Flexibility options in electricity markets with high shares of renewable energies

An agent-based analysis of economic viability and system impacts

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*"A system is more than the sum of its parts.
It may exhibit adaptive, dynamic, goal-seeking, self-preserving, and sometimes evolutionary behavior."*

— DONELLA H. MEADOWS, *Thinking in Systems: A Primer*

Abstract

As part of the energy transition, the electricity sector and its power generation infrastructure must be extensively transformed to reduce greenhouse gas emissions. Intermittent renewable energy sources are rapidly replacing fossil fuel-based electricity generation. Consequently, there is an increasing need for balancing supply and demand. Flexibility options are critical technological solutions for this challenge, however, significant knowledge gaps remain regarding their profitability and deployment in future electricity systems.

This thesis contributes to closing these gaps by conducting agent-based electricity market simulations that target several key research objectives. First, it investigates operational strategies for flexibility options and their economic performance in electricity markets. The analysis reveals that strategies must consider the price impacts of flexibility options on both an individual and collective level. Second, the research examines profitable technical parameters and demonstrates that medium-term storage configurations likely offer the greatest revenue potential in day-ahead markets. This is particularly relevant in scenarios with increased competition between flexibility options. Third, the analysis identifies significant cannibalisation effects when substantial flexibility option capacity is integrated into the system. Due to their impact on electricity price dynamics, the overall revenue decreases, thus affecting profitability.

These findings lead to the following recommendations for future research and policy. Endogenous modelling of large-scale flexibility options is necessary to understand future energy systems, as isolated analysis significantly underestimates market interactions. Additionally, the profitability of flexibility options is strongly linked to cost assumptions, particularly storage costs, which require consideration in investment decisions. Furthermore, planned investments in flexibility options should be accurately monitored, as cannibalisation effects and changing market dynamics will substantially impact profitability.

The endogenous modelling of these complex phenomena represents a key methodological advancement of this thesis. This is achieved through extensions and application of a state-of-the-art electricity market model coupled with machine learning-based electricity price forecasting. This thesis contributes multiple software packages and data sets that adhere to FAIR principles, thereby enhancing reproducibility and facilitating future research. The presented work advances the understanding of the role of flexibility options in energy transition scenarios, while also revealing important avenues for future investigation. Key limitations to be addressed in further research include the focus on day-ahead market analysis rather than multi-market simulations, and simplified consideration of sector coupling dynamics.

Kurzzusammenfassung

Im Rahmen der Energiewende müssen der Elektrizitätssektor und seine Stromerzeugungsinfrastruktur umfassend umgestaltet werden, um die Treibhausgasemissionen zu verringern. Erneuerbare Energiequellen ersetzen zunehmend die fossile Stromerzeugung. Durch die fluktuierende Einspeisung von Wind- und Solarenergie ist jedoch eine Ausbalancierung von Angebot und Nachfrage erforderlich. Flexibilitätsoptionen sind technologische Lösungen, um diese Herausforderung zu bewältigen.

Dennoch bestehen erhebliche Wissenslücken bezüglich ihrer Rentabilität und ihres Einsatzes in zukünftigen Elektrizitätssystemen. Diese Dissertation trägt zur Schließung dieser Lücken bei, indem agentenbasierte Strommarktsimulationen durchgeführt werden, die mehrere wichtige Forschungsziele verfolgen. Zunächst werden Betriebsstrategien für Flexibilitätsoptionen analysiert und hinsichtlich ihrer Wirtschaftlichkeit auf Elektrizitätsmärkten bewertet. Es zeigt sich, dass Betriebsstrategien die Preisauswirkungen von Flexibilitätsoptionen sowohl auf individueller als auch auf kollektiver Ebene berücksichtigen müssen. Zweitens werden rentable Speichersystemparameter untersucht. Dabei werden mittelfristige Speicherkonfigurationen als Systeme mit dem besten Ertragspotenzial auf Day-Ahead-Märkten identifiziert. Dies gilt insbesondere in Szenarien mit verstärktem Flexibilitätswettbewerb. Drittens werden Kannibalisierungseffekte sichtbar, sobald erhebliche Flexibilitätskapazitäten in das System integriert werden. Aufgrund ihrer signifikanten Auswirkungen auf die Strompreisdynamik kommt es zu sinkenden Gesamterträgen, welche wiederum Auswirkungen auf die Rentabilität von Flexibilitätsoptionen haben.

Auf Basis dieser Ergebnisse lassen sich die folgenden Empfehlungen für die künftige Forschung und Politik ableiten. Um künftige Energiesysteme besser zu verstehen, ist die endogene Modellierung von Flexibilitätsoptionen erforderlich, da bei einer isolierten Analyse die Marktinteraktionen erheblich unterschätzt werden. Die Rentabilität von Flexibilitätsoptionen hängt außerdem stark von Kostenannahmen ab, insbesondere von den Speicherkosten, die bei Investitionsentscheidungen sorgfältig berücksichtigt werden müssen. Geplante Investitionen in Flexibilitätsoptionen sollten darüber hinaus genau beobachtet werden, da Kannibalisierungseffekte und veränderte Marktdynamiken ihre Rentabilität erheblich beeinflussen werden.

Die endogene Modellierung dieser komplexen Phänomene stellt einen wichtigen methodischen Fortschritt dieser Dissertation dar. Erreicht wird dies durch Erweiterungen und die Anwendung eines modernen Elektrizitätsmarktmodells, das mit Methoden des maschinellen Lernens für die Erstellung von Strompreisprognosen gekoppelt ist. Mit die-

ser Dissertation werden mehrere Softwarepakete und Datensätze bereitgestellt, die den FAIR-Prinzipien entsprechen. Dadurch wird die Reproduzierbarkeit verbessert und weiterführende Forschung in diesem Bereich erleichtert. Zudem erweitert diese Dissertation das Verständnis der Rolle von Flexibilitätsoptionen in Energiewendeszenarien und zeigt gleichzeitig wichtige Aspekte für künftige Untersuchungen auf. Zu den wichtigsten Einschränkungen, die in der weiteren Forschung adressiert werden müssen, gehören die Beschränkung auf die Analyse des Day-Ahead-Marktes anstelle der Simulation mehrerer Märkte sowie die vereinfachte Berücksichtigung der Dynamik der Sektorenkopplung.

Declaration

I hereby certify that I have independently authored the submitted dissertation titled *Flexibility options in electricity markets with high shares of renewable energies: An agent-based analysis of economic viability and system impacts* without external assistance, have not used sources other than those referenced in it, and have duly acknowledged all directly or indirectly adopted text passages, as well as utilised graphics, tables, and analysis programmes. Furthermore, I confirm that the electronic version presented corresponds to the written version of the dissertation, and that the thesis, in this or a similar form, has not been previously submitted and evaluated elsewhere.

Erklärung

Ich versichere an Eides statt, dass ich die eingereichte Dissertation mit dem Titel *Flexibility options in electricity markets with high shares of renewable energies: An agent-based analysis of economic viability and system impacts* selbstständig und ohne unzulässige fremde Hilfe verfasst, andere als die in ihr angegebene Literatur nicht benutzt und dass ich alle ganz oder annähernd übernommenen Textstellen sowie verwendete Grafiken, Tabellen und Auswertungsprogramme kenntlich gemacht habe. Außerdem versichere ich, dass die vorgelegte elektronische mit der schriftlichen Version der Dissertation übereinstimmt und die Abhandlung in dieser oder ähnlicher Form noch nicht anderweitig als Promotionsleistung vorgelegt und bewertet wurde.

Felix Johann Nitsch

Bochum, 21. Juli 2025

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Contents

List of tables

List of figures

List of acronyms

ABM agent-based model

aFRR automatic Frequency Restoration Reserves

API application programming interface

DAM day-ahead market

DLR German Aerospace Center

E2P energy-to-power

ESA energy systems analysis

ESOM energy systems optimisation model

FAIR findable, accessible, interoperable, reusable

FO flexibility option

MAE mean absolute error

ML machine learning

NN neural networks

RE renewable energy

RMSE root mean squared error

RTE round-trip-efficiency

SoC state of charge

1 Introduction

This chapter provides an introduction to the content of this thesis, with Section 1.1 explaining the need for flexibility options (FOs) in future electricity markets. Section 1.2 provides a brief overview of the current state of the literature in this field, followed by a presentation of the identified research gaps and research targets. The structure of the thesis is outlined in Section 1.3.

1.1 Background and motivation

The Paris Agreement, which was reached in December 2015, is a significant milestone defining global efforts to combat climate change (Schleussner et al. 2016). Its main objective is to limit the global temperature increase to well below 2°C above pre-industrial levels. It has shaped international climate policy and set ambitious targets for reducing greenhouse gas emissions. However, recent reports once again highlight the urgency of accelerating climate action (IPCC 2024). Therefore, a rapid and comprehensive energy transition from fossil fuels to renewable energy (RE) sources is critical.

At the heart of the energy transition is the balance between three fundamental pillars: energy security, social and environmental considerations, and cost efficiency (Löschel et al. 2020). Energy security refers to the reliable availability of electricity at all times, which is essential for human welfare and economic stability. The increasing integration of RE sources, which are inherently variable and weather dependent, poses new challenges in maintaining this security. Therefore, it is necessary to ensure that electricity can be generated or stored to meet demand, even when RE sources are insufficient or unavailable at that time. Social and environmental considerations cover a wide range of factors, from public acceptance of RE technologies to biodiversity protection and land use concerns. Public perception of energy systems and their transformation can have a significant impact if there is opposition to certain infrastructure projects (Enserink et al. 2022). In addition, the environmental impact of the technologies used, whether through land use, resource extraction, or impact on ecosystems, must also be considered (Rahman, Farrok, and Haque 2022). Cost efficiency is another important aspect, as it is necessary to ensure that the transition to RE sources is economically viable. In liberalised markets, the energy transition depends on individual investments that are incentivised by attractive business cases. Investors must evaluate capital expenditures, ongoing operational costs, and expected revenues within a low-emission energy system. At the same time, policy and market frameworks should also account for the broader, long-term economic benefits of achieving climate targets and mitigating climate change at the system level (Bogdanov, Ram, et al. 2021; Osman et al. 2023). Therefore, it is critical to consider both these micro- and macroeconomic perspectives for the success of the energy transition.

