PyPSA-Eur.

that combines high spatial and temporal resolution. The suitability of PyPSA-Eur for operational studies and long-term power system planning studies is described in [24, 25, 33]. This section briefly introduces the model structure and applied data. The full model formulation of PyPSA-Eur is given in the Section 2.3.

PyPSA-Eur covers the European transmission model and processes electricity system data from diverse sources. Existing conventional generators, transmission lines, substations, and hydro storage systems, as well as planned network reinforcements, are included with their size and location. Wind and solar based technologies are greenfield optimised, which means that existing solar and wind capacities are disregarded. The time series for wind and solar generators are derived from satellite and earth observatory data [24]. Regarding power demand, the load time series are collected from ENTSO-E data for each country and redistributed by GDP and population over the regions. A spatial resolution of 181 nodes matched with an hourly resolution across an entire year accounts for the complex spatio-temporal patterns of renewables and grid congestion events that shape investment decisions [72].

In terms of market economics, the model assumes perfect competition and foresight for one reference year. A detailed model description and formulation is included in [19, 24, 25, 63]. Here, only key features and constraints are highlighted. The model's objective is to minimise the total system cost in the European electricity system at the transmission level. The total system costs consist of

- investment costs, which includes the annualised capital cost of onshore and offshore wind turbines, storage components and both HVAC and HVDC transmission lines, and
- operating costs, which includes fixed operation and maintenance, and variable operating cost.

The objective is subject to

- nodal power balance constraints that guarantee that supply equals demand at all times,
- linearised power flow constraints modelling the physicality of power transmission,
- Solar and wind resource constraints that limit the theoretical generation time-series. Here a single weather year is chosen for the analysis; however, this can be extended for a more robust prediction of weather year anomalies or variations [188].
- Renewable availability constraints which restrict solar and wind technical potential based on environmental protection areas, land use coverage and distance criteria.
- Emission constraint introduces a limit of carbon dioxide CO_2 equivalent emission in the model that impacts technology investment and generation.

The model has many adjustable constraints. This study, similar to many others such as [189], does not include the available Unit Commitment (UC) constraints. In fact, UC constraints are becoming increasingly negligible in future energy systems with increasing shares of renewables and energy storage. Mainly, because it was observed that they only have minor impacts on investment and operational outcomes [189]. Further, UC constraints introduce extra computational burdens by the mixed-integer formulation, which removes model convexity and, hence, leads to a nonlinear program that requires more effort for solving. Therefore, this work excludes UC constraints due to their minor impact on the results and large impact on the already heavy computational requirements for the optimization (8 cores, 180 GB RAM solved for roughly 13h with Gurobi). Nevertheless, if a more detailed technological performance in a high renewable electricity system with flexibility constrained nuclear power plants is essential, this UC formulation could be included.

For the input cost and technical assumptions, the documented dataset provided in [87] is used, referring to an electricity system scenario in 2030. The following analysis only adjusted the dataset of [87] by the battery and hydrogen storage system inputs summarised in Table 6.1 and Table 6.2.

Tab. 6.1.: Power related energy storage model inputs representing 2030 data

Energy storage components	Electrolysor		Fuel cell		Battery Inverter
LCOS Scenario	[Low]	[High]	[Low]	[High]	[-]
Investment $[EUR/kW_{el}]$	339	677	339	423[b]	209[c]
FOM[a] $[\%/year]$	2	3	2	3	3
Lifetime $[a]$	25	15	20	20	10
Efficiency $[\%]$	68	79	47	58	90
Discount Rate $[\%]$	7	7	7	7	7
Based on Ref.	[148] Alkaline	[148] SOEC[d]	[190] PEM[e]	[190, 191] SOFC[f]	[191, 192] Li-Ion Battery[g]

[a] Fixed operation and maintenance cost as percent of the annualised investment costs
[b] Includes fuel cell stack replacement after 10 years which cost 30% of initial cost
[c] Includes 80 EUR/kW balance of plant, mainly assigned to wiring and connection [192]
[d] Solid-Oxide Electrolyser
[e] Proton Exchange Membrane or Polymer Electrolyte Membrane
[f] Solid-Oxide Fuel Cell
[g] Lithium-Ion Battery

Tab. 6.2.: Energy related energy storage model inputs representing 2030 data

Energy storage components	H_2 storage		Battery storage
LCOS Scenario	[High]	[Low]	[-]
Investment $[EUR/kWh_{el}]$	8.4	8.4	188[b]
FOM[a] $[\%/year]$	-	-	-
Lifetime $[a]$	20	20	10
Efficiency $[\%]$	-	-	-
Based on Ref.	[191] H_2 steel tanks	[191]	[192] Li-Ion Battery

[a] Fixed operation and maintenance cost as percent of the annualised investment costs
[b] Includes 81 EUR/kWh for engineering, procurement and construction costs [192]

6.2.3 Energy storage scenarios

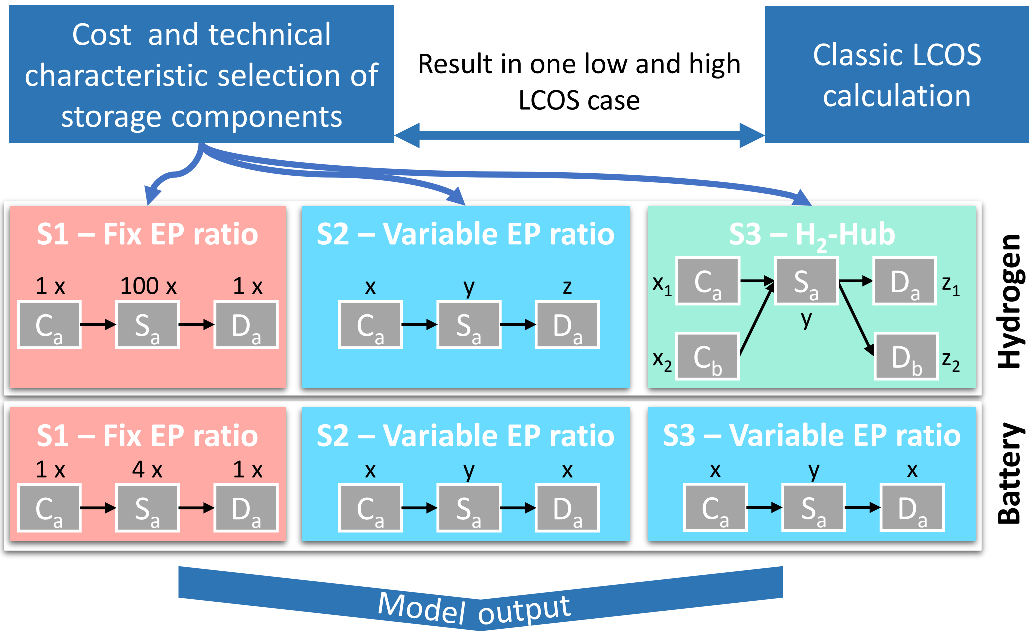
This study looks at three different constraint energy storage scenarios in one fully emission-free energy system scenario. As explained in Section 6.2.1, one energy system scenario is just exemplary chosen and sufficient for this research. Multiple system scenarios from trusted organisations such as ENTSO-E should be applied if technology decisions are made with the Market Potential Method (MPM). As mentioned in [21], the energy technology impacts the system value, however, the energy system layout and constraints also impact the technology value. Therefore Section 6.2.1 goes through the main scenario design elements, the energy system and storage scenario design.

Starting with the energy system layout and constraints, Figure 6.3 shows an example of the optimised European electricity landscape for the variable energy-to-power ratio scenario, which is minimised in terms of total system costs in a 181 bus spatial resolution. One should note that the network structure is based on ENTSO-E data which is aggregated to show realistic line capacities between the buses.

Different to [36], the scenarios include the existing European nuclear power fleet but acknowledge the German, Spanish, Belgium and Swiss nuclear exit. The inclusion of nuclear power plants reduces the required VRE capacity expansion and, at the same time, increases the share of dispatchable power plants – a measure that reduces energy storage demand. However, the flexibility of nuclear plants is overestimated in this study as typical ramp rates reaching up to 36%/h and minimum allowable power of 20% per nominal power [193] are ignored. However, this chapter ignores such unit commitment constraints to keep the model formulation convex and reduce the number of variables for computational speed (see more details in Section 6.2.2). It implies that this study will tend to underestimate the energy storage potential.

Further, similar to [63], an equity constraint is included that requires every country to produce at least 80% of its total electricity demand, leading to a smooth distribution of generators across all of Europe. This constraint is motivated by the fact that political leaders avoid depending entirely on electricity imports but are willing to trade considerable amounts to handle the trade-off between the economic benefits of importing cheaper electricity and the sometimes costly independence of supply such for isolated networks.

The network expansion is constrained to a volume of 25% compared to the existing network capacity, acknowledging the increasing political difficulty to develop new transmission lines. A limited network expansion can potentially lead to higher storage demand [19]. Further constrained are hydro storage technologies. While



LCOS ranges + market potential indicator

Fig. 6.4.: Description of the three storage scenarios. The cost and technical storage parameters are chosen once and serve as input for all storage scenarios. Scenario 1 shows the fixed energy-to-power ratio of the hydrogen and battery unit a. In Scenario 2 and 3 all components can be freely scaled. However, the battery is constrained to the same charger to discharger ratio. Further, the 'b' in the $H_2 - Hub$ scenario indicates a new technology addition. A least-cost optimization is run with each scenarios, whose results are used to create the spatially resolved LCOS and market potential signals.

these are based on actual power plant data, no further capacity expansion is allowed due to natural limitations in most regions.

The energy storage scenario design is described in Figure 6.4. First, technical and economic parameters are chosen as model input for each storage component (see Table 6.1 and Table 6.2) to represent a low and high LCOS case for classical LCOS calculations. Afterwards, the resulting techno-economic details are inserted in the model environment into three scenarios. The scenarios differ mainly in technological design freedoms. 'Fix EP ratio' is the most constrained energy storage scenario having a fixed energy-to-power ratio of 100 h for the hydrogen and 4h for the battery storage technology – such as applied in a similar range in research [147, 160, 194]. Similar to previously mentioned research publications, this fix EP scenario also assumes that charger and discharger size are equally sized. Otherwise, 'Variable EP ratio' optimises for the hydrogen storage unit each component size, charger, storage and discharger so that the energy-to-power ratio is variable. Here, the battery remains constrained in flexible sizing as charger and discharger represent the same component, namely the inverter, so that the battery storage can only size inverter and battery capacity related design separately (see Battery component size variables x, y, x in Figure 6.4). While both fix and variable EP ratio scenario optimise low-LCOS and high-LCOS hydrogen components separately, the 'H_2-Hub' scenario permits cross operation of hydrogen technologies. This can be considered a H_2-Hub, having at one location techno-economically different low and high LCOS charging and discharging technologies that operate the same hydrogen storage. After applying the scenarios in the optimization, the model results are used to create the spatially resolved LCOS and market potential signals which are further discussed in Section 6.3.

This study creates energy storage scenarios that focus on energy arbitrage benefits under spatially resolved perfect and complete markets. Scarcity signals relevant to seasonal balancing are considered through 'unconstrained' locational marginal prices, also known as nodal prices. These nodal prices can increase to extremely high prices such as more than 20000€/kWh and let energy storage be optimised as a seasonal reserve, shifting cheap energy of one season to times of high prices. As introduced in Section 5.1, the complete market considerations include the often unaccounted or 'hidden' values of energy storage systems, such as:

- Avoided investment cost of network expansion
- Avoided investment and operational cost of dispatchable generators
- Increased power plant utilisation/ less curtailment

Emission targets play for the energy storage market potential a vital role. To keep the comparability between scenarios and a decent amount of market potential for energy storage, this chapter sets in all scenarios the CO_2 emission reduction target to 100 %.

6.3 Results and Discussion

6.3.1 Relaxing design constraints of energy storage and its benefits

As introduction to the cost and value analysis scenarios, this section discusses the impact of design freedom on the storage components and the total system.

Increasing design freedom of energy storage can lead to significant benefits in the electricity system. When investigating the competitiveness of energy storage, many studies assume that the energy-to-power ratio is fixed [13, 158]. However, assuming a fix energy to power ratio on a continental scale is an unrealistic extreme as well as assuming that all market participants choose the perfect sizing for the market.

Table 6.3 shows that the increasing sizing complexity, however, seems worthwhile to consider as it can lead to per annum total system cost savings of approximately $13B$€or 10% in the modelled zero CO_2 electricity system scenario while not leading to significant generation portfolio changes (see Figure 6.5). Looking at the generation portfolio, the optimization result are representing currently installed power plants in the EU for nuclear, biomass and run-of-river [81]. This analysis prohibits these technologies from additional expansion to replicate political constraints. That is why they are not increasing in volume. Similarly, these technologies are not decreasing in volume because they are optimized and, hence, desirable options in the given least-cost scenarios. While geothermal is allowed for expansion it does not expand in future scenarios. This indicated that the technology does not contribute to the least cost optimization result for the existing cost assumptions in the power only scenario. Note that this result might change when changing assumptions or adding sectors such as heating and cooling.

The total system cost thereby includes the optimisation relevant costs, which consist of newly installed generation, storage and network components, including any operational costs. Another approach to comprehensively quantify the savings is by calculating the relative investment cost, which divides the total system costs by the total electricity demand. It shows that the introduction of optimised sizing can lead to electricity bill savings of roughly half a cent, with the H_2-Hub scenario contributing only to negligible more savings. As a result, increasing design freedom of energy storage can be desirable for a cheaper electricity system and should be considered while designing technology.

Tab. 6.3.: Annual total system costs, relative investment and curtailment data. Variable sizing of energy storage reduces the system costs by 10%.

Scenario	Total system cost	Relative investment[a]	Curtailment [% of annual demand]
Fix EP ratio	152.9 B€	4.874 ct/kWh	0.61%
Var EP ratio	139.9 B€	4.460 ct/kWh	0.73%
H2-hub	139.7 B€	4.453 ct/kWh	0.37%

[a] Total system cost per annual demand

The optimal storage design depends on location and technology. Figure 6.6 shows the EP-ratio for multiple locations and technologies with relevant market potential in an optimal European future scenario.

Hydrogen chargers are smaller sized, and reveal a wider span of EP-ratios than their discharger opponents, which means that slow charging and quick release seem to be beneficial from an EU system perspective at most locations. Further, the Li-Ion batteries are optimised with a 2-4 h EP-ratio, much smaller than the hydrogen components. The reason for that heterogeneous design is that local diverse electricity system situations with its network constraints, supply and demand curves, as well as the different storage characteristics (see Table 6.1 and 6.2) benefit from a variety of storage scaling to reach an optimal solution that minimises the electricity bills.

6.3.2 Static LCOS vs modelled LCOS

The LCOS is currently an influential metrics to benchmark technology and to discuss their competitiveness. Therefore it is not surprising to see that technology design is even optimised for minimum levelised costs (see Section 5.1). To show the drawbacks of this measure, static and modelled values are calculated according to the methodology described in Equation 5.1.

The main difference between static and modelled LCOS is what assumptions are used. The static LCOS calculation uses directly assumed or exogenous variables such as for full load hours, electricity prices and energy-to-power ratios. In contrast, the modelled LCOS is based on endogenous variables determined by the energy system model and its inherent assumptions. It means that full load hours, electricity prices

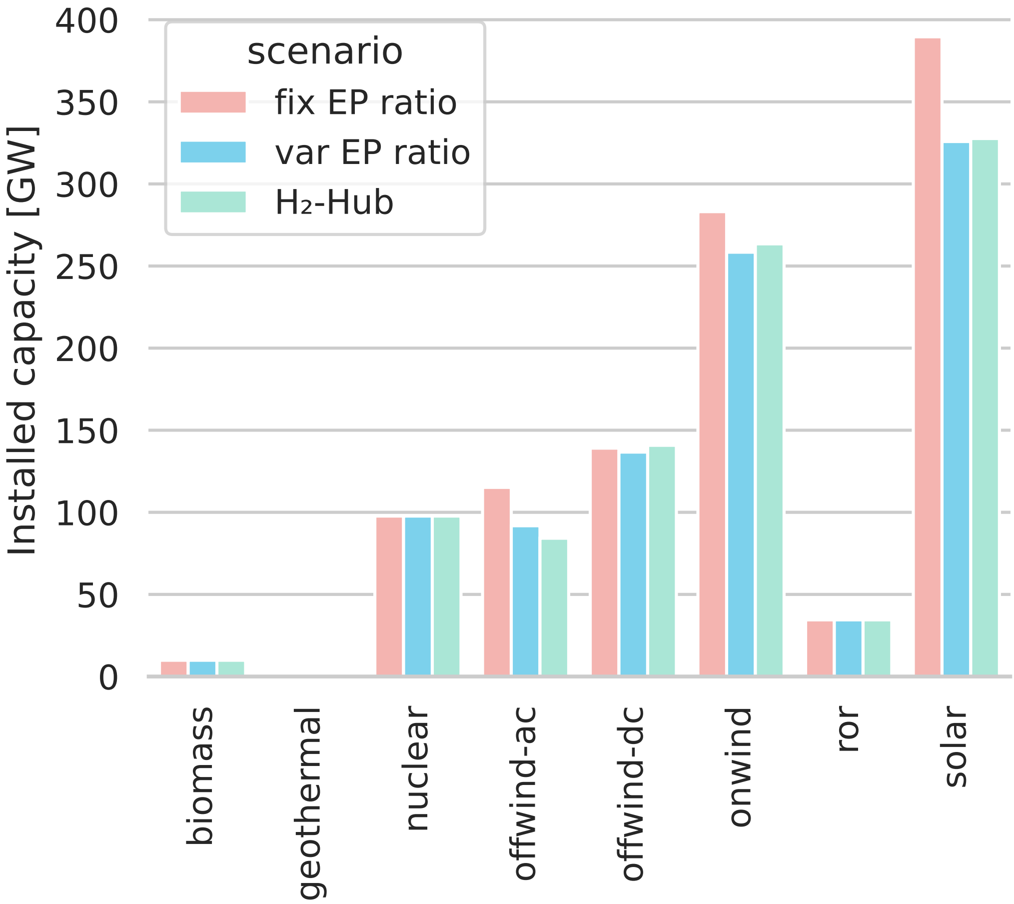


Fig. 6.5.: Optimization result for future installed generation capacity in the exemplary 100% emission reduction scenarios. The abbreviations 'ror' stands for run of river, offwind-ac and -dc for AC and DC connected offshore wind plants, respectively.

and energy-to-power ratios are determined for each location by the European power system model.

The static LCOS is calculated with the technical and economic component characteristics in Table 6.1 and 6.2, and the LCOS assumptions given in Table 6.4. The results of the static LCOS calculation also given in Table 6.4 show a 19.2% or 5 ct/kWh difference for the two hydrogen storage units, whereby the battery storage seems much more competitive.

In contrast, the modelled LCOS results are given in Figure 6.7 for most buses in the EU electricity system for the 'variable EP ratio' scenario. Despite having the same input cost, lifetime, discount factor and efficiency data as the static LCOS calculation, a wide LCOS range can be observed for each optimised storage unit which consists of charger, storage, discharger. The LCOS ranges are roughly between 20-100, 20-55

Tab. 6.4.: Additional inputs for LCOS calculation oriented on [147] and [160]

	Hydrogen storage		Battery storage
LCOS scenario	[Low]	[High]	[-]
Discharging ratio $[h]$	100	100	4
Electricity price $[Eur/MWh]$	50	50	50
Yearly full load hours $[h]$	2500	2500	3400
Roundtrip efficiency[a] $[\%]$	32.0	45.8	81,0
Lifetime $[a]$	25	15	10
Static LCOS[b] $[ct/kWh]$	0.21	0.26	0.12

[a] calculated product from energy storage component efficiencies in Table 6.1
[b] calculated with Equation 5.1, and inputs from Table 6.1 and 6.2, 6.4

and 4-14 ct/kWh for the low, high LCOS H_2 unit and the battery. One reason for the wide LCOS ranges is the heterogeneous charging and discharging behaviour, which is indicated by diverse full load hours observed between 80-3000h; another one, the heterogeneous nodal prices or electricity price profiles at each region; and, finally, the heterogeneous sizing of the storage chain. While the battery technology seems more competitive under the LCOS framing, it becomes ambiguous for hydrogen with the overlapping LCOS ranges.

A minimum LCOS metrics as a solely technology design objective is not enough to argue about competitiveness. Regardless of the low or high LCOS indication, the 'variable EP scenario' shows that all included energy storage technologies are valuable. As noted earlier, this chapter defines a technology as valuable if it reduces the total system costs. This is the case if a technology is part of an optimised energy system. In Figure 6.7, all technologies reveal a market potential indicating to be required assets to achieve the minimum total system costs. As a result, instead of improving energy storage by minimising the LCOS, one could maximise the system-value and assess the market potential indicator. Why reducing the total system cost should also be in the interest of technology developers will be discussed in Section 6.3.4.

6.3.3 Market potential method as value indicator

This section reveals the market potential indicator for each technology and scenario and evaluates it exemplary with the market potential criteria. Exemplary, because as described in Section 6.2.1 the MPM scenarios should be chosen according to institutional scenarios or 'beliefs' that might be more likely to impact decision

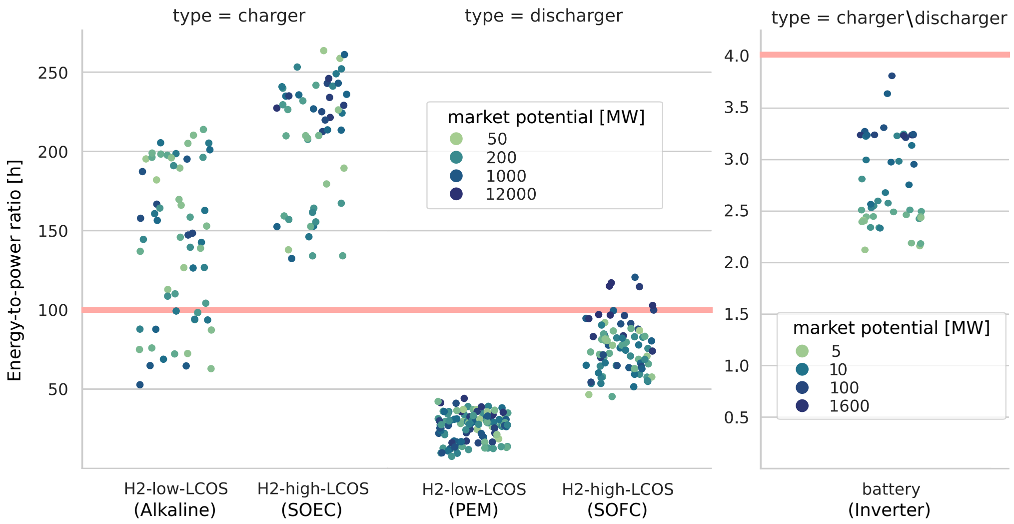


Fig. 6.6.: Optimal energy to power ratio ranges in the variable EP ratio scenario. The red line represents the fixed EP-ratio scenario assumption. The energy to power ratios are very diversely sized in the 181 buses of the cost-optimal European system layout and in regards to hydrogen and not necessarily equal for charger and discharger. The electrolyser capacity is generally smaller than the fuel cell capacity, which means that slow charging and quick discharge at few moments is desired in the system.

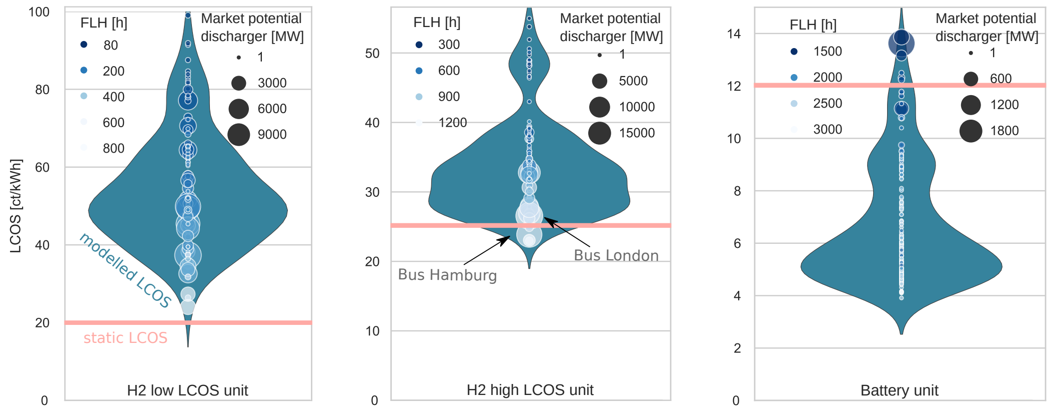


Fig. 6.7.: Static LCOS results compared to European wide modelled LCOS. The static LCOS is marked by a red horizontal line and was calculated for a set of assumption in Table 6.4. In contrast, the modelled LCOS is given as points and uses spatial-temporal dissolved European energy modelling outputs for its calculation. The size of each point shows the optimised market potential of discharger in a given region and helps indicating the relevance. The colour reveals full load hours for each storage technology and helps understanding the operational behaviour which partially lead to the LCOS. The width of the violin plot shows the occurrence in the kernel density estimation, hence, the wider the plot the more buses are located at the respective LCOS cost range. In all cases, buses with less than 1 MW market potential or 80 FLH are removed, keeping the visualisation readable.

making. As noted earlier, the scenario design of this study is described in Figure 6.4 and helps to interpret the results.