The ultimate goal of the energy transition is to reduce global greenhouse gas emissions (Rogelj et al. 2019). This thesis thereby focuses particularly on the electricity sector, which is a major contributor (IEA 2024). To achieve the emission reduction targets, new power plants must be implemented, especially those based on RE sources, such as wind, solar, and hydropower (Twidell 2021). It also involves electrification of various sectors, which will increase demand for electricity (Staffell and Pfenninger 2018). In particular, the transition to electric vehicles, the electrification of heating systems through heat pumps, and the transformation of industrial processes away from fossil fuels all contribute to this increase in demand. Growing shares of fluctuating RE sources also require a flexible and responsive energy system that can adapt to changes in supply and demand across timescales from seconds to seasons (Leonard, E. Michaelides, and D. Michaelides 2020). This flexibility can be provided through various technological solutions, collectively referred to as flexibility options (FOs) (Zöphel et al. 2018).

FOs can be characterised by several key parameters such as capacity (the total amount of energy that can be stored, i.e., MWh), power (the rate at which energy can be charged or discharged, i.e., MW), ramping capability (the rate of change of power, i.e., MW/min), and cost (both capital and operating costs, i.e., EUR/MW, EUR/MWh) (Alizadeh et al. 2016). A well-established example of a FO is pumped hydro storage (Babatunde, Munda, and Hamam 2020). This mature and widely used technology stores energy by pumping water uphill to a reservoir during periods of low demand/price and releasing it during periods of high demand/price to generate electricity, profiting from this arbitrage. Although it offers significant capacity, its scalability can be limited by geographical restrictions that require significant up-front investment (Hunt et al. 2020). In contrast, battery storage systems, particularly lithium-ion batteries, have experienced rapid cost reductions and efficiency improvements in recent years (Cole, Frazier, and Augustine 2021). These systems are highly scalable and can provide short-term flexibility services, making them an increasingly attractive solution for integrating RE sources into the energy system. Another concept for providing flexibility is "sector coupling", which refers to the integration and coordination of different energy sectors (Fridgen et al. 2020). This involves linking the electricity sector with other areas, such as heating, industry, and transportation (Orths et al. 2019). Although, it is estimated that the flexibility potential is significant (Bernath, Deac, and Sensfuß 2021), it is challenging to assess specific economic feasibility as all solutions compete with each other (Ramsebner et al. 2021).

As with RE technologies, there are additional considerations in addition to technical specifications that are relevant to the successful application of FOs. These are related to scalability and expansion potential. Social acceptance can have a significant impact on the feasibility of projects, as shown by public opposition to new pumped hydro projects in environmentally sensitive or scenic areas (Pickard 2011). Many technologies are still evolving and may not yet be available on a scale or at the cost required for widespread deployment. This may already affect today's investment decisions (Koltsaklis and Knápek 2023). As these projects typically are large in capital with long payback periods, an accurate evaluation of their economic potential is essential (Keles 2013). Therefore, a thorough ex ante analysis is needed to assess the economic and operational viability of these FOs for application in future market scenarios (Ölmez, Ari, and Tuzkaya 2024). Several analyses have already been carried out in this area and will be discussed in the next section.

1.2 Research targets

Existing studies of FOs in electricity systems generally fall into two categories. The first category focuses on individual devices, examining the technical and economic performance of individual storage devices without considering their market implications (Elalfy et al. 2024). While these studies provide valuable information on operational characteristics, they often use historical price time series. This is a critical limitation because they cannot capture the potential impact of large-scale FOs deployment on electricity market dynamics and profitability (Lund et al. 2015). The second category uses system optimisation with a "central planner" approach, assuming perfect coordination between all components of the system to achieve a global optimum (Mancò et al. 2024; A. M. Barbosa et al. 2024). These models often assume perfect foresight, which does not reflect the reality of decision-making under multiple uncertainties (Fodstad et al. 2022). In addition, they tend to be computationally expensive, which limits the number of scenarios that can be explored (Ma and Nakamori 2009). Furthermore, energy systems are highly complex because they are interconnected across multiple dimensions, from technical and social to environmental concerns (Bale, Varga, and Foxon 2015). Therefore, models studying FOs must capture not only technical aspects, but also social aspects such as the behavior of individual actors (Pfenninger 2024). These limitations and challenges highlight the need for modeling approaches that can handle such complexity.

What is missing is a comprehensive analysis that accounts for agent behaviour in electricity markets characterised by increasingly high RE shares while explicitly considering operational uncertainty and forecasting limitations (Bessa et al. 2019). Future electricity markets will exhibit fundamentally different price dynamics. On the one hand, RE will increase the price spreads between peak (low RE generation) and off-peak prices (high RE generation). On the other hand, various FOs will exploit these attractive spreads through arbitrage, thereby reducing them over time. Yet current FO profitability assessments remain largely based on historical market patterns that neglect these dynamic interactions. Market imperfections and uncertainty, such as participants not bidding at marginal cost, can further significantly affect revenue potential, but are often overlooked in current studies (Reza et al. 2023). Moreover, the impact of strategic individual behaviour by market participants, especially FOs, should be accounted for in these transformed market conditions (Siala et al. 2022). To address these complex interactions between individual agent decisions and system-wide market outcomes, electricity market simulation methods offer a proven analytical framework (Weidlich and Veit 2008). Agent-based models (ABMs) are a particularly powerful approach within this framework, as they place individual actors at the centre of analysis and examines how system-level effects emerge from their strategic interactions (J. Castro et al. 2020). Despite this potential, more research applying ABMs to energy systems analysis (ESA) is needed to explicitly address these identified research gaps (Heider et al. 2021).

There is also a gap in open research software and data availability. Although there are notable developments in the domain of open science in ESA (Gils et al. 2022), open software that is well documented, thoroughly tested, and modularised for flexible application can further contribute to the field. Adherence to the findable, accessible, interoperable, reusable (FAIR) principles (Barker et al. 2022) for research software would enhance the transparency and reproducibility of the results. Open data repositories, which can be freely used, facilitate simple and convenient application and extension of ESA models, and thus accelerating progress in the field (Chang et al. 2021).

This thesis addresses the identified research gaps through advancements in two interconnected domains: energy economics and energy informatics. Within the energy economics domain, the following research targets are identified.

1.1 Identify operational strategies for FOs that perform reliably in future electricity market scenarios with increasingly high RE shares.
1.2 Evaluate how technical specifications (e.g., capacity & power) of FOs influence refinancing potential under varying cost assumptions.

1.3 Quantify the impact of increasing market penetration of competing FOs on their profitability in day-ahead market (DAM).

From an energy informatics perspective, the objective is to extend and enhance existing models to enable a detailed representation of FOs and their market interactions, as outlined below.

2.1 Expand ABM to simultaneously capture both individual FO economics and their collective impact on system dynamics.
2.2 Develop modular open-source software packages to enhance reproducibility and facilitate comparative assessment of FOs.

The novelty of this research lies in the combination of different modelling techniques, from ABM to optimisation and machine learning (ML), to provide a more comprehensive understanding of FO in systems with high shares of RE. Given that individual actions can aggregate into emergent, often unintended outcomes at scale (Schelling 2006), I explicitly examine this phenomenon in the context of increasing FO deployment. Furthermore, this work contributes numerous software packages to the field, adhering to open science practices, specifically following the FAIR principles (Barker et al. 2022), thus facilitating future research. By bridging the gap between theoretical optimality and realisable outcomes, this research provides valuable insights for policy makers, investors, and system operators navigating the complexities of the energy transition.

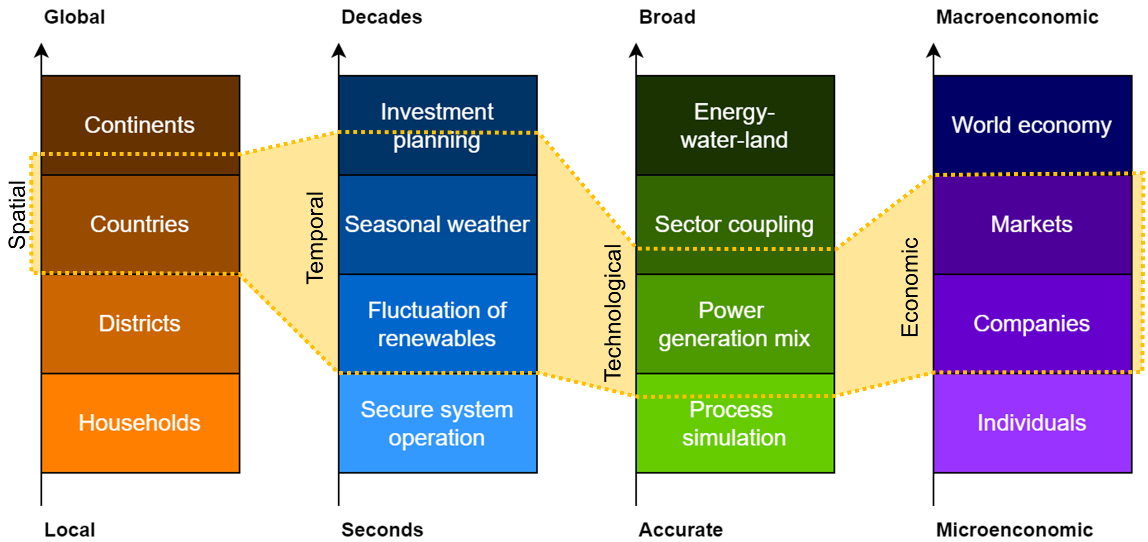


Figure 1.1: Spatial, temporal, technological, and economic scopes of the applied energy system models. Illustration based on Cao et al. 2021.