Figure 6.8 shows the total market potential indicator for all expandable storage components in the European market. How this market potential can be disaggregated over Europe is demonstrated for chargers and the variable EP ratio scenario in Figure 6.9.

The first scenario shows a fixed energy to power ratio of 100h (10TWh/95GW) for hydrogen technologies and 4h (0.07TWh/17GW) while the charging and discharging market potential are constrained to be equal for one storage unit. In this scenario, the main optimised hydrogen technology is the high LCOS case of the static LCOS calculation, whereby the low LCOS case reveals a negligible market potential. It means in simple terms that the high LCOS hydrogen unit is more likely to be valuable and worthwhile to design or manufacture due to the approximately two orders of magnitude higher market potential.

In the second scenario, when all hydrogen storage components, and the battery inverter to capacity ratio, are independently scalable, one can observe a noteworthy reduction of the market potential of battery components. This means that flexible scaling of storage technologies can reduce the viable market for batteries. Further, the optimised energy to power ratio impacts the market potential for hydrogen technologies. Now, both high and low LCOS technologies possess a good market potential and seem desirable as complementary technologies. However, the variable sizing of hydrogen components leads to a market potential shift from charger towards discharger components. For a fixed, variable and $H_2 - Hub$ scenario, the total amount of hydrogen charger market potential (summing low and high LCOS components) shifts from 95, 68 and 80 GW to a hydrogen discharger market potential of 95, 219 and 211 GW, respectively. This makes the hydrogen discharger components the clear winner of variable sizing through a rough doubling in market potential.

Concerning the $H_2 - Hub$ scenario, when components are variable sized and diverse H_2 electrolyser and fuel cell technologies can simultaneously use the same storage tank, then the storage technologies' market potential changes remarkable again. It makes the before well desirable solid oxide electrolyser as technology almost negligible in terms of market potential.

As a result, the market potential indicator reveals that the design freedom of storage is crucial because it impacts the value assessment. For instance, when variable component sizing is possible, the Proton Exchange Membrane (PEM) fuel cell and the

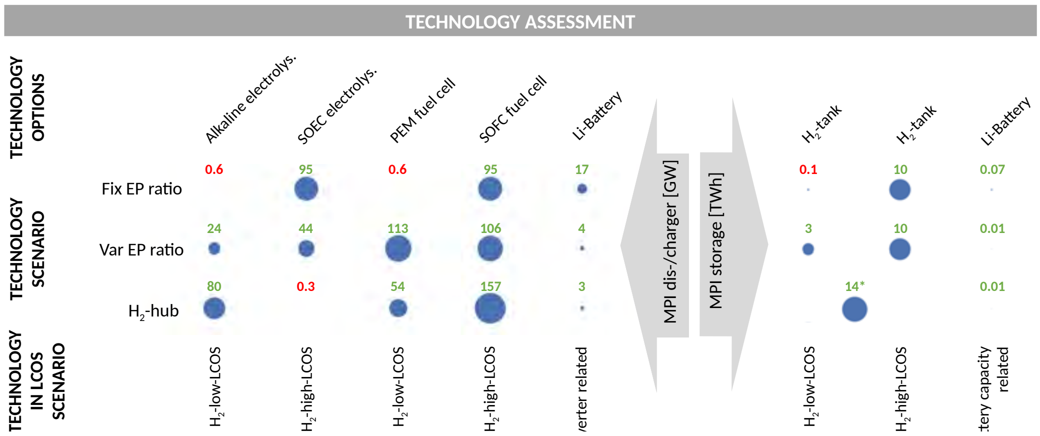


Fig. 6.8.: Market potential indicator for all charging and discharging components in Europe for three technical storage scenarios in a zero emission electricity system. Despite having the same economic and technical input data the market potential vary drastically between the scenarios. The SOFC fuel cell and Li-battery are according to the market potential method, the technologies which are most likely to be valuable in the exemplary set of scenarios. Because they have an optimised market potential indicator in each scenario. *Refers to the total shared storage capacity.

Alkaline electrolyser seem to be more desirable while Li-batteries lose importance in the electricity system.

Applying the full MPM with the market potential criteria leads to the insight that all the implemented storage components can be considered valuable. The value is thereby derived from the fact that at least one scenario possesses a positive market potential indicator. However, only the Li-battery, as well as the SOFC fuel cell, are the most likely valuable technologies as they are optimised in all scenario's and exceed a self-defined 1 GW threshold criteria. As noted earlier, such a threshold might be set by a manufacturer to define a minimal viable market for a technology worth to invest. The knowledge derived from the market potential criteria can lead to implications, for instance, that the Alkaline electrolyser manufacturer can actively mitigate their value risk by promoting variable sizing.

Finally, the presented insights underline the misleading concept of solely cost minimising technologies. Not always a technology with the lowest investment or LCOS is most valuable. It can also be the more expensive technology that can lead to a cheaper future electricity system.

6.3.4 The relevance of the market potential method

The market potential indicator is a helpful metric from a practical and computer modelling perspective for manufacturers, developers and researchers. The most important reason for the usefulness is that the market potential is a driver for business. Successful companies want to generate money for their stakeholders and, hence, are driven by two things, growth and profitability. The market potential indicator for a specific product can relate the growth potential to profitability. For instance, when a company expects to offer a future product for net costs of 10 €/kWh, it could include these costs in the energy system model with a profit and risk premium of 5 €/kWh. The modelling output is the market potential indicator, which is related to the profit and risk premium of 50%. As a result, the market potential method can be useful for growth and profit evaluations of future storage technology.

Second, the market potential can give insights into where growth markets are located and for what reason. This can be achieved since the disaggregated market potential can identify regions with future technology expansion (see Figure 6.9). The electrolyser distribution reveals that in many locations, high and low LCOS units complement each other. Additionally, when storage components are compared to the generation distribution from Figure 6.3, most hydrogen units are co-located at regions with wind plants (mostly northern regions). At the same time, batteries gravitate towards solar plant optimised areas (mostly southern regions). A reason for the observed co-location might be the diurnal solar power pattern and the multi-day to weekly wind power pattern, which creates a network constrained mismatch suitable for the given storage characteristics [195].

Third, the market potential is useful as an indicator of future cost reductions. Because with the market potential, one can assume future technology deployment, which is an implicit factor in learning by doing cost reduction effects [179] or a factor that can be incorporated into process-based cost analysis to evaluate the cost reduction potential [153, 154].

Forth, the market potential can reduce the structural uncertainty of the linear programming energy system model itself. Initial cost assumptions as model inputs are often made without knowing deployment numbers achieved in the optimisation. Nevertheless, it is known that more extensive deployment can reduce costs due to learning effects [179]. Since after the first model run the market potential can function as a cost reduction signal, one can in an iterative or sequential solution approach improve the input accuracy and, hence, lower the structural uncertainty.

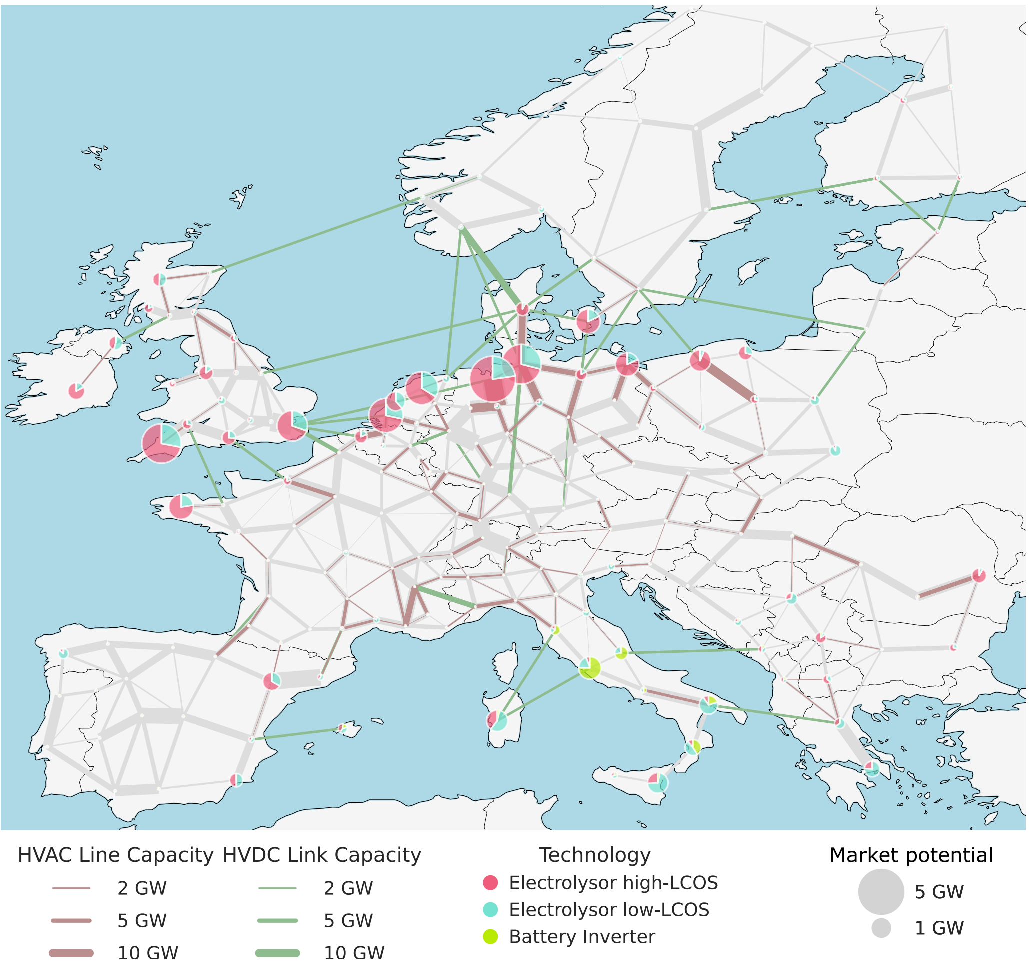


Fig. 6.9.: Optimal energy storage charger distribution in the variable energy to power sizing scenario. Showing the location of market potential in a 100% emission reduction scenario. When compared to Figure 6.3, most hydrogen units are co-located with wind plants while batteries gravitate towards solar plant optimised areas [195].

Finally, the operational behaviour can be analysed with the spatially distributed market potential due to the use of energy system models, which gives operational times series of optimised technologies. These time series can be used to identify operational patterns and full load hours, which might be helpful in technology design decisions.

6.4 Critical Appraisal

What the market potential gives its power to resolve the complex value of energy storage - the energy system model - also introduces typical limitations found in this domain. The fundamental challenge of any mathematical energy model is to represent a realistic future energy system that includes all relevant physical, social and political details [196]. Current approaches encounter limitations to represent these details. For instance, models often aggregate in space, time and technological resolution, and ignore unit commitment constraints to reduce the computational requirements at the cost of reduced accuracy to represent future scenarios; or assume perfect and complete markets, where actors have perfect foresight. Both deviate from what can be accomplished in reality [24], and as discussed in Section 5.2, it can be important to address additional values of energy storage.

These energy model limitations can be understood as (1) structural uncertainty related to the imperfect mathematical description of the physics and (2) parametric uncertainty that refers to imperfect knowledge of input values, i.e. impacted by innovation or behaviour. Both compromise every kind of mathematical model with increasing uncertainty looking into the more distant future and vary from model to model [17, 18, 19]. The most important uncertainties of PyPSA-Eur are summarised in [24], for instance, that demand profiles for regions in a country are not disaggregated and only scaled by the GDP of the regions, hence, representing not local differences; or missing multi-horizon optimisation, which can help to describe investment pathways and lock-in effects; or the only focus on the electricity system, missing alternative flexibility competitors from other sectors.

Nevertheless, most of the uncertainties can be reduced by improving future mathematical descriptions of the reality and by strategies to reveal remaining uncertainties [196]. For instance, one compelling way to address parametric uncertainty is to give robust insights about what actions are viable within given cost assumptions by exploring systematically scenarios and the feasibility space near the optimum, such as applied in [22]. An approach to address the structural uncertainty, includes this study's missing energy storage values for sub-hourly grid services and risk confronted investment and operation. In PyPSA-Eur many of these certainty creating features can be implemented in short-term by state of the art techniques.

In the context of the above-described uncertainties, this study does not seek to reveal the one true future prediction. It instead shows a set of possible future scenarios with different technological design freedoms for the only purpose of comparing different storage design evaluation methods.

Future work can reduce the limitations of this study, such as the inclusion of sector coupling and pathway optimisation. Further, this study considered energy arbitrage under perfect and complete markets. Another branch of work can include more services relevant to grid stability and risk approaches, for instance, by investigating the impact of imperfect and incomplete market conditions and higher spatio-temporal resolutions regarding market potential method results. Finally, what might be valuable in Europe could look different in other regions. Technology developers would benefit from a global value assessment. Therefore, it is of utmost importance to expand open energy system models to cover most parts of earth.