Figure 1.1, which is based on an illustration by Cao et al. 2021, shows the spatial, temporal, technological, and economic scope of the ESA models applied in this thesis. The spatial scope primarily targets the German DAM zone with extensions to neighbouring market zones. Temporarily, the analysis ranges from accounting for RE fluctuations to seasonal weather effects, partially covering investment planning perspectives. Although the work features some aspects of sector coupling and system services, the technological scope focuses primarily on the mix of power generation. From an economic perspective, I address the interactions between companies who could operate a FO, and whole markets.

1.3 Structure of the thesis

The structure of the thesis is presented in Figure 1.2. Chapter 2 provides a high-level presentation of the applied materials and methods. This includes a detailed description of the applied ESA models in Section 2.1, complementary tools and methods in Section 2.2, and model calibration in Section 2.3. The four main research papers are presented in Chapter 3, specifically in Sections 3.1 to 3.4, each with bibliographic information including an executive summary and author contributions. A synthesis of all the research papers presented is provided in Section 3.5, which describes how the papers contribute to filling the identified research gaps. Chapter 4 outlines the limitations of the presented theses, summarises the overarching findings, and draws conclusions. The Appendix contains supplementary peer-reviewed and supplementary non-peer-reviewed papers in Chapters A and B respectively. A short academic curriculum vitae is presented in Chapter C.

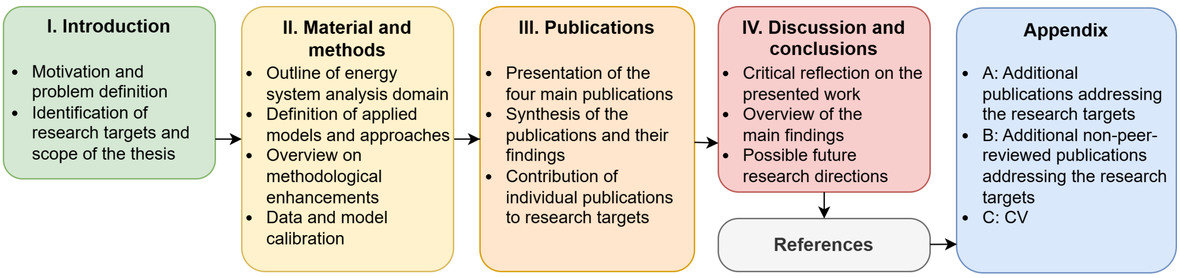


Figure 1.2: Outline of the thesis.

2 Material and methods

This chapter presents an overview of the approaches and models used to address the research targets presented. In contrast to the individual materials and methods sections in the research papers (see Chapter 3), this chapter provides an overview of the primary methods used and lists my major methodological contributions. In the beginning, the field of energy systems analysis (ESA) is introduced in Section 2.1 by outlining two prominent and widely used approaches, agent-based models (ABMs) (Subsection 2.1.1)and energy systems optimisation models (ESOMs) (Subsection 2.1.2). An overview of complementary methods, such as machine learning (ML) and model coupling, is given in Section 2.2. Section 2.3 on scenario definition and data provides insights in the modelling assumptions, model validation, and also tools which are used to perform multi-scenario analysis.

2.1 Energy system models

System models in the energy domain were already in use in the mid 20th century (Barnett 1950). During the oil crisis in the 1970s, ESA contributed to the public discussion (Meadows et al. 1972; Hoffman and Wood 1976). More recently, the transition to low-carbon energy systems and its implications along the transformation lead to increasingly complex problems (Nakata, Silva, and Rodionov 2011). It is important to find an optimal allocation of power plant technologies under the consideration of meeting the demand while staying below the emission limits (Davis et al. 2018). For many stakeholders, from policy makers to investors, it is crucial to know how target systems may be specified. This allows them to pursue relevant investments and avoid potential lock-in effects (Bertram et al. 2021).

ESA modellers have faced new challenges in the last decade due to the increasing complexity of both real-world systems and the models employed (Pfenninger, Hawkes, and Keirstead 2014). There is a wide range of ESA models available, each with its own temporal, technological, sectoral, or spatial focus (Fodstad et al. 2022). Increasing computational capacities foster the development and application of comprehensive ESA models, realising detailed model coupling workflows. Open modelling approaches, including methodological transparency and data accessibility, enhance the credibility and impact of energy systems research (Pfenninger, Hirth, et al. 2018).

In this thesis, I focus on two main approaches, ESOMs and ABMs. ESOMs are widely applied to identify optimal energy systems under the consideration of, e.g., emission constraints (Hoffmann et al. 2024). They can also be used for dispatch planning and unit commitment purposes. ABMs focus on individual or prototypical agents and model the outcomes by agent interaction. These models can be used to assess specific system designs in an exploratory way, combining micro- and macroeconomic viewpoints. These analyses may be attributed to the field of energy economics, which studies the supply and demand of energy. In this regard, electricity markets are a fundamental component of energy systems, as they facilitate the allocation of energy from producers to consumers. As the energy transition leads to more electrification across all sectors, the demand for electricity is expected to increase (IEA 2024). Electricity markets will therefore become more important. In the context of this research, my focus is primarily on day-ahead markets (DAMs), which provide crucial price signals to all market actors in several markets (Silva-Rodriguez et al. 2022). In particular, the electricity exchange collects bids and asks, and periodically clears the market. The electricity market is shaped by various actors, including producers, consumers, traders, flexibility providers, and regulators. These actors can be represented as (prototypical) agents in an ABM.

2.1.1 Agent-based simulation

ABM is a computer simulation approach explicitly modelling interactions between agents that can reveal emergent behaviour (Helbing and Balietti 2012). Starting from an initial scenario configuration, ABM allows exploratory analysis of potential outcomes (Tesfatsion 2006). In the context of ESA, ABM offers a number of significant strengths (Ringler, Keles, and Fichtner 2016). First, by incorporating the perspective of individual actors, researchers can identify potential emergent effects (Frey, Klein, et al. 2020). Secondly, the use of heterogeneous agents in an ABM simulation allows for the representation of a range of actor characteristics, including their objectives, risk profiles, information levels, and interactions with their environment (Kraan, Kramer, and Nikolic 2018). Thirdly, ABM offers superior practical applicability to address real-world energy transition challenges while maintaining computational feasibility (Hansen, Liu, and Gregory M. Morrison 2019b). Fourthly, uncertainties of various origins can be considered, ranging from system design to imperfect information (Hansen, Liu, and Gregory M Morrison 2019a). Finally, in contrast to optimisation models, there is no global objective function to be maximised or minimised (Ma and Nakamori 2009), however, individual agents can use optimisation models for their own decision-making (Klein, Frey, and Reeg 2019).

It is also important to consider the challenges of ABM, which can be caused by parameterisation issues (Hammond 2015). As (prototypical) actors are the core of any ABM problem, detailed knowledge on the individual actor's is critical (Janssen and Ostrom 2006). Due to its exploratory nature, even minor changes in input parameter configurations can yield significantly different results (J. Castro et al. 2020). Therefore, model validation, such as backtesting against historical data, is an important step in ABM application (F. Maurer et al. 2024).

2.1.1.1 AMIRIS

The open *A*gent-based *M*arket model for the *I*nvestigation of *R*enewable and *I*ntegrated energy *S*ystems AMIRIS is a state-of-the-art ABM to analyse renewable energy (RE) market integration and policy effects (Schimeczek, Nienhaus, et al. 2023). It was created by the German Aerospace Center (DLR) over a decade ago and has been continuously developed ever since, with the software being openly available since 2021. The various types of agents perform tasks based on their own inputs and their surrounding environment, as illustrated in Figure 2.1. Modellers can adjust the level of information for each agent individually by defining the so-called contracts. They represent a formalised method of exchanging information at a specified time between agents.