6.5 Conclusion

In the context of storage technology evaluation methods, cost reduction approaches are failing to account for system values. This study observed that most energy storage technologies are designed with the aim to reduce their component or storage system costs ignoring the interaction with the energy system. However, the presented work showed that two hydrogen long-term storages, both cheap and expensive, can simultaneously provide benefits to the wider energy system. Therefore, missing with existing cost reduction approaches values a technology can or cannot provide in a wider energy system might misguide technology innovation.

System-value approaches aim to acknowledge wider energy system benefits, however, existing approaches are not practical in the current design for technology evaluation. This chapter overcomes many existing limitations with the newly introduced market potential method that can be described as a systematic deployment assessment. The market potential method provides a complementary approach to evaluate energy storage technology from a system value perspective.

In summary, the market potential method has implications for practical and modelling relevant insights for manufacturers, developers and researchers. It can be used to

- support technology design-decision making with growth signals of magnitude and location,
- improve the technology by changing operational behaviour or adapting material or process selection to be most valuable for the energy system,
- concentrate policy endeavours to come closer to perfect market circumstances, or to
- enhance energy modelling as evaluation tool itself.

The new method strongly depends on energy system modelling. Improving energy system model design and reducing uncertainty is essential for a successful adoption.

Here it is of unquestionable value to use open data and open source models to build trust and credibility for decisions.

The economist Milton Friedman said that “there is one and only one social responsibility of business–to use its resources and engage in activities designed to increase its profits so long as it stays within the rules of the [market] game, which is to say, engages in open and free competition without deception or fraud." This might sound convenient in many cases, but in the context of developing energy technology, the ’game’ is constantly changing due to the energy transition and sector coupling, aiming at complete and perfect markets. Thus, maybe it is time to look beyond the cost reduction paradigm and short-term profit focus - to develop technology that leads to lower system cost and winning the market of the future. The market potential method could contribute to this.

The next chapter "The System-Value of Competing Energy Storage in Decarbonized Power Systems", extends the discussion by incorporating uncertainty into the evaluation of up to 20 energy storage technologies. The chapter explores the system benefits of optimizing energy storage in competition and identifies key technologies that are relevant for optimization. This analysis provides valuable insights for investment decision-makers, helping them prioritize energy storage technologies based on their overall system value.

7 Assessing Competing Energy Storage in Decarbonized Power Systems

In economic life, competition is never completely lacking, but hardly ever is it perfect.

— **Joseph Schumpeter**
Economist

Contents of this chapter are based on

Maximilian Parzen et al. "PyPSA-Earth. A new global open energy system optimization model demonstrated in Africa". In: *Applied Energy* 341 (2023), p. 121096. DOI: https://doi.org/10.1016/j.apenergy.2023.121096. URL: https://www.sciencedirect.com/science/article/pii/S0306261923004609

Declaration

This chapter is my own work, not peer-reviewed and only submitted as arXiv preprint.

Infobox

A thesis outline is given in section 1.3 that contextualise the chapters.

Abstract

As the world seeks to transition to a sustainable energy future, energy storage technologies are increasingly recognized as critical enablers. However, the macro-energy system assessment of energy storage has often focused on isolated storage technologies and neglected competition between them, thus leaving out which energy storage to prioritise. In this chapter, I apply a systematic deployment analysis method that enables system-value evaluation in perfect competitive markets and demonstrates its application to 20 different energy storage technologies across 40 distinct scenarios for a representative future power system in Africa. Here, each storage solution is explored alone and in competition with others, examining specific total system costs, deployment configuration, and cost synergies between the storage technologies. The results demonstrate the significant benefits of optimizing energy storage with competition compared to without (+10% cost savings), and highlight the relevance of several energy storage technologies in different scenarios. This work provides insights into the role of energy storage in decarbonizing power systems and informs future research and policy decisions. There is no one-size-fits-all energy storage, but rather an ideal combination of multiple energy storage options that are designed and operated in symbiosis.

7.1 Introduction

As the world looks to decarbonise its power systems in order to mitigate the impacts of climate change, power modeling scenarios have made it increasingly clear that energy storage will play a critical role in the transition to a more sustainable future [160, 175, 176, 197, 198]. The rise of renewable energy sources such as solar and wind power has presented a significant challenge for the electricity grid, which must balance the variable and intermittent nature of these sources with the electricity demand. Energy storage technologies provide a solution to this challenge by allowing excess renewable energy to be stored and used when needed, effectively decoupling the generation and consumption of electricity while adding system-value. Here, as in [10], the system-value of energy storage refers to the broader economic benefits that storage can provide to the power system beyond its immediate application. These benefits include the displacement of firm generation and network infrastructure, greater renewable energy utilisation, and the reduction of transmission and distribution losses, which often reduces the reliance on fossil fuels and lowers carbon emissions. In this context, energy storage, with its system-value provision, is a key enabler of transitioning to a cleaner, more sustainable energy system worldwide.

Building on the discussion from chapter 5, assessing the competitiveness or suitability of energy storage in larger power systems with well-known LCOS methods as applied in [147, 158, 199, 200] are less suitable compared to system-value assessment methods as applied [13, 174, 175, 176, 201]. However, all these system-value assessments explore isolated storage technologies that do not consider any competition with other storage technologies. For instance, the inspiring work in [176] assessed a single generic energy storage in two representative decarbonised power systems. Through a design-space exploration of the generic storage, they identified what energy capacity costs are required to replace firm generation, which are the most critical storage performance parameters and sizing characteristics that contribute to the system-value. However, it is also known that adding more technology options to models often results in synergies. These synergies reduce the significantly total system costs, which are defined as the sum of all operational and investment costs, raising at least questions of the validity of the previously found results of single energy storage scenarios [4]. Expanding on this knowledge, [4] introduces and demonstrates a systematic deployment analysis method that enables system-value evaluation in perfect competitive markets but demonstrates the method by ignoring uncertainty and only considering a limited amount of storage technologies, namely hydrogen and lithium-ion energy storage.

In this chapter, I assess multiple energy storage with the newly suggested systematic deployment analysis, also addressing uncertainty. In total, I assess the system-value of 20 energy storage (see Figure 2.1) with and without competition across 40 distinct scenarios for a representative future power system in Africa. I use a global coverage open energy system model suitable for investment and operational co-optimization, including grid infrastructure and detailed operating decisions and constraints [2]. Further, I apply this model to its already validated Nigerian power system [2], configure it with high temporal resolution (8760h) and a spatial interconnected 10-node system to keep some of the underlying grid and environmental information within the simplification. Within this model, I integrate for the first time 20 storage technologies, which data is collected and expanded from Pacific Northwest National Laboratory (PNNL) (see Table 8.2, and Methods 7.2.1). I explore two unanswered questions: how significant is the system-benefit from optimizing energy storage with competition compared to without, and which energy storage is optimization relevant considering uncertainty.

To answer the research questions, I focused on two scenario trees as illustrated in Figure 7.1. The first scenario tree, defined as 'single storage' scenario, involves optimizing each of the energy storage solutions in isolation, assuming business-as-usual costs. This scenario set includes 20 optimization runs and excludes any competition between the different storage solutions. By doing so, it is possible to investigate the specific total system costs (€/MWh) and deployment configuration (GW for charger/discharger or GWh for store). The second scenario tree also involves 20 optimization runs, but in this case, all energy storage solutions can be optimized within each scenario. This approach allows for perfect competition and cost synergies between the different technologies. To facilitate this, this work uses the here coined 'lonely optimist' approach, where one storage option has optimistic capital costs while the others have pessimistic assumptions. This extreme parameterization enables us to suggest which energy storage solutions provide system-value and which can potentially be neglected - at least within the modelled power system conditions. By applying the new systematic deployment analysis from [4], this work suggests that optimizing scenarios with multiple energy storage, compared to scenarios with single energy storage, can lead to significant system benefits between $3-29\%$. Considering the extreme parameterization, it was also found that 9 out of 20 storage technologies are optimization-relevant, often providing system benefits due to synergies in storage design and operation. The often praised Lithium energy storage [147, 199] was only found highly competitive in a single scenario with optimistic cost assumption of (112 €/kWh and 24 €/kW). In contrast, the often studied hydrogen storage was indeed consistently optimization relevant as well as the sand-based thermal energy storage. However, other technologies added competitive pressure, including gravity-brick, underground and above-ground water-based gravity and pump-heat energy storage, compressed-air and nickel-based electricity storage. Therefore, the system-value technology assessments with multiple energy storage technologies can be considered as an advanced conceptual approach that could find more application in research and industry compared to approaches that ignore competition by isolated technology considerations.

7.2 Methods

7.2.1 Storage data collection

I extracted from a 2022 Pacific Northwest National Laboratory (PNNL) study 20 energy storage technologies and prepared it for reuse in any model [202]. All

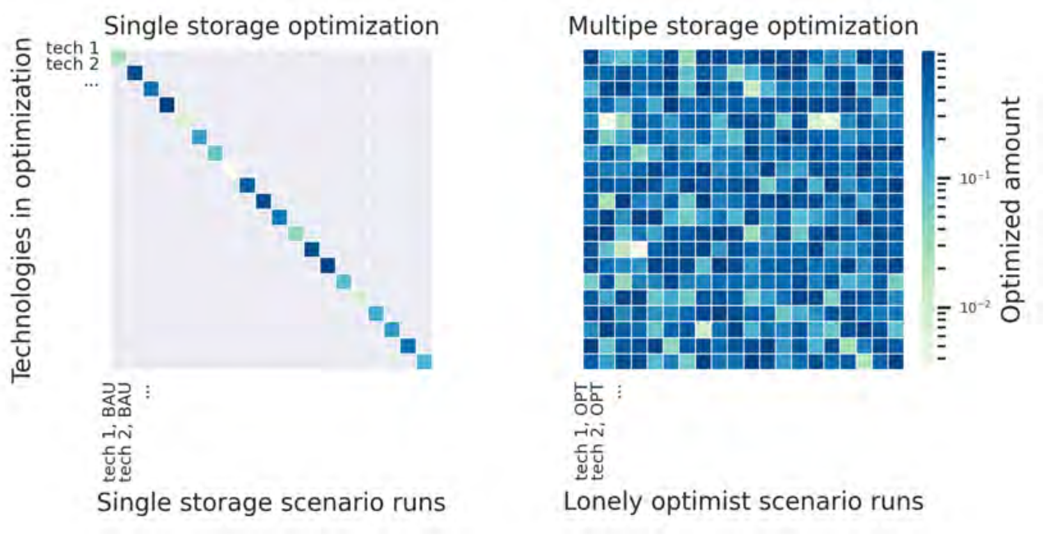


Fig. 7.1.: Illustration of scenario concept in this study.

included technologies are listed in Figure 2.1. The report provided techno-economic information for various storage reference sizes for 2021 and 2030. I focused on assumptions for the largest scale applications that range between $10 - 1000MW$ and $10 - 24h$ energy-to-power ratio. A linear extrapolation was not applicable for the 2050 compiled data (see Table 8.2) as values would turn negative. To cover more of the existing non-linearity in cost developments [203], I created a piecewise linear approximation based on a geometric series for the years between $2034 - 2059$ with data points in 5-year steps. To explore the data, I build an interactive web application available at https://pz-max-energy-storage-data-explorer-app-o5viwg.streamlit.app/. The original data, as well as the processing to clean and extrapolate, is integrated into an open-source tool *'technology-data'* with https://github.com/PyPSA/technology-data/pull/67.

7.2.2 Model and parameters

This study used the PyPSA-Earth model described and formulated in [2]. The model is limited to the geographical scope of the representative power system in Nigeria because its 2021 representation is already validated and described in [2]. I apply techno-economic assumptions given in Table 8.1 to represent a 2050 decarbonised power system. Further, to reduce the computational requirements, I clustered the original, open available transmission network to 10 nodes (see Figure 7.2). Each node captures an area for calculating renewable potential and demand.

I contributed open-source code in https://github.com/pypsa-meets-earth/pypsa-earth/pull/567 that makes adding new energy storage technologies to energy models simple. For instance, instead of adding new code for each added technology in several Python scripts, it is now possible to only add new data, and the model will automatically add these technologies. As illustrated in Figure 2.1, energy storage with unconstrained design is modelled such that the model can independently optimize any functional component (charger, discharger, store). In contrast, design-constrained technologies such as the Lithium-battery are modelled so that the charger and discharger are constrained to be equal and share costs, representing the battery inverter. Moreover, this work excludes self-discharge losses, which were found to have negligible impact on the model outputs as the optimised technologies predominately store energy below 18 days [201]. All required data for the energy storage technologies is described in Table 8.2.

Fig. 7.2.: Clustered 10 bus representation of Nigeria's power system.

7.2.3 Explored scenarios

Two scenario trees are explored for the 2050 fully decarbonized power system with cost-optimal grid expansion in the model region, Nigeria. All scenarios consider a 2013 based weather year and demand profile. The latter is scaled to align with 2050 predictions as in [2]. Era5 reanalysis data is used to derive the renewable potential calculation, and 'Shared Socioeconomic Pathways' [74] are used for the 2050 hourly demand prediction (more details in [2]). Further, the scenarios include minimal variable operating and maintenance costs of $0.5\,€/MWh$ to avoid unintended storage cycling Parzen et al. [3] to reduce the risk of model distortions.

The 'single storage scenario' tree's attributes include optimising each energy storage solution in isolation, assuming 2050 Business as Usual (BAU) cost assumptions given in Table 8.2. In contrast, the 'lonely optimist scenario' tree can optimize all storage technologies simultaneously, assuming that always one storage technology is optimistic (70% of BAU capital costs) while the others are pessimistic (130% of BAU capital costs).

7.2.4 System-value measurement

According to Section 7.3, the concept of 'system-value' for technologies is defined as the market potential arising from the possible and probable least-cost scenarios in capacity expansion models. This definition originates from [4], which introduces the 'market potential method,' comprising two distinct components. The first component, the 'market potential indicator,' evaluates the total optimized technology size, such as an energy storage system's energy or power capacity. The second component, the 'market potential criteria,' seeks to support the decision-making process in the design of storage technologies by examining possible and probable scenarios. As per the criteria, only an optimized energy storage system can provide system-value in a least-cost power system optimization. The importance of technologies according to the system-value increases with its optimized capacity, and its provision of system-value is reinforced and more confident with its repeated optimization across multiple probable and possible scenarios. Notably, the total system costs, including any operation and investment costs, only indirectly impact the system-value assessment for technologies. Decision-makers might use it to define probable scenarios. What is likely most interesting for technology innovators, manufacturers, and regulators is the amount of a particular technology required to be deployed to benefit the power systems.

7.3 Modelling single vs multiple energy storage

The 'system-value' of technologies can be defined as its market potential resulting from possible and probable least-cost scenarios in capacity expansion models (see Section 7.2). Figure 7.3 presents a range of optimised market potentials for various single-optimised energy storage technologies. Because only one storage is included in each optimization run, these scenarios represent a case that ignores any competition. It can be observed that the most and least optimised charger technology ranges between $25-54GW$ for the gravity-brick (gravity) and compressed air energy storage (pair), the most and least optimised dischargers ranging between $26 - 54GW$ for pump-heat (phes) and the compressed air energy storage (pair), and the most and least optimised stores ranging between $0.18 - 1.46\ TWh$ for lead battery (lead) and hydrogen cavern (h2cavern) storage systems, respectively. These results are unrealistic as there are always multiple options available; nevertheless, they reveal that every energy storage technology can serve the energy system or, in other words, contain system-value.

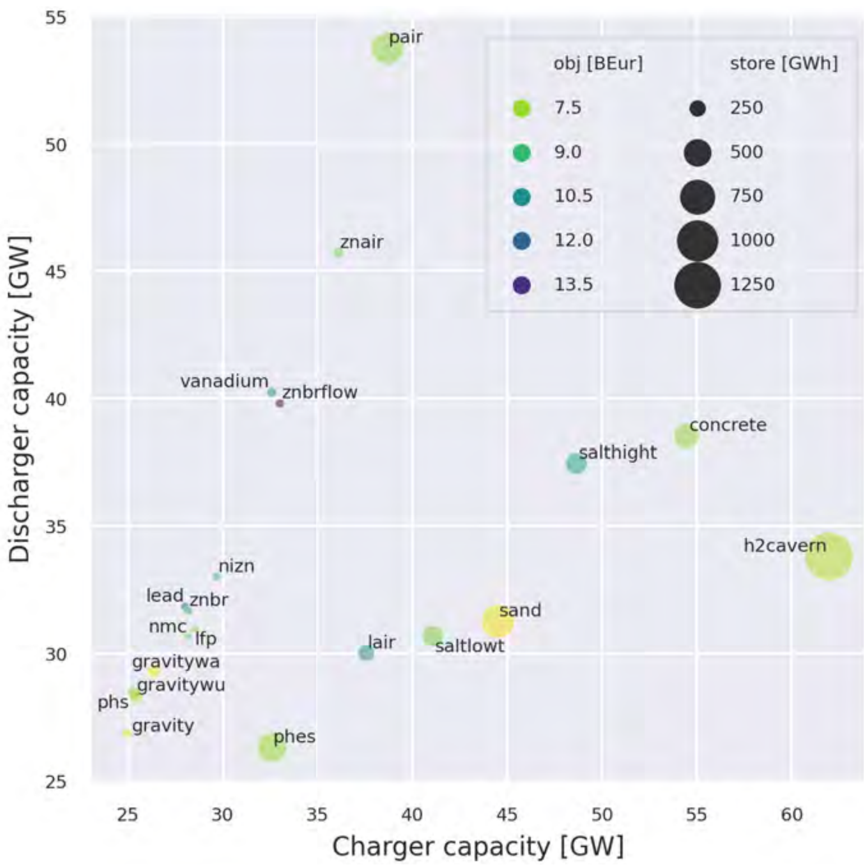


Fig. 7.3.: Optimization results for single energy storage scenarios. The y-axis, x-axis, and marker size show the deployment required for a least-cost 2050 power system in Nigeria. The colour indicates the total system costs.

Further, observing Figure 7.3, one can see that the least-cost system model optimizes various energy storage ratios between charger, store and discharger depending on the technologies. As for most models [19], storage technologies are constrained such that perfect balancing is guaranteed, ensuring no mismatch between electricity supply and demand. However, there is a general trade-off between storage, grid, and supply expansion, allowing for significantly different storage designs. Theoretically, creating a power system without any storage or grid is feasible if renewables can be massively overbuilt and curtailed. The addition of energy storage to power systems allows for smoothing out mismatches in time, while grid infrastructure helps reduce mismatches in space and to exploit better resource potentials [191, 204]. Since every storage technology has different capital costs and efficiencies in the component chain (charger, store, discharger), the design of storage technologies changes to exploit its role in the power system to achieve the minimum total system costs. It is important to note that the scenarios shown in the figure are only one possible outcome of the least-cost power system optimization model, and there may be many other factors that could influence the market potential of a technology. One important factor, making scenarios not only possible but also more probable, is the competition between storage technologies which is discussed next.

Figure 7.4 shows that power systems with perfect storage competition (lonely optimist scenario) are, on average, significantly cheaper compared to those without storage competition (single storage scenario). First and most apparent, the competitive scenarios are 29% cheaper compared to single storage optimization scenarios. While the competitive scenario tree has few cost increases for some technologies initially, the cost gradient becomes relatively low after the optimistic 'phes' scenario with changes of less than 0.1%. In contrast, one can observe continuous significant cost increases for single storage scenarios. Surprisingly, comparing both x-axes that are sorted according to total system costs, it was found that the order of cost-optimal storage systems for the power system is identical. This identical order implies that the storage that leads to the lowest total system in the single-optimized storage scenarios, is likely also the most valuable and important storage in the context of contributing to system benefits in the other scenario tree. Second and most important, the power systems benefits from synergies provided by a perfect competing storage market even under the worst cost assumptions. The total system of the most expensive storage scenario in the competitive situation is 3% (6.295/6.108) cheaper than the best storage scenario in the non-competitive scenario. This is remarkable because the 'single storage' scenario assumes business-as-usual costs for the most favourable technology, while the most expensive 'lonely optimist' scenario considers optimistic costs for the least favourable storage technology (-30% of BAU) while simultaneously for all other storage technologies pessimistic costs ($+30\%$ of BAU). Thirdly, comparing the 'gravitywa' storage from both scenario trees, one can find significant cost savings when considering perfect competitive storage markets. When considering 'gravitywa' with BAU assumptions in both scenario trees, one can observe 8% cost saving or 500 million € in absolute terms. Interesting, but less of an apple-to-apple comparison, setting the 'gravitywa' technology as optimistic, as given in the original lonely optimist scenario, the savings add up to 13%.

These results suggest that studies that assess the system-value with single optimized energy storage such as [13, 175, 176] miss significant benefits from synergies caused by co-optimizing multiple energy storage technologies. It is also likely that power systems with two or three modelled energy storage, such as [14, 195], could benefit from system cost reduction when including more of the technologies that were found highly optimization relevant, for instance, the gravity or sand based thermal energy storage. When assuming similar power system conditions as in the study, the system cost can be up to $5 - 13\%$ for fully decarbonized power systems.

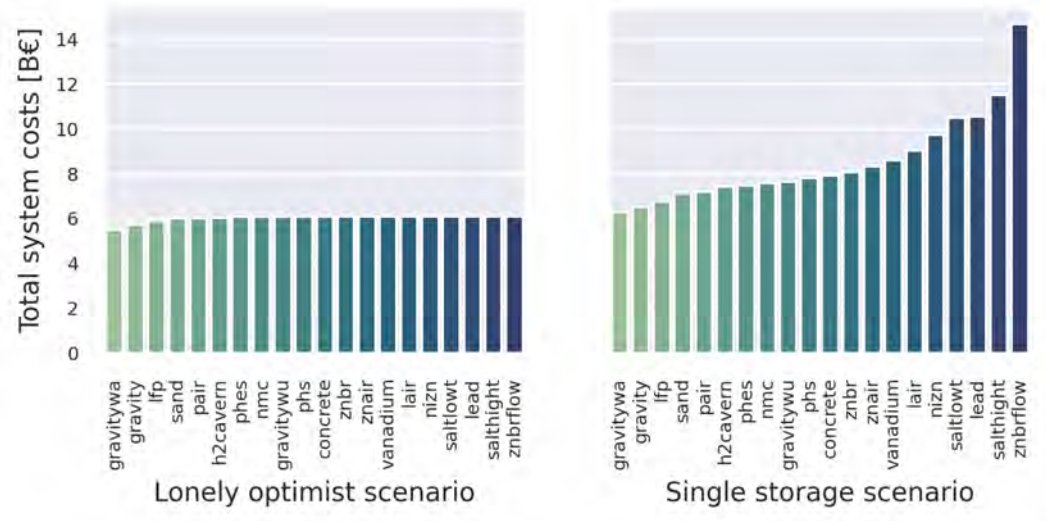


Fig. 7.4.: Total system cost for energy storage scenario with (left) and without (right) competition. Scenarios are sorted according to the total system costs.

7.4 Assessing technology importance

The presented results in Figure 7.5 illustrate the market potential of 20 lonely optimist scenario optimizations with 2050 techno-economic assumptions explained in Section 7.2. Each scenario given on the x-axis requires a single optimization run, with all technologies listed on the y-axis treated as variables. The colour gradient, normalised to the maximum value across all runs, indicates the extent to which the technologies are deployed in each optimization result. For example, the concrete lonely optimist scenario assumes optimistic capital costs for concrete-based energy storage, while the others possess pessimistic values. The following paragraphs will discuss the frequency and magnitude of storage technologies that are deployed in the optimization scenarios. These results will provide a more comprehensive understanding of the relevance and importance of each technology in the least-cost power system.

Beginning with the frequency technologies are optimized, it is observed that 9 out of 20 technologies are optimized to a significant degree, implying that not all technologies are relevant for least-cost power systems. These optimization irrelevant technologies, which are here defined as being optimized below 1% of the maximally optimized technology, include concrete, lead, liquid-air, vanadium, both salt-based, pump-hydro, and any of the four zinc-based energy storage. They can likely be excluded here without consequences from further parameter studies such as global sensitivity analysis. Conversely, sand-based thermal and hydrogen cavern-based energy storage consistently provide system benefits with high certainty across all 20 scenarios examined. Further, several technologies, such as gravity-brick, underground water-based gravity, lithium ferrous phosphate (LFP), lithium nickel manganese cobalt (NMC), and pump-heat energy storage, could only compete under optimistic capital cost assumptions, while simultaneously all other technologies are attributed pessimistic values (see scenario design in Section 7.2.3). On the other hand, compressed-air, above-ground water-based gravity technologies can generally compete unless specific technologies are assumed with optimistic capital cost assumptions. For instance, the above-ground gravity storage is not optimized in a power system where gravity brick storage or Lithium LFP batteries possess optimistic capital cost assumptions. Similarly, compressed-air energy storage is not optimized when hydrogen cavern or sand energy storage is assumed to be optimistic. While analysing the frequency of energy storage optimization in various extreme parameterised scenarios is useful in determining its relevance, evaluating the magnitude is also crucial in understanding the technology's significance.