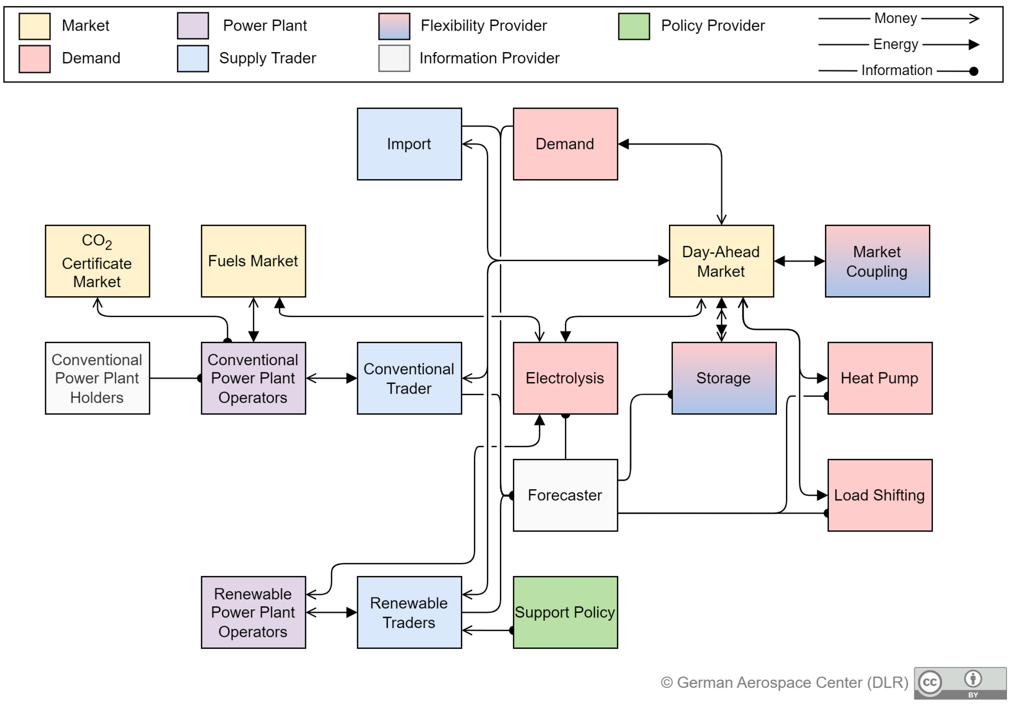


Figure 2.1: AMIRIS model structure revealing agent types and their connection (Schimeczek, Nienhaus, et al. 2023).

The focus of AMIRIS is the DAM, where uniform electricity prices are determined in an hourly resolution. In order to achieve this, the energy exchange agent collects bids and asks from the relevant agents, either providing electricity supply or requesting to meet electricity demand. Electricity supply can be provided by conventional power plants or a RE plants. These units can be as detailed as a single block of a power plant to an aggregated fleet of power plants. Each power plant operator maintains a connection with a respective trader whose objective is to sell their power generation potential on the DAM. In order to facilitate this, the trading agent receives marginal cost information from the power plant operators, which are determined by operational costs, fuel costs, and emission certificate costs. Traders are then able to add optional markups to marginal costs, accounting for ramp-up costs (Liberopoulos and Andrianesis 2016), and markdowns, accounting for ramp-down costs (Pape, Hagemann, and Weber 2016), both of which represent non-convex nature of such costs (Makkonen and Lahdelma 2006). Demand traders are defined as actors who seek to procure a specified quantity of energy at a designated point in time. A "value of lost load" is assigned to the bid, which represents the maximum price the bidder is willing to pay for the requested demand. Flexibility option (FO) agents, such as storage operators, control a storage device, enabling them to purchase and sell energy to the market according to their internal state of charge (SoC). As this is a time-dependent matter, the operator must develop an operational schedule based on a forecasted electricity price. This optimisation problem is solved using dynamic programming (Bellman 1957) and discrete levels of SoC. From a strategic point of view, the objective may be to maximise profits or to minimise overall system costs. A policy agent enables the examination of various policy instruments with the objective of supporting the operations of RE power plants. Furthermore, additional neighbouring DAMs can be interconnected through a central market coupling agent (Nitsch and El Ghazi 2023). Time-dependent transmission capacities between market zones account for the comprehensive states of interconnected electricity markets. The central coupling algorithm is designed with the objective of optimising the collective welfare of all interconnected markets. A comprehensive account of all agent types can be found in the AMIRIS-Wiki[1].

The Python package AMIRIS-Py provides a convenient wrapper for all modelling tasks (Schimeczek and Nitsch 2024). Specifically, AMIRIS-Py handles the installation, setup, model execution, and post-processing of the results. With AMIRIS-Examples, there is also an open scenario data collection available (Nienhaus et al. 2025). This ensures an easy on-boarding for new users, but also convenient workflow adaptations for more ex-

[1]`https://gitlab.com/dlr-ve/esy/amiris/amiris/-/wikis`

perienced users. All components of AMIRIS are designed in a modular way, so that model extensions and model coupling are easily possible, such as AMIRIS-PriceForecast (see Section 2.2.1.2) or AMIRIS-Scengen (see Section 2.2.3). Converters to other ESA models allow for a convenient coupling of the model, such as AMIRIS-CHARGIN which converts the results of AMIRIS to the electric vehicle simulation model CHARGIN (Nitsch 2025a). Thorough software development standards, such as unit testing, documentation, tutorials, and individual user support, are important aspects to establish AMIRIS in the ESA modelling domain (Nitsch 2023a). Strong efforts are put into community building, which is a declared target of the AMIRIS developers (Nitsch, Schimeczek, Nienhaus, et al. 2025).

AMIRIS has been used in several research projects and publications, the most prominent of which are described below. In-depth interviews and detailed agent parameterisation have been carried out, focusing on the transformation of real actors into simulated agents in (Reeg 2019). A feedback loop caused by inadequate policy instruments in scenarios with high shares of RE lead to undesirable price effects, demonstrating the need for ongoing policy evaluation (Frey, Klein, et al. 2020). Strong efforts in model harmonisation led to uniform model results between an optimisation model and AMIRIS, revealing the so-called "efficiency gap" of energy system scenarios (Torralba-Diaz et al. 2020). The effects of extreme weather events, in particular periods of low RE generation and high electricity demand, have been investigated quantifying the mitigation potential of international trade, finding that additional transmission capacity can only partially limit large-scale events in Central Europe (Nitsch, Scholz, et al. 2023). AMIRIS is coupled with an optimisation model in (Sarfarazi, Sasanpour, and Bertsch 2024) which addresses the integration of energy communities in the electricity market. The potentials for demand response, i.e. shifting power on the demand side, have been analysed by a new load shifting agent that provides flexibility to the system (Kochems 2024). A study on flexible heat pump operation showed that significant electricity cost savings can be achieved, but also revealed substantial impact on overall market dynamics (Sperber et al. 2025).

From a technical point of view, AMIRIS is implemented in Java and configured using YAML and CSV files. The FAME framework manages agent creation and communication overhead, as well as overall model execution. The next section provides more detail on FAME.

2.1.1.2 FAME

The need to rapidly adapt scientific models to changing environments, while maintaining the highest scientific standards and providing users with easy-to-use tools, requires a dedicated framework for agent-based electricity market analysis. The "Open *F*ramework for Distributed *A*gent-Based *M*odelling of *E*nergy Systems" FAME (Schimeczek, Nitsch, et al. 2020) addresses these challenges by providing robust tools for developing, executing and managing ABM (Figure 2.2). It simplifies model parallelisation, reduces programming effort, and achieves low overhead, enabling researchers to create accurate and easily adaptable models that reflect the real-world complexity of modern energy systems.

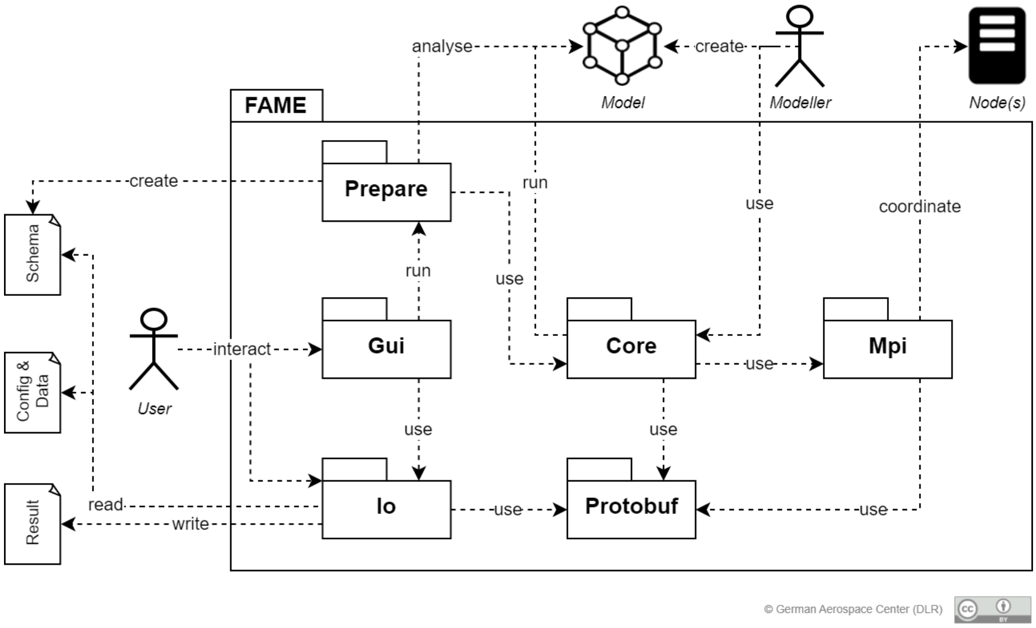


Figure 2.2: FAME components and their roles within the framework (Schimeczek, Nitsch, et al. 2020).

There are two main components to the FAME framework, namely FAME-Core (Schimeczek, Deissenroth-Uhrig, et al. 2023) and FAME-Io (Nitsch, Schimeczek, Frey, et al. 2023). FAME-Core is a Java library that supports the development and execution of ABM simulations. It also provides options for running models in parallel on different platforms, reducing the complexity and skill requirements typically associated with high-performance ABM development. It streamlines the management of common tasks, such as input/output handling and agent scheduling, simplifying the creation and maintenance of ABM. It also provides discrete event scheduling, guaranteed message delivery, and suitability for scientific modelling through extensive documentation and adherence to high coding standards.

FAME-Io facilitates the creation, validation and conversion of complex ABM simulation configurations, ensuring data integrity and simplifying the workflow for researchers. Specifically, it handles configuration files in YAML and CSV formats, allowing easy setup and pre-run validation of simulations, speeding up programming exercises. The package allows configurations to be split into multiple files, supports structured YAML configurations, and validates these against schemas derived from the associated ABM. The Python package is operating system independent and follows state-of-the-art software development practices while efficiently handling large data sets and configurations.