Analysing each scenario's optimised magnitude, one can observe a wide range of deployed amounts per scenario and technology. In particular, gravity and sand-based energy storage have, on average, the highest deployed amounts indicating their potentially essential role in the power system. Exploring some extremes of the scenario tree, the most optimized charger is the thermal electrode charger for the sand energy storage with $24GW$ as well as an average and minimum percentage of this value of 79% and 37%. Similarly, the compressed air charger has a minimum, average, and maximum value of 0%, 1% and 5%, while the hydrogen cavern optimization results are 1%, 15% and 27%, respectively. The most optimized discharger is the lithium LFP battery inverter with $25GW$. Note that the lithium battery was not the maximum charger component due to roundtrip efficiency of 0.92%, which reduces the optimized amount from $25GW$ to $23GW$ such that charger and discharger are of equivalent size. Here, the relative minimum, average, and maximum values for the compressed air discharger are 0%, 2% and 7%, for the hydrogen cavern-based fuel cell 1%, 7% and 14%, respectively. The most optimized store is the thermal storage of the sand storage with $877GWh$ with minimum and average relative values of 16% and 27%. Similarly, the relative minimum, average, and maximum values for the compressed air discharger are 0%, 16% and 65%, for the hydrogen cavern-based fuel cell 1%, 7% and 67%, respectively. As a result, while sand and gravity storage plays an important role in the power system, the other relevant technologies also sometimes contribute significantly to the least-cost power systems.

Comparing the results to other studies, one can confirm the observation from [174] that pumped heat energy storage can provide system benefits. However, unlike their study, liquid air energy storage is likely not optimization relevant even when optimizing multiple energy storage technologies. Interestingly, this work discovers that lithium energy storage might not be optimization relevant in many cases due to competition from other technologies, which challenges its previously overstated role in the power system decarbonisation for energy to power ratios above one hour [147, 205]. Finally, the results reveal that gravity and sand thermal energy storage are promising technologies that warrant further investigation and inclusion in system planning.

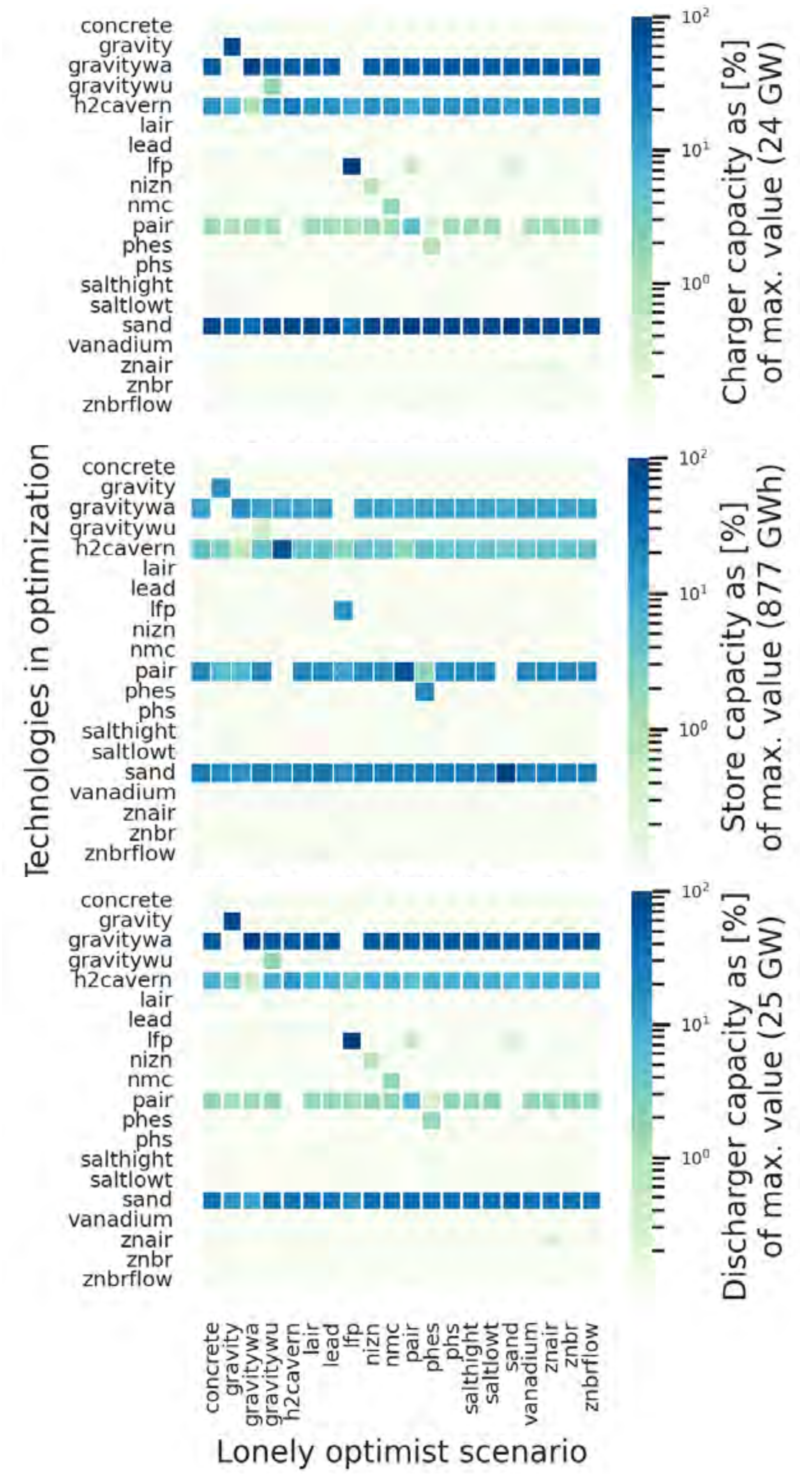


Fig. 7.5.: Optimized charger, store, and discharger capacity for the lonely optimist scenario in Nigeria. All technologies on the y-axis are available for the optimization scenario in each run. One column refers thereby to one scenario run. The x-axis shows the lonely optimist scenarios, which assume optimistic capital costs assumptions (-30%) for the mentioned technology while the others technologies on the y-axis are assumed to have pessimistic capital cost assumptions (+30%).

7.5 Technology design variation

It was found that energy storage technologies span vast sizing designs by analyzing the sizing magnitude ratios between store-to-discharger components, also known as the energy-to-power ratio (EP ratio). One can observe EP ratios for the nine relevant storage technologies between $4-7h$ for any gravity storage, $6h$ for Lithium LFP, $8-21h$ for hydrogen cavern, $9-36h$ for sand-based, $3-19$ days for compressed air and 36 days for pumped-heat energy storage. The results imply that for the given power system, the most critical storage categories are peak shifters (roughly $< 8h$), storage that can balance mismatches also over one or multiple nights (roughly $9-36h$) and energy storage that balance through seasonal effects (roughly $7-36d$). Different to [191], the results suggest different sizing patterns for hydrogen energy storage. Compared to EP-ratios of roughly $14-21$ days, this work found the hydrogen storage to be mostly sized to balance mismatches for one or two nights. The role of the weekly storage took the compressed-air and pumped-heat storage, which were generally not primarily optimized, reflecting that synoptic or seasonal mismatches are not as significant as predicted for the modelled power system close to the equator.

While there is an extensive design space for energy storage [176, 201], the resulting charger-to-discharger ratios suggest that there is a general tendency that the power system benefits from oversizing the discharger components. Figure 2.1 shows that some technologies are sizing-constrained because their charger and discharger are the same components. Moreover, for sizing-unconstrained technologies such as sand-based and hydrogen cavern energy storage, the results suggest charger-to-discharger ratios between $0.28-0.61$, respectively. Only for the single case for which the pumped-heat energy storage is significantly optimized this sizing tendency is reversed such that the pumped-heat storage is sized with a charger-to-discharger ratio of 2.33, meaning that oversizing the charger is beneficial to the power system. Similar results were found in [4] for a European transmission system optimization that always oversizes, if possible, the discharger component by, on average, a factor of two or three.

7.6 Limitation

While this study provides valuable insights into the energy storage technologies that are most likely to provide system benefits, several limitations concerning the model and the data should be considered when interpreting the results and making decisions based on them. First, this analysis assumed that all energy storage technologies have the same uncertainty range, which may be unrealistic. Incorporating a sense of technology readiness level could provide better signals on uncertainty ranges, as suggested in previous research [206]. Second, this analysis could benefit from considering the feasibility of implementing certain energy storage technologies in all regions. For example, hydrogen cavern-based energy storage may not be feasible in some areas. Future research could include technology restrictions that account for such limitations, similar to renewable energy limitations [26]. Third, this study included only some possible energy storage technologies. Additional research could identify and evaluate other technologies that could potentially provide system benefits. Fourth, this analysis did not consider competing flexibilities, such as those introduced by the transport sector or industry load-shifting potentials, which could challenge the system-value of energy storage [195]. Finally, to consider better uncertainty, one could consider multiple weather years and multi-year energy storage [14], apply global sensitivity analysis with Monte-Carlo [207] and perform near-optimal solution explorations [19].

7.7 Discussion

The importance of system-value analysis for energy storage is increasing as it allows decision-makers to evaluate the overall impact and value of multiple energy storage options within a power system. In this study, traditional system-value analysis that considers only single energy storage options in power system models may overlook significant benefits that can be obtained by designing and operating multiple energy storage options in symbiosis.

This analysis shows that scenarios with multiple energy storage options can result in total power system cost savings of up to $3-29\%$ compared to those with only a single energy storage option. However, it is worth noting that not all energy storage options contribute equally to achieving these system benefits. Of the 20 energy storage options that were analysed, 11 are neither significantly nor frequently deployed in scenarios that considered extreme cost uncertainty, making them non-competitive.

The implications of the study for decision-makers are significant. By applying system-value analysis, investment decision-makers in industry, research, and governments can better evaluate and prioritise energy storage technologies based on their overall value in the system rather than solely on cost reduction as approached in [205]. The findings suggest that certain energy storage technologies may not be worth investing in, while others provide good investment opportunities since they consistently provide system benefits even under high-cost uncertainty. Understanding which energy storage options provide the most frequent and significant benefits to a given power system can help decision-makers focus their limited research and deployment funds on the most viable options, potentially saving society billions of hidden costs.

Moreover, the analysis can help manufacturers and project developers design energy storage systems most valuable to a power system. Different to [13, 176, 201], by taking into account the benefits of multiple energy storage options, one can can derive more realistic and practical design recommendations that consider the competition and synergies between different storage options. The study finds that energy storage technologies should be heterogeneously sized to exploit the individual system conditions and that energy-to-power ratios can vary significantly between technologies. Manufacturers can use this information to prioritise designing technologies most likely valuable to future system configurations. In contrast, project developers can apply the methods in the study to make more informed decisions about where and how to deploy energy storage systems.

However, there are limitations to the study, and it is vital to continue to improve methods, models, and data to ensure more informed decision-making in the future. Incorporating technology readiness levels, implementing realistic technology restrictions considering environmental and social limits, expanding the list of energy storage technologies, analysing various other power systems and considering competing flexibilities from other sectors such as transport and industry load shifting potentials are some areas that are more discussed in the limitation Section 7.6, which can be explored further. Another critical point is that technology assessments should be ideally performed globally, which requires global bottom-up model efforts such as provided in [2, 208]. Nonetheless, this study provides valuable insights into energy storage technologies. By incorporating these insights into decision-making processes, one can improve the overall system-value of energy storage and accelerate the transition to a cleaner, more sustainable and affordable energy future. To achieve this, actors in the field should avoid creating new models and instead focus on improving existing models. An open and inclusive community that promotes open research, software and data can help us progress step by step towards more informed decision-making for energy storage.

8 Conclusion and Outlook

This dissertation set out with the hypothesis that improved energy system modeling and novel system-value optimization methods can enhance the economic viability and integration of diverse energy storage technologies into wider power systems. Addressing critical research questions, it aimed to (1) develop globally applicable energy system models, (2) mitigate unintended modeling artefacts, (3) introduce and validate new energy storage valuation methods, and (4) understand the optimization relevance of various energy storage technologies considering uncertainty.

Summary of key findings

Part I - Improving Energy System Modelling with Energy Storage

This thesis has made significant strides in energy system modeling by tackling critical challenges that impede the models' applicability, accuracy, and effectiveness in aiding decision-makers.

Objective 1 was met with the introduction of the first global applicable open energy system model with high resolution data in chapter 3. This model provides a flexible approach for data extraction and preparation with global coverage and supports a range of clustering and grid meshing strategies, e.g. k-edge line augmentation borrowed from graph theory, to adapt the model to computational and practical needs. The chapter demonstrates the model's efficacy by conducting a deep decarbonisation planning study for Nigeria's power system, showcasing the potential of the model for energy planning studies to support policy decision-making. This substantial contribution broadens the horizons for energy system modeling, offering a versatile tool that is accessible and applicable worldwide.

Objective 2 was addressed in chapter 4 by presenting an innovative approach to mitigate unintended modelling artefacts in energy system models considering energy storage. The chapter highlights that these artefacts can lead to implausible outputs and mislead decision-making. The suggested approach recommends using appropriate variable costs, effectively removing unintended storage cycling and other similar misleading effects. By doing so, computationally expensive and sometimes less effective approaches, such as formulating the optimization problem as MILP or using multi-stage optimization, can be avoided. The chapter also provides a list of recommended variable cost model inputs and a minimum threshold that can significantly reduce the magnitude and likeliness of unintended storage cycling. The applied approach not only addresses the challenge of unintended storage cycling but also has the potential to address similar issues, such as unintended line cycling or sector cycling, that can unknowingly distort energy model results. This holistic approach enhances the model's accuracy and reliability, thereby improving its utility in decision support and technology design.

Part II - Applied Energy Storage System-Value Optimization

The thesis also provides substantial contributions toward assessing and optimizing energy storage technologies in decarbonized power systems.

Objective 3 was pursued in chapter 5 by critically examining the benefits and limitations of various evaluation methods, highlighting the potential of system-value analysis to explore the value of energy storage. Building upon this analysis, chapter 6, the dissertation also introduced the market-potential method as a new complementary valuation approach, acknowledging that the value of energy storage is not always directly proportional to its cost of components (e.g. charger, store, discharger). The thesis demonstrates the effectiveness of this method in a renewables-based European power system model, emphasising the significance of modifying storage sizing and component interactions to enhance energy system efficiency and cost savings.

Objective 4 was tackled in chapter 7 by extending the analysis to include uncertainty considerations and evaluated with 20 energy storage options, the optimization relevancy of the most energy storage technologies in any energy system model. The thesis demonstrates that optimizing multiple energy storage options in symbiosis can provide significant system benefits and that heterogeneously sizing energy storage technologies can maximise their value in diverse system conditions. This novel approach provides valuable insights for decision-makers in industry, research, and governments to better evaluate and prioritise energy storage technologies based on their value in the power system.

Overall, this work makes significant contributions to the discourse on energy storage evaluation and optimization, highlighting the need to consider both cost and value in decarbonized power systems. It provides novel methodologies and insights to guide innovation and investment in a landscape with multiple energy storage options, aiming for more affordable, efficient, and sustainable energy systems.

The Role of Open Data, Open Science and Open-Source Software

Open data, open-source software, and open science have been fundamental in advancing this research and promoting knowledge sharing. Open data ensures unrestricted access and use, open-source software allows for shared development and distribution, and open science makes research and its outcomes accessible and free from restrictions.

This work has built 'on the shoulder of giants', those who devoted decades on open data collection and open source software development. Among others, it has benefited from OpenStreetMap data [69], extensive open storage data from PNNL [202], and open-source tools like Python, Numpy, Pandas, Atlite, GenX, PyPSA and PyPSA-Eur [24, 25, 26, 209]. Without this work, the thesis wouldn't be possible. Therefore, the thesis aimed to contribute back to the community by facilitating open data access, fostering global model and data collaboration, and enhancing open-source software with contributions like PyPSA-Earth [2]. The benefits of this openness include fostering collaboration, increasing research visibility and impact, and enabling broader participation in scientific endeavours.

Enhancements and Outlook

The limitations section of each chapter discussed several potential areas for future research. Nevertheless, as the thesis concludes, a summary of essential enhancements is given, as well as a perspective on where future research might go next.

Model design and data improvements

Energy system models are crucial to informing decision-makers about the wider system benefits of energy storage. Therefore, if the system representation changes, it will influence any technology assessment studies, e.g. system value assessment for energy storage. In Part I, the work focused on solving existing challenges of energy system models, including improving their energy storage representation and availability worldwide. Due to the complexity of energy systems, many other challenges should be addressed to improve the accuracy and usefulness of these models.

In terms of model design, one possible improvement is to include sector-coupling on a global scale, which would involve modelling not just the electricity sector but also other sectors such as transport, heating, and industry [210]. In particular, sector coupling can also heavily impact the storage design and integration [201]. A convex gas dynamics representation can be added to capture the behaviour of gas systems when being co-optimized with the power system or other sectors. With the power to gas movement, this is increasingly important in the energy transition, for instance, in the case of carbon dioxide, methane or hydrogen transport modelling [210]. Moreover, pathway optimization that describes not only what and where infrastructure should be built but also when, considering multi-decade horizons, can give new insights. The multi-decade perspective can also be linked to 'learning by doing' induced cost reductions which influence any energy model outcomes [211].

Data improvements also greatly benefit energy system modelling. Better representation of energy infrastructure could be achieved through more and better GIS-tagged data ideally provided in global databases such as OpenStreetMap [69]. Here, a promising way to automate data monitoring and new data provision is using satellite-based object detection based on machine learning [115, 212]. Demand data improvements would also provide a more accurate representation of energy usage patterns. Most energy systems models like PyPSA-Eur and PyPSA-Earth are limited to the same demand profile characteristics per country. Creating more realistic heterogeneous demand profiles based on machine learning approaches can potentially improve energy model scenarios [55, 76]. Moreover, technology readiness level data, such as applied for energy storage in [206, 213], would allow for a more accurate representation of storage options in energy systems.

Finally, computational speed improvements would allow for more complex and accurate models to be developed. In particular, increasing temporal and spatial resolution can help create more realistic energy system results [72, 88, 214]. However, the more detailed models become, the longer the model scenarios compute. One interesting approach is to exploit the block-angular structure of massive linear problems to parallelise computations [215]. Another approach to improving optimisation solver speed is developing problem-specific solvers [7].

Overall, these model and data improvements can significantly enhance the accuracy and usefulness of energy system models, allowing for more informed decision-making related to the energy transition.

Improving system-value optimization studies

In Part II, the chapters describe a new system-value optimization method. However, the thesis could have more extensively accounted for the uncertainty that presents further research opportunities.

Uncertainty reduction methods are essential for improving the design and operation of energy systems. One such method is the Monte-Carlo Method, also described as parameter sweep [19], which involves creating hundreds or thousands of scenarios by systematically sampling various input parameters. This allows for a stochastic interpretation of the system's uncertainty derived from deterministic signals. Another complementary method is the modelling-to-generate-alternatives approach, which explores the near-optimal space of a single convex hull by adding objective constraints to a single scenario with fixed input parameters [22]. In addition, considering intra-annual or multi-year modelling can provide a comprehensive picture of system behaviour and reduce uncertainty, particularly for energy storage, which can provide benefits across years [14]. Accounting for multiple weather years in studies can also help reduce uncertainty from weather variability and improve planning resilience [188]. Lastly, robust optimization methods can provide robust solutions that avoid expensive infeasible solutions that classical stochastic approaches do not account for [216, 217]. These methods, when applied effectively, can lead to more reliable and resilient energy system planning decisions for energy infrastructure as well as technology system-value assessment and optimizations in future.

Appendix

> *Everything has an end, but the sausage has two.*
>
> — **Jacob Parzen**
> Butcher

Supplemental material

Energy storage and power system assumptions

Tab. 8.1.: Infrastructure investment cost assumptions per technology for 2050. All costs are given in real 2015 money.

Technology	Investment (€/kW) or (€/kWh)	Fixed O&M (%/year)	Lifetime (years)	Efficiency (%)	Source
Onshore Wind	963	1.2	30		[218]
Offshore Wind	1487	2.0	30		[218]
Solar PV (utility-scale)	265	2.5	40		[218]
Solar PV (rooftop)	475	1.6	40		[218]
Reservoir hydro	2208	1.0	80	0.9	[219]
Run of river	3312	2.0	80	0.9	[219]
HVDC overhead	432	2.0	40		[220]

```python
#!/usr/bin/env python
def geo_series(nom, denom=1, no_terms=1, strt=1):
    """
    A geometric series is a series with a constant ratio between
    successive terms. When moving to infinity the geometric series
    converges to a limit.
    https://en.wikipedia.org/wiki/Series_(mathematics)

    Example:
    --------
    nom = 1  # nominator
    denom = 2  # denominator
    no_terms = 3
```

```
    strt = 0  # 0 means it starts at the first term
    result = 1/1**0 + 1/2**1 + 1/2**2 = 1 + 1/2 + 1/4 = 1.75

    If moving to infinity the result converges to 2
    """
    return (sum([nom/denom**i for i in range(strt, strt+no_terms)])
```

Listing 8.1: Contributed code of the required geometric series to infer realistic cost assumptions. The code is contributed to the open-source package technology-data which the model implements an energy storage data interface for.

Tab. 8.2.: Electricity storage overnight investment cost assumptions per technology for 2050. Derived with geometric series applied on 2021 and 2030 PNNL data. All costs are given in real 2015 money. All costs are given in real 2015 money.

Technology	Investment (€/kW) or (€/kWh)	Fixed O&M (%/year)	Lifetime (years)	Efficiency (%)	Source
Compressed-Air-Adiabatic-bicharger	946	0.9	60	0.72	[202]
Compressed-Air-Adiabatic-store	5	0.4	60		[202]
Concrete-charger	106	1.1	35	0.99	[202]
Concrete-discharger	427	0.3	35	0.43	[202]
Concrete-store	19	0.3	35		[202]
Gravity-Brick-bicharger	415	1.5	41	0.93	[202]
Gravity-Brick-store	131		41		[202]
Gravity-Water-Aboveground-bicharger	365	1.5	60	0.9	[202]
Gravity-Water-Aboveground-store	102		60		[202]
Gravity-Water-Underground-bicharger	905	1.5	60	0.9	[202]
Gravity-Water-Underground-store	80		60		[202]
HighT-Molten-Salt-charger	107	1.1	35	0.99	[202]
HighT-Molten-Salt-discharger	428	0.3	35	0.44	[202]
HighT-Molten-Salt-store	78	0.3	35		[202]
Hydrogen-charger	190	0.7	30	0.7	[202]
Hydrogen-discharger	179	0.6	30	0.49	[202]
Hydrogen-store	4	0.4	30		[202]
Lead-Acid-bicharger	111	2.5	12	0.88	[202]
Lead-Acid-store	282	0.3	12		[202]
Liquid-Air-charger	451	0.4	35	0.99	[202]
Liquid-Air-discharger	317	0.5	35	0.55	[202]
Liquid-Air-store	135	0.3	35		[202]
Lithium-Ion-LFP-bicharger	69	2.2	16	0.92	[202]
Lithium-Ion-LFP-store	160	0.0	16		[202]
Lithium-Ion-NMC-bicharger	69	2.2	13	0.92	[202]
Lithium-Ion-NMC-store	182	0.0	13		[202]
LowT-Molten-Salt-charger	139	1.1	35	0.99	[202]
LowT-Molten-Salt-discharger	559	0.3	35	0.54	[202]
LowT-Molten-Salt-store	48	0.3	35		[202]
Ni-Zn-bicharger	69	2.2	15	0.9	[202]
Ni-Zn-store	202	0.2	15		[202]
Pumped-Heat-charger	723	0.4	33	0.99	[202]
Pumped-Heat-discharger	507	0.5	33	0.63	[202]
Pumped-Heat-store	7	0.2	33		[202]
Pumped-Storage-Hydro-bicharger	1397	1.0	60	0.89	[202]
Pumped-Storage-Hydro-store	57	0.4	60		[202]
Sand-charger	137	1.1	35	0.99	[202]
Sand-discharger	548	0.3	35	0.53	[202]
Sand-store	5	0.3	35		[202]
Vanadium-Redox-Flow-bicharger	111	2.5	12	0.81	[202]
Vanadium-Redox-Flow-store	207	0.2	12		[202]
Zn-Air-bicharger	129	2.4	25	0.79	[202]
Zn-Air-store	156	0.2	25		[202]
Zn-Br-Flow-bicharger	36	1.8	10	0.83	[202]
Zn-Br-Flow-store	357	0.2	10		[202]
Zn-Br-Nonflow-bicharger	129	2.4	15	0.89	[202]
Zn-Br-Nonflow-store	207	0.2	15		[202]

Tab. 8.3.: Electricity storage overnight investment cost assumptions per technology for 2021. Derived from original PNNL data. All costs are given in real 2015 money.