Other FAME components, such as FAME-Mpi and FAME-Protobuf, serve as supporting tools for FAME-Core and FAME-Io. The example model FAME-Demo shows the main features and illustrates the interaction of all components. In addition, FAME-Gui provides a graphical user interface.

2.1.2 Energy system optimisation

The domain of ESOMs is diverse, ranging from a single-unit dispatch optimisation to planning global energy systems (Hoffmann et al. 2024). State-of-the-art ESOMs are very comprehensive tools that can solve extensive real-world problems. New advances, such as multi-criteria optimisation (Finke 2024), or solving highly sector-coupled systems (Bogdanov, Gulagi, et al. 2021), provide in-depth insights to pressing questions in ESA. Prominent open source ESOMs are, e.g., Backbone (Helistö et al. 2019), oemof.solph (Krien et al. 2025), OSeMOSYS (Howells et al. 2011), PyPSA (Brown et al. n.d.), and REMix (Wetzel et al. 2024). All applications have in common that an objective function is maximised or minimised by defining the decision variable(s) under consideration of constraints (Hillier 1967). A simplified energy system model for dispatch optimisation could be formulated where the demand d_t has to be met at all times t by the supply $s_{i,t}$ of technology i. Generation of electricity causes emissions of e_i and operational cost $c_{i,t}$. The total system cost c^{total} should be minimised as

$$C^{\text{total}} = \min \sum_t c_{i,t} \times s_{i,t}$$

The following constraints must be taken into account. First, the demand d_t must be met at all times

$$\sum_t s_{i,t} = d_{i,t}$$

Secondly, the supply cannot exceed its individual limits $s_{i,t}^{\max}$

$$0 \leq s_{i,t} \leq s_{i,t}^{\max} \quad \forall i, t$$

Thirdly, total emissions should not exceed a specified maximum emission limit $e_{\max}$

$$\sum_t e_i \times s_{i,t} \leq e_{\max}$$

The optimiser would therefore decide on the optimal dispatch of all technologies i leading to minimised total cost. If one were to find the optimal capacity expansion of power plants, the problem could be adapted as follows. The calculation of the total system cost c^{total} could also be extended considering the expansion cost c_i^{invest} as

$$c^{\text{total}} = \min \sum_t c_{i,t} \times s_{i,t} + c_i^{\text{invest}} \times s_{i,t}$$

Optimisation methods are applied not only for comprehensive ESA but also widely for detailed FO schedule planning (Song et al. 2024).

2.2 Complementary tools and methods

In the context of the rapidly evolving landscape of computer science and methods, the development and deployment of comprehensive, reliable, and modular research software becomes more important. This section therefore lists the tools and methods used or developed specifically for this research to complement ESOMs and ABMs.

2.2.1 Machine learning

ML enables computers to perform tasks without explicit instructions (Zhou 2021). It relies on learning from data to discover patterns and to make decisions or predictions. There are several steps in the successful application of ML including data collection and preparation, model selection and training, and evaluation and (hyperparameter) optimisation (Alpaydin 2021). Data collection involves gathering and preprocessing data to ensure its quality and relevance. Model selection refers to choosing the appropriate algorithms, such as decision trees, support vector machines, or neural networks (NN), which are then trained on the data to learn the underlying patterns. Evaluation and optimisation involve assessing the model's performance using metrics like accuracy or mean squared error and fine-tuning the model to improve its predictive power. ML is used in various applications achieving significant advancements in recent years. Notable achievements include the prediction of three-dimensional protein structures (Jumper et al. 2021), synthetic image generation (Rombach et al. 2022), robust speech recognition (Radford et al. 2023), and generative models capable of processing image or text inputs (OpenAI et al. 2024).

Although time series forecasting might not capture as much public attention, extensive research is being conducted in various domains (Petropoulos et al. 2022). These applications range from climate time series (Mudelsee 2019), emergency patient volume (Jones et al. 2008), retail sales (Alon, Qi, and Sadowski 2001; Böse et al. 2017), tourism arrivals and overnight stays (Claveria and Torra 2014), web traffic (Madan and Mangipudi 2018), commercial electricity demand (Pallonetto, Jin, and Mangina 2022), industrial electricity demand (Walser and Sauer 2021), to crop prices (Jha and Sinha 2013). In addition to classical statistical methods such as autoregressive–moving-average models, NN, particularly deep learning, are gaining popularity due to impressive performance and increased availability of computational power (Lim and Zohren 2021; Vaswani et al. 2023). Recurrent NN are capable of directly modelling seasonality and provide a competitive method in timeseries forecasting (Hewamalage, Bergmeir, and Bandara 2021). Quantification of uncertainty represents another critical aspect of time series forecasting (Gal and Ghahramani 2016; Bjerregøard, Møller, and Madsen 2021; Nado et al. 2021), a prominent issue in weather forecasting research (Rasp and Lerch 2018; Baran et al. 2020; Schulz and Lerch 2022).

2.2.1.1 FOCAPY

FOCAPY (Nitsch 2023b) is a Python package that offers a feature-complete time series forecasting pipeline. In detail, FOCAPY handles data pre-processing, model training, and results evaluation in a convenient way, see Figure 2.3. It is based on the powerful library DARTS (Herzen et al. 2022). In order to forecast n target values, the user provides input data such as past target values and optional covariate values, see Figure 2.4. Based on the selection of the forecasting technique, FOCAPY handles the data flow to the training procedure. A comprehensive configuration file provides convenient analysis of multiple approaches and data sets. During model training, the class structure in FOCAPY ensures that the data are stored separately in training, test and validation sections, see Figure 2.5a. The corresponding data scaler object, which is used to normalise and de-normalise the data, is also stored alongside. Several different types of chunks, specific slices of the training data, allow for a versatile training routine. The evaluation of the results is structured similarly, specifically in a dedicated class structure as shown in Figure 2.5b. Each FOCAPY result contains the trained model with some accompanying information such as timestamps, colour codes, and scenario names, as well as a structured view of the error metrics. For each specified error metric, such as mean absolute error (MAE) or root mean squared error (RMSE), corresponding errors are calculated on multiple temporal scales, from individual hourly values to aggregated errors by hour of the day, allowing for a detailed examination of error distribution patterns (Nitsch and Schimeczek 2023). It can be called via the terminal or imported as a dependency in external scripts. To use the models trained with FOCAPY during runtime in AMIRIS, a specific interface was created, AMIRIS-PRICEFORECAST, see Section 2.2.1.2 below.

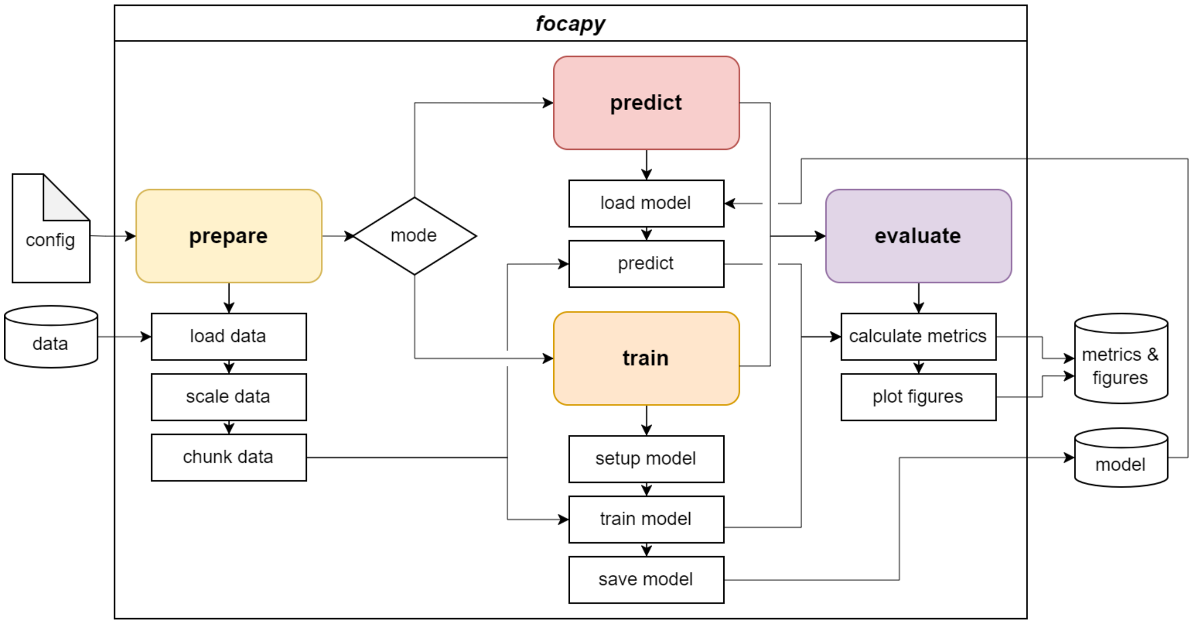


Figure 2.3: FOCAPY model workflow.

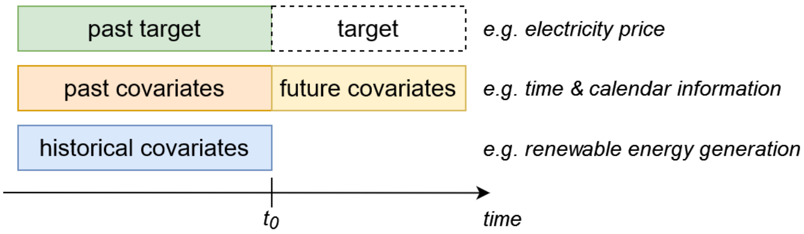
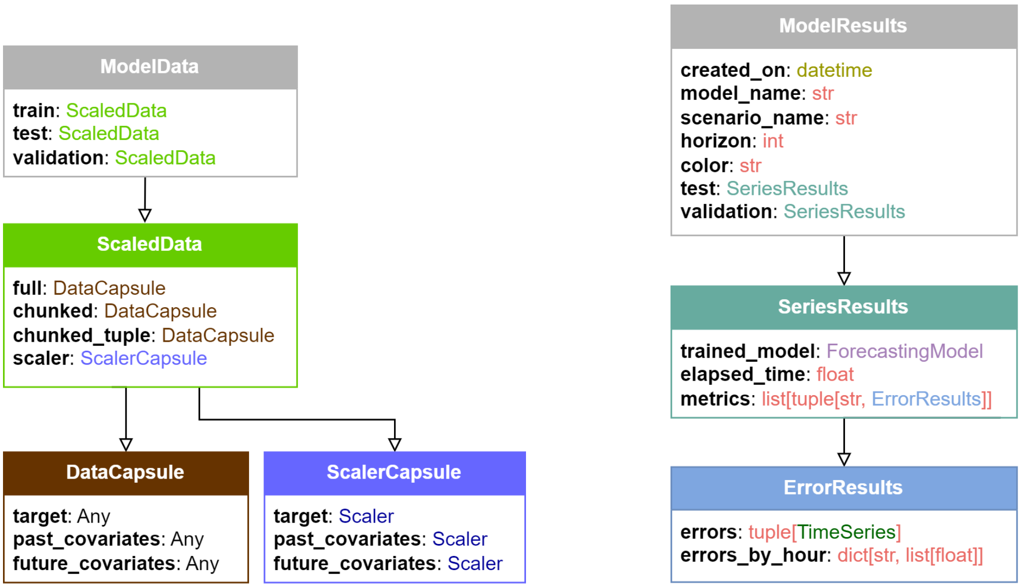


Figure 2.4: FOCAPY input data.



(a) Training workflow in FOCAPY. (b) Evaluation workflow in FOCAPY.

Figure 2.5: FOCAPY class diagrams.

2.2.1.2 AMIRIS-PriceForecast

FOs, such as battery storage systems, play a key role in most energy scenarios by shifting energy over time. Both in reality and in many electricity market simulations, FOs typically require electricity price forecasts to optimise their operational schedules. For instance, Figure 2.6 shows how this procedure is implemented in AMIRIS. Specifically, a ForecastAgent collects preliminary bids and asks from supply and demand traders, except those of the FOs. It then sends a "naive" - as it does not include any actions of the FOs - electricity price forecast to the FOs. This electricity price information, either a point in time or a merit order information, is used to optimise the bidding behaviour of the FOs. If there is only a single simulated FO in a scenario, it can accurately consider its own impact on the electricity price forecast, and therefore it can be considered a perfect forecasting situation. However, when multiple FOs are simulated simultaneously, the naive electricity price forecast does not take into account the bidding behaviour of (competing) FOs. Therefore, the revenue of individual FOs are negatively affected by the so-called "avalanche effect", where multiple actors react on the same signal, thus they may not achieve their expected outcome (Kühnbach, Stute, and Klingler 2021). This can also occur when the collective impact of individual actions reduces the overall revenue potential through "cannibalisation effects," as observed for RE sources (Hirth 2013) or FOs (Ölmez, Ari, and Tuzkaya 2024).

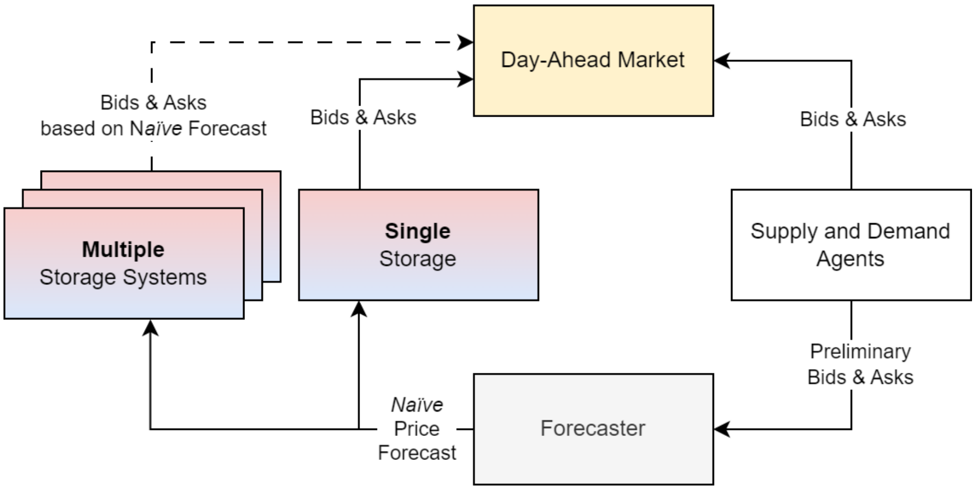


Figure 2.6: Flexibility option implementation in AMIRIS.

To address the limitations of these naive forecasts, I have developed a dedicated Python package that extends the current forecasting procedure in AMIRIS by coupling external forecasting algorithms (Nitsch and Schimeczek 2025b). The package AMIRIS-PriceForecast (Nitsch and Schimeczek 2025a) hosts modular forecasting architectures from simple time-shift models (Hyndman 2018) to comprehensive NN based forecasts like Transformers (Lim, Arık, et al. 2021). Figure 2.7 shows the interaction between PriceForecasterApi, a new Java agent designed to improve electricity price forecasting, its ForecastClient, such as a StorageTrader in AMIRIS, and the external AMIRIS-PriceForecast model itself (Nitsch 2025b). The ForecastClient requests an electricity price forecast for a defined period, e.g., the next 24 hours in the simulation. The PriceForecasterApi agent receives the request and passes it to AMIRIS-PriceForecast where the actual forecast is calculated. Once the forecast electricity price time series has been received, the PriceForecasterApi agent returns the price time series to its client. Communication between AMIRIS and AMIRIS-PriceForecast is handled by HTTP requests with data in JSON format using FastAPI[2]. AMIRIS waits for the response message from the external model and then continues the simulation.

[2] `https://github.com/fastapi/fastapi`

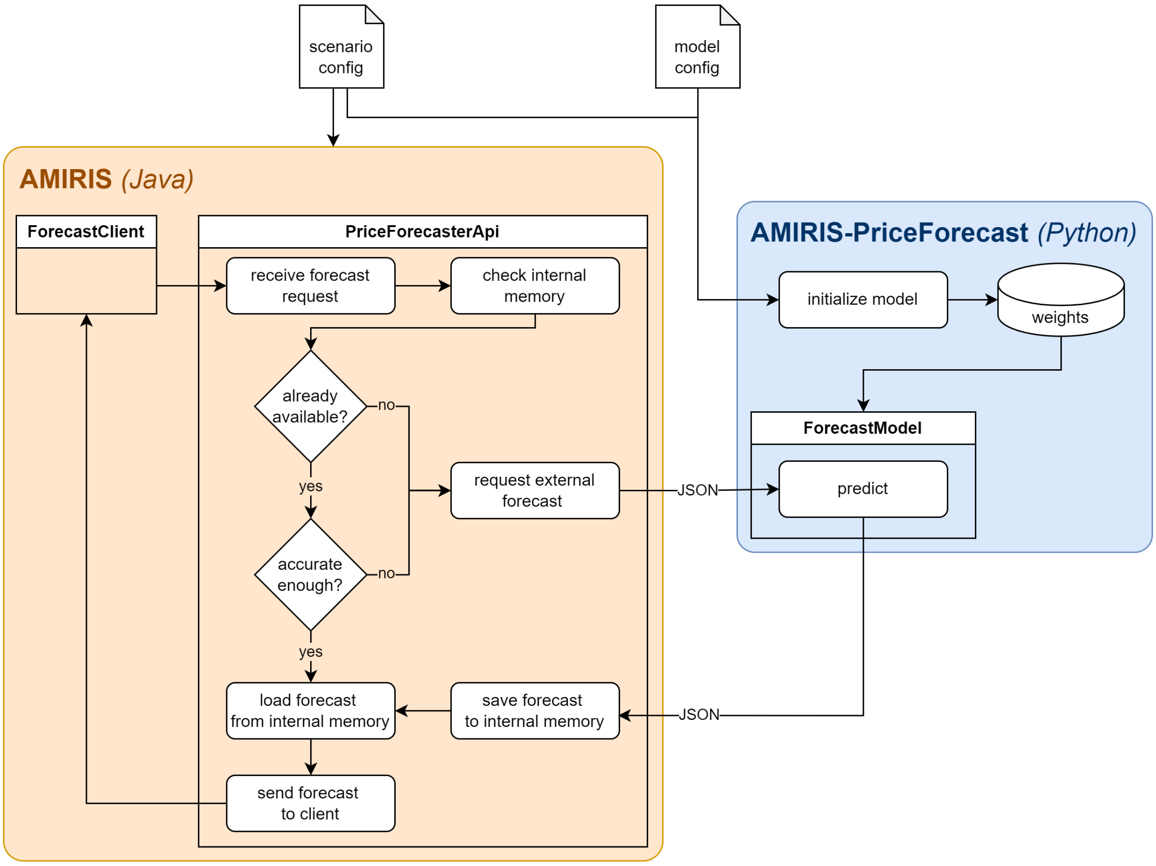


Figure 2.7: Enhanced electricity price forecasting in AMIRIS by calling an external forecasting model.