Technology	Investment (€/kW) or (€/kWh)	Fixed O&M (%/year)	Lifetime (years)	Efficiency (%)	Source
Compressed-Air-Adiabatic-bicharger	946.18	0.9	60	0.72	[202]
Compressed-Air-Adiabatic-store	5.448	0.4	60		[202]
Concrete-charger	183.635	1.1	35	0.99	[202]
Concrete-discharger	734.543	0.3	35	0.41	[202]
Concrete-store	28.893	0.3	35		[202]
Gravity-Brick-bicharger	415.57	1.5	41	0.93	[202]
Gravity-Brick-store	184.331		41		[202]
Gravity-Water-Aboveground-bicharger	365.63	1.5	60	0.9	[202]
Gravity-Water-Aboveground-store	142.417		60		[202]
Gravity-Water-Underground-bicharger	905.158	1.5	60	0.9	[202]
Gravity-Water-Underground-store	112.097		60		[202]
HighT-Molten-Salt-charger	183.528	1.1	35	0.99	[202]
HighT-Molten-Salt-discharger	734.115	0.3	35	0.42	[202]
HighT-Molten-Salt-store	110.714	0.3	35		[202]
Hydrogen-charger	1208.632	0.5	30	0.7	[202]
Hydrogen-discharger	1177.152	0.5	30	0.49	[202]
Hydrogen-store	4.779	0.4	30		[202]
Lead-Acid-bicharger	147.643	2.4	12	0.88	[202]
Lead-Acid-store	360.824	0.2	12		[202]
Liquid-Air-charger	500.869	0.4	35	0.99	[202]
Liquid-Air-discharger	351.674	0.5	35	0.52	[202]
Liquid-Air-store	183.974	0.3	35		[202]
Lithium-Ion-LFP-bicharger	94.181	2.1	16	0.91	[202]
Lithium-Ion-LFP-store	316.769	0.0	16		[202]
Lithium-Ion-NMC-bicharger	94.181	2.1	16	0.91	[202]
Lithium-Ion-NMC-store	361.858	0.0	16		[202]
LowT-Molten-Salt-charger	148.856	1.1	35	0.99	[202]
LowT-Molten-Salt-discharger	595.425	0.3	35	0.52	[202]
LowT-Molten-Salt-store	68.283	0.3	35		[202]
Ni-Zn-bicharger	94.181	2.1	15	0.89	[202]
Ni-Zn-store	337.129	0.2	15		[202]
Pumped-Heat-charger	802.648	0.4	30	0.99	[202]
Pumped-Heat-discharger	563.561	0.5	30	0.61	[202]
Pumped-Heat-store	29.319	0.1	30		[202]
Pumped-Storage-Hydro-bicharger	1397.128	1.0	60	0.89	[202]
Pumped-Storage-Hydro-store	57.074	0.4	60		[202]
Sand-charger	151.781	1.1	35	0.99	[202]
Sand-discharger	607.125	0.3	35	0.51	[202]
Sand-store	7.883	0.3	35		[202]
Vanadium-Redox-Flow-bicharger	147.857	2.4	12	0.81	[202]
Vanadium-Redox-Flow-store	311.66	0.2	12		[202]
Zn-Air-bicharger	129.023	2.4	25	0.77	[202]
Zn-Air-store	192.847	0.2	25		[202]
Zn-Br-Flow-bicharger	129.023	2.4	10	0.81	[202]
Zn-Br-Flow-store	470.192	0.3	10		[202]
Zn-Br-Nonflow-bicharger	129.023	2.4	15	0.87	[202]
Zn-Br-Nonflow-store	273.108	0.2	15		[202]

Tab. 8.4.: Electricity storage overnight investment cost assumptions per technology for 2030. Derived from original PNNL data. All costs are given in real 2015 money.

Technology	Investment (€/kW) or (€/kWh)	Fixed O&M (%/year)	Lifetime (years)	Efficiency (%)	Source
Compressed-Air-Adiabatic-bicharger	946	0.9	60	0.72	[202]
Compressed-Air-Adiabatic-store	5	0.4	60		[202]
Concrete-charger	144	1.1	35	0.99	[202]
Concrete-discharger	576	0.3	35	0.43	[202]
Concrete-store	24	0.3	35		[202]
Gravity-Brick-bicharger	415	1.5	41	0.93	[202]
Gravity-Brick-store	157		41		[202]
Gravity-Water-Aboveground-bicharger	365	1.5	60	0.9	[202]
Gravity-Water-Aboveground-store	121		60		[202]
Gravity-Water-Underground-bicharger	905	1.5	60	0.9	[202]
Gravity-Water-Underground-store	95		60		[202]
HighT-Molten-Salt-charger	144	1.1	35	0.99	[202]
HighT-Molten-Salt-discharger	576	0.3	35	0.44	[202]
HighT-Molten-Salt-store	94	0.3	35		[202]
Hydrogen-charger	312	0.7	30	0.49	[202]
Hydrogen-discharger	414	0.5	30	0.7	[202]
Hydrogen-store	4	0.4	30		[202]
Lead-Acid-bicharger	128	2.4	12	0.88	[202]
Lead-Acid-store	320	0.2	12		[202]
Liquid-Air-charger	475	0.4	35	0.99	[202]
Liquid-Air-discharger	334	0.5	35	0.55	[202]
Liquid-Air-store	159	0.3	35		[202]
Lithium-Ion-LFP-bicharger	81	2.1	16	0.92	[202]
Lithium-Ion-LFP-store	236	0.0	16		[202]
Lithium-Ion-NMC-bicharger	81	2.1	13	0.92	[202]
Lithium-Ion-NMC-store	269	0.0	13		[202]
LowT-Molten-Salt-charger	144	1.1	35	0.99	[202]
LowT-Molten-Salt-discharger	576	0.3	35	0.54	[202]
LowT-Molten-Salt-store	58	0.3	35		[202]
Ni-Zn-bicharger	81	2.1	15	0.9	[202]
Ni-Zn-store	267	0.2	15		[202]
Pumped-Heat-charger	761	0.4	33	0.99	[202]
Pumped-Heat-discharger	534	0.5	33	0.63	[202]
Pumped-Heat-store	11	0.2	33		[202]
Pumped-Storage-Hydro-bicharger	1397	1.0	60	0.89	[202]
Pumped-Storage-Hydro-store	57	0.4	60		[202]
Sand-charger	144	1.1	35	0.99	[202]
Sand-discharger	576	0.3	35	0.53	[202]
Sand-store	6	0.3	35		[202]
Vanadium-Redox-Flow-bicharger	129	2.4	12	0.81	[202]
Vanadium-Redox-Flow-store	258	0.2	12		[202]
Zn-Air-bicharger	129	2.4	25	0.79	[202]
Zn-Air-store	174	0.2	25		[202]
Zn-Br-Flow-bicharger	81	2.1	10	0.83	[202]
Zn-Br-Flow-store	412	0.3	10		[202]
Zn-Br-Nonflow-bicharger	129	2.4	15	0.89	[202]
Zn-Br-Nonflow-store	239	0.2	15		[202]

Examples of other energy storage scenarios

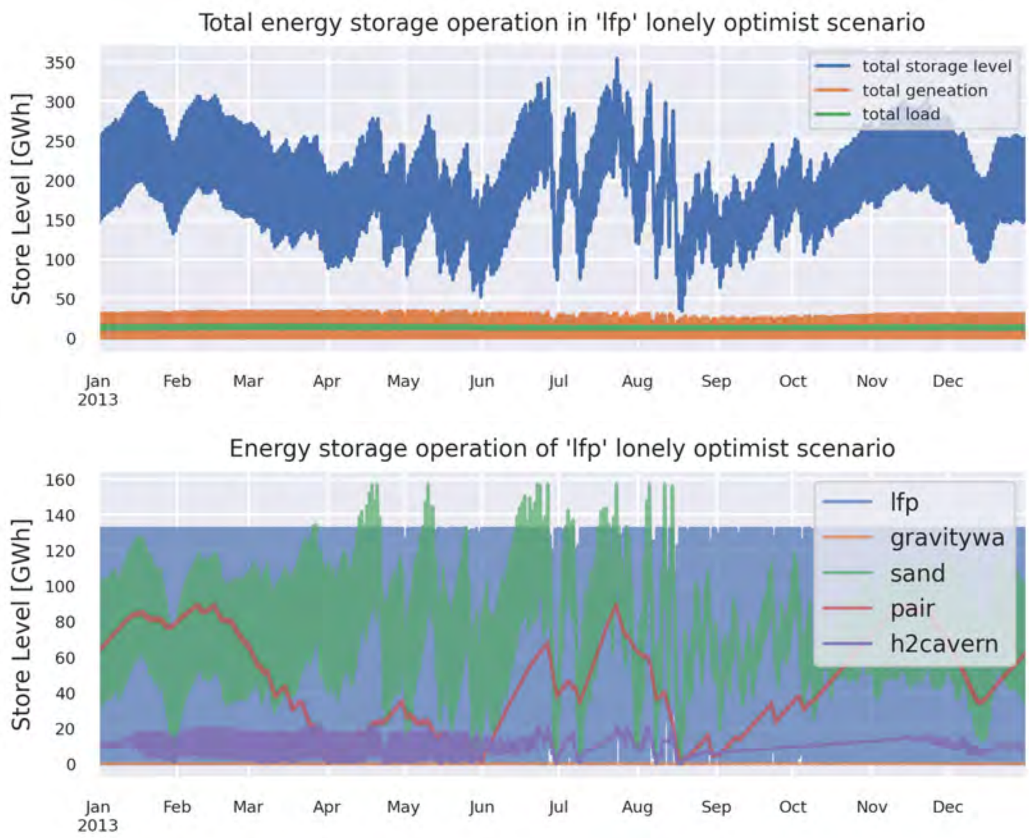


Fig. 8.1.: Storage operation in lonely optimist scenario with Lithium Ferrous Phosphate (LFP) as optimistic capital costs in a group of pessimistic alternatives. The time-series is smoothed by a 12 hour rolling aggregation, where the upper figure shows the total storage operation, generation and load time-series, and the lower figure the storage operation of a selected subset of technologies. Here, the hydrogen cavern represent the blue line with maximal storage volume of around 20GWh.

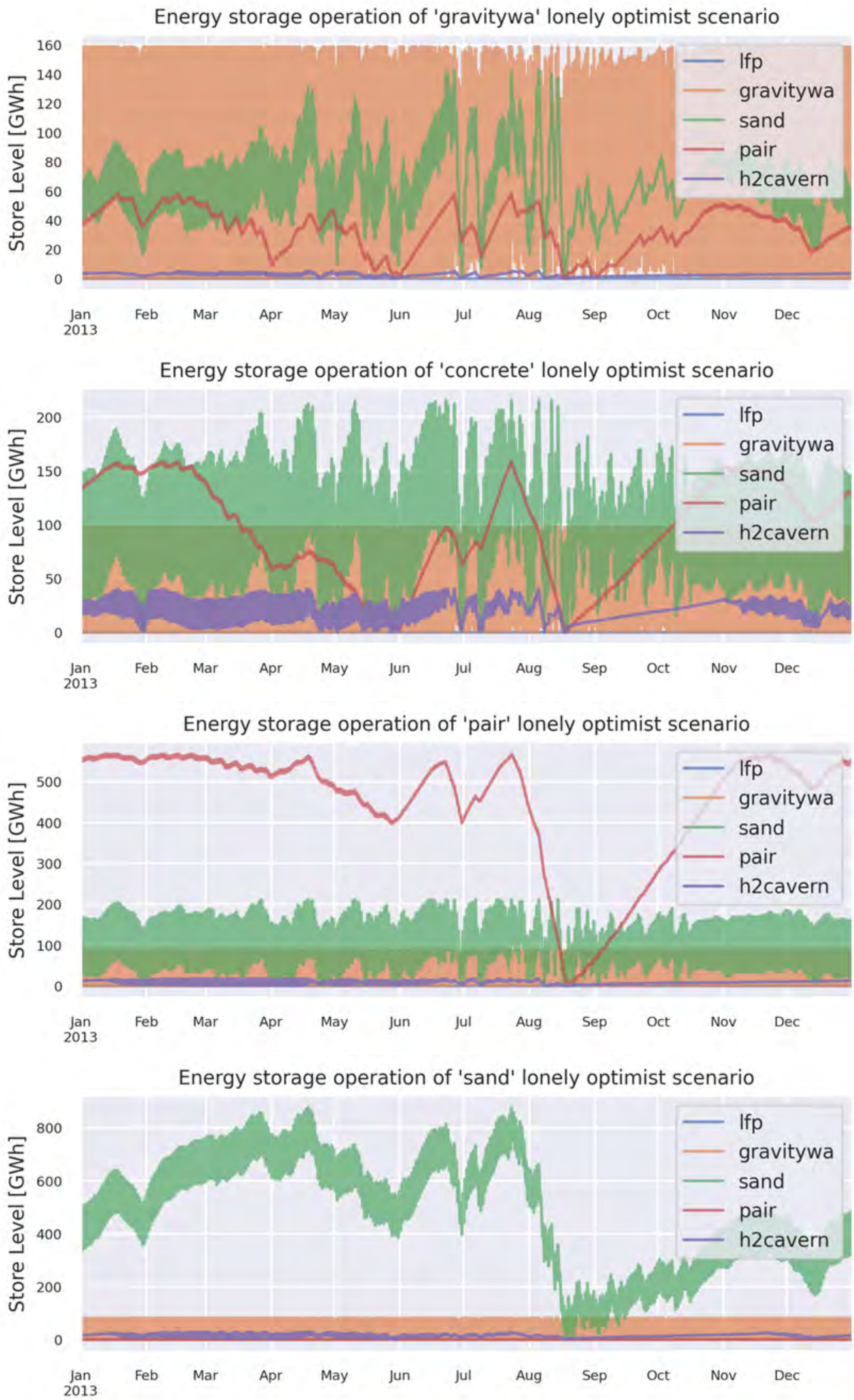


Fig. 8.2.: Storage operation in lonely optimist scenario with changing optimistic storage scenarios. The time-series is smoothed by a 12 hour rolling aggregation and shows only a selected set of technologies.

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