During a stress test (Nitsch, Sperber, et al. 2025), AMIRIS-PriceForecast was called every simulation hour with a payload consisting of 16 time series, each containing 168 time steps. The communication overhead between the models had a minimal impact on the overall runtime. The main cost driver is the execution of the ML prediction itself. In general, a yearly AMIRIS simulation with hourly resolution takes about 20 seconds when using the external model, compared to just 10 seconds for a standard run. If runtime of the model is critical, users can reduce the number of calls to AMIRIS-PriceForecast by specifying an extension window that contains additional forecasted time steps. If the realised electricity prices remain below the specified tolerance threshold, PriceForecasterApi will fulfil the forecast requests using its internal memory.

Table 2.1 provides an overview of the forecast algorithms available in AMIRIS-PriceForecast and accessible from AMIRIS. At the time of writing, there are three "naive" models and two NN models. The first group are TimeShift models, which use the last 1, 24 or 168 hours as a forecast and shift it into the future. If the requested forecast horizon exceeds the last prices, they are propagated continuously. For example, when p_T represents the price at time T, $\hat{p}_{T+h|T}$ denotes the forecasted price at time $T+h$ which follows a 24 hour pattern:

$$\hat{p}_{T+h|T} = p_{T+h-24}$$

There is also a SimpleNN model which consists of PyTorch (Paszke et al. 2019) layers. The exact specification and depth can be parameterised using a flexible YAML configuration file. Finally, there is a Transformer (Lim, Arık, et al. 2021) implementation based on the darts (Herzen et al. 2022) package. This architecture has proven to be a powerful yet flexible algorithm for modeling future electricity markets (Nitsch, Schimeczek, and Bertsch 2024). To account for forecast uncertainty through ensemble forecasting, a common approach in practice, the model can be called multiple times to generate individual forecasts. This then enables the application of probabilistic operational strategies. As the field of time series forecasting advances rapidly, AMIRIS-PriceForecast was designed in such a way that adding new forecasting architectures, such as TabPFN-TS (Hoo et al. 2025) is straightforward. Depending on the complexity of the underlying energy system scenario, time series forecasting can be a challenging task that demands detailed domain knowledge for selecting appropriate models and (hyper) parameters (Keles et al. 2016). Within this thesis, Paper III investigates anticipated shifts in energy transition scenarios, focusing specifically on how electricity price dynamics change in systems with significant shares of RE.

Table 2.1: Available forecast algorithms in AMIRIS-PriceForecast.

Name	Description	Probabilistic	Features
TimeShift1	Predictor using last hour as forecast	–	Past Targets
TimeShift24	Predictor using last 24 hours as forecast	–	Past Targets
TimeShift168	Predictor using last 168 hours as forecast	–	Past Targets
SimpleNN	Basic NN based on PyTorch (Paszke et al. 2019)	–	Past & Future Covariates
Transformer	Temporal Fusion Transformer (Lim, Arık, et al. 2021)	Yes	Past & Future Covariates

Figure 2.8 shows the workflow used for automated ML training. In contrast to focapy, this workflow extends the functionality by also generating synthetic training data using AMIRIS-Scengen (see Section 2.2.3). Specifically, user-generated scenario templates are converted into actual AMIRIS simulation input files and prepared for training. Then a ML of choice is trained within the AMIRIS-PriceForecast package. Finally, both model and the scenario data are saved to disk.

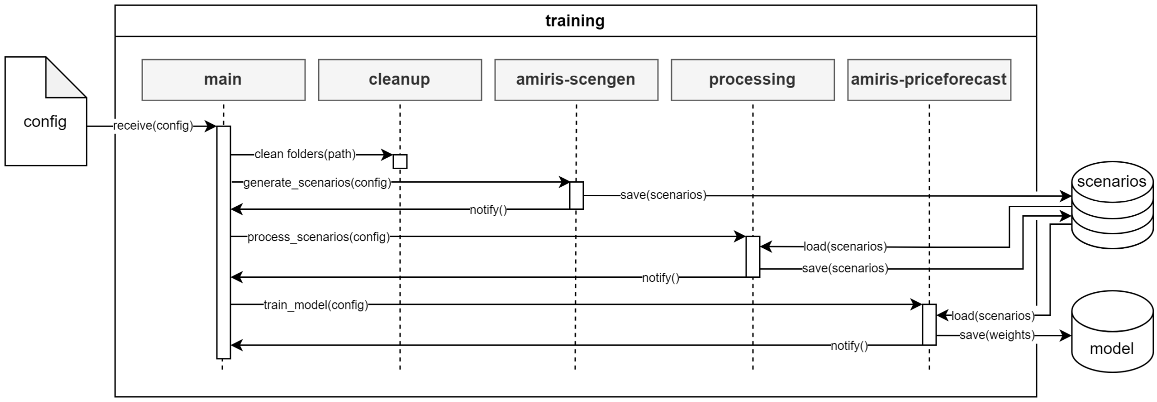


Figure 2.8: AMIRIS-PriceForecast training workflow.

After model training is completed, it can be used for inference during an AMIRIS simulation. The associated workflow, shown in Figure 2.9, handles AMIRIS-PriceForecast and the actual AMIRIS simulation. First, the trained model is loaded and the forecasting service endpoint is set up. Second, the AMIRIS simulation is started, where the PriceForecasterApi agent can request external electricity price forecasts. Once the model has run, all programmes, including the forecasting service endpoint, are shut down.

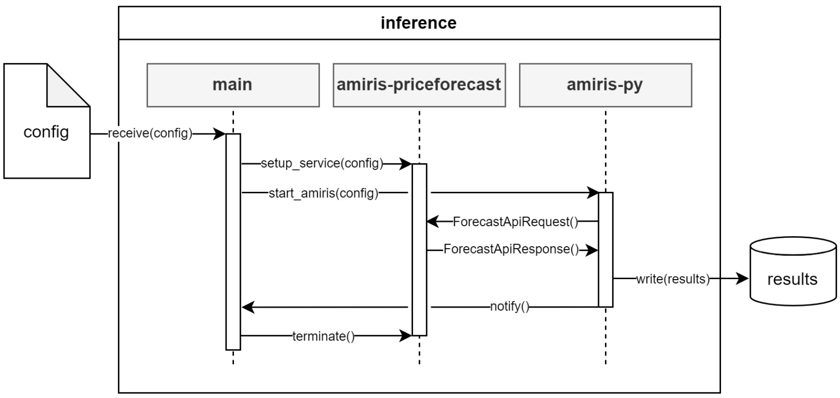


Figure 2.9: AMIRIS-PriceForecast inference workflow.

2.2.2 Model coupling and workflow management

Models in ESA are often specialised in a particular aspect or focus on a method. In order to extend the capability and functionality of a model, we can use model coupling. Model coupling can be achieved at different levels, ranging from loose/soft types (e.g. data exchange) to tight/hard types (e.g. interconnected modules) (Yourdon and Constantine 1979). In this thesis, there are different implementations of model coupling, which are outlined below.

In the first paper (Nitsch, Deissenroth-Uhrig, et al. 2021) the ABM AMIRIS is coupled with a dispatch optimisation model from the perspective of a storage operator trading on the DAM and automatic Frequency Restoration Reserves (aFRR). In the second paper (Nitsch, Wetzel, et al. 2024) a coupling between two comprehensive ESA models, namely REMix (Wetzel et al. 2024) and AMIRIS, is implemented. For this, REMix defines the power plant park from an optimal system perspective, while AMIRIS analyses the performance of the Carnot battery storage. The technical component of such a coupling is ideally performed by a workflow manager. In this thesis, the Python workflow manager IOPROC (Fuchs et al. 2020) is used for such tasks. It provides a powerful framework for flexible coupled workflows, such as IOG2X (Nitsch, Schimeczek, Wetzel, et al. 2023) which is also used in (Nitsch, Wetzel, et al. 2024).

2.2.3 Multi scenario analysis using AMIRIS-Scengen

Conducting multiple model runs enables comprehensive analysis of the scenario dynamics and parameter sensitivity. However, this requires variation of the input data, which can be tedious and error-prone when created manually. I have therefore developed the scenario generator AMIRIS-Scengen (Nitsch, Frey, and Schimeczek 2023). AMIRIS-Scengen is a lightweight Python package that runs with minimal requirements on Windows and UNIX-based operating systems. It is designed for the electricity market model AMIRIS (Section 2.1.1.1), but with little modification it could also be applied to other FAME models (Section 2.1.1.2). As shown in Figure 2.10, AMIRIS-Scengen divides the workflow into dedicated tasks, facilitating integration with external programmes and enabling model coupling (Section 2.2.2).

The core functionality of AMIRIS-Scengen is to randomly generate AMIRIS scenarios based on a user-defined set of rules, assess the plausibility of the scenarios, feed the scenarios to AMIRIS where they are executed, and evaluate the final results. Specifically, the user defines a scenario that allows parameters to be associated with certain keywords, such as

- a random draw of discrete values of type string, integer or float,
- a random file path within a given directory,
- a random integer or float between a minimum and maximum value, or
- a fixed value.

In addition, agents and their associated contracts can be automatically added. Finally, the user specifies the number of different scenarios to be generated. Reproducibility is ensured by a trace file that stores the random seed and a counter for the number of scenarios generated, allowing AMIRIS-Scengen to assign a unique and traceable identifier to each generated scenario. The generated scenario is passed to a pre-simulation check ("Estimation" stage) where the user can define a set of rules that make certain parameter configurations invalid. If this is the case, the current scenario is discarded and a new scenario is generated. The valid scenarios are then passed to AMIRIS, which performs the actual simulation. The processing of the result files is carried out in a post-simulation check ("Evaluation" stage) where the user can define certain conditions for a scenario, e.g. uncovered load due to missing electricity generation potential. Similarly to the "Estimation" stage, scenarios that fail any of the tests are discarded. This workflow ensures that the user can easily and reliably create numerous AMIRIS scenarios in a flexible and convenient way, see also Figure 2.11. AMIRIS-Scengen is employed in this thesis to generate training, test, and validation data sets for the paper on time series forecasting (Nitsch, Schimeczek, and Bertsch 2024) and to conduct multi-scenario analysis in preparatory work (Nitsch and Schimeczek 2024) for main Paper IV (section 3.4), which assesses FOs potential (Nitsch, Schimeczek, and Bertsch 2025).

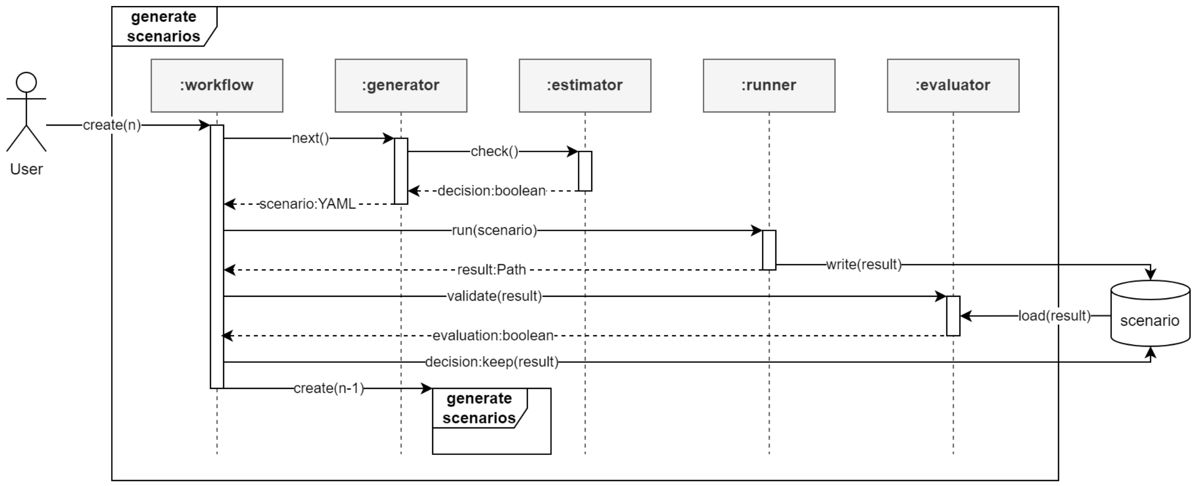


Figure 2.10: AMIRIS-Scengen model workflow showing the different modules and their interactions (Nitsch, Frey, and Schimeczek 2023).

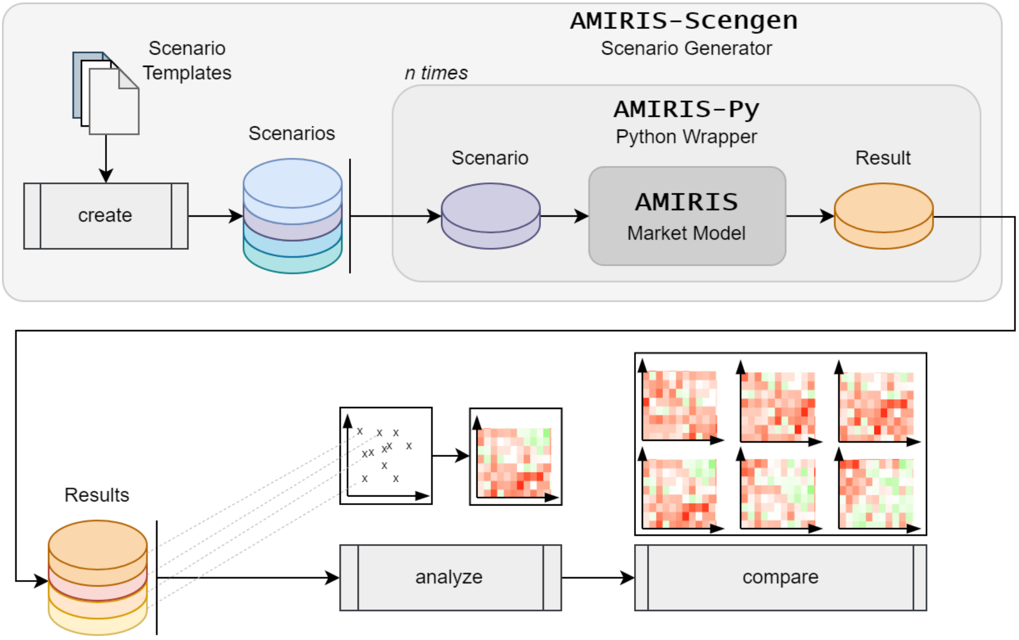


Figure 2.11: Multi-scenario analysis using AMIRIS-Scengen.

2.3 Model calibration

Model calibration and back-testing are critical steps in the development of reliable analytical tools for ESA. The accuracy and impact of any modelling approach depend significantly on both the quality of the input data and the structural validity of the model itself. Comparison with historical DAM results ensures that models can reproduce historical patterns before being applied to future scenarios or policy assessments.

2.3.1 Data

This thesis uses open data sources primarily, adhering to the principles of transparency and reproducibility of research. The AMIRIS-Examples data set (Nienhaus et al. 2025), first published in 2022 and continuously updated since then, serves as the primary source of AMIRIS data, providing comprehensive data under the Creative Commons Attribution 4.0 International (CC BY 4.0) licence. This data set integrates information from several sources, including the European Network of Transmission System Operators for Electricity (ENTSO-e), the German Electricity Market Data Platform (SMARD), the Federal Statistical Office of Germany (Destatis), the Federal Ministry for Economic Affairs and Climate Action (BMWK), the European Power Exchange (EPEX SPOT), and the Austrian Power Grid (APG). The compilation includes key parameters for energy system modelling, including generation profiles across different technologies, temporal demand patterns, installed power plant capacity, and costs. At the time of writing, the data mainly covers the German and Austrian market zones and spans historical years from 2015 to 2019. The ongoing expansion efforts aim to include additional years and market zones, which will further enhance the utility of the data set for a broader analysis and long-term trend assessment (Nitsch, Schimeczek, Nienhaus, et al. 2025).

2.3.2 Benchmarking

Benchmarking against other established models is an effective way to understand the specifics of a model and identify strengths and limitations, while promoting transparency within the research community. The AMIRIS model was systematically compared with the ASSUME market model (F. Maurer et al. 2024). This comparison showed that both models can reproduce the dynamics on the German DAM with errors below 6.4 EUR/MWh. The dispatch of power plants was also compared, where AMIRIS achieved a good fit of the simulation results to the historical data from 2019. Additional AMIRIS back-testing against historical data was performed for the German DAM (Nitsch, Deissenroth-Uhrig, et al. 2021) and the Austrian DAM (Nitsch, Schimeczek, and Wehrle 2021). These validation analyses examine how accurately the model reproduces historical market clearing prices and dispatch patterns when calibrated with historical input data. Both studies identified specific areas for model refinement, in particular regarding the representation of strategic bidding behaviour of FOs and RE operators in situations where negative prices occurred in reality.

3 Publications

This chapter provides a summary of the publications included in this cumulative thesis. The thesis comprises four research papers, three of which have been published in peer-reviewed journals and one of which is currently under review. For each full paper, Sections 3.1 to 3.4 provide bibliographic information. This includes an executive summary, which differs from the individual abstract by providing targeted results without repeating extensive general contextualisation. I then describe the contributions of myself and all co-authors. These descriptions are in line with the contribution statements included in the publications, but are more detailed in certain aspects. In addition, the journal articles are included in full text in their respective journal format[1]. Finally, in Section 3.5, I elaborate on how the publications are connected and form a coherent overall structure, contributing to the individual research targets identified in Section 1.2. For this, some additional complementary papers are provided in the Appendix A (peer-reviewed) and Appendix B (non-peer-reviewed).

[1]Abbreviations and reference numbering are specific to each individual article. Additionally, the journal articles use American English while this thesis uses British English.

3.1 Paper I: Economic evaluation of battery storage systems bidding on day-ahead and automatic frequency restoration reserves markets

Authors: Felix Nitsch, Marc Deissenroth-Uhrig, Christoph Schimeczek, Valentin Bertsch
Corresponding Author: Felix Nitsch
Journal: Applied Energy
Volume: 298
DOI: 10.1016/j.apenergy.2021.117267
Status: Published 23 June 2021

Executive Summary: In the transition to low-carbon electricity systems, not only electricity generation but also frequency stabilisation must be managed through low-carbon technologies. Battery storage systems offer a promising solution to address this challenge, but uncertainties regarding their revenue potential can hinder investment. To explore this, I used the agent-based electricity market model AMIRIS to simulate both a DAM and an aFRR market, focusing on scenarios with high shares of REs. I first back-tested the model using historical DAM data from Germany in 2019, finding that the simulated mean DAM prices (39.20 EUR/MWh) were very close to the historical prices (38.70 EUR/MWh), validating the model's accuracy. I then modeled both markets for 2030, projecting higher average DAM prices than today, with 550 hours annually where RE fully covers the load. The variance in prices was slightly higher than historically observed. Bids for the aFRR market, based on the opportunity costs of not participating in the DAM, showed prices of up to 45 EUR/MW for positive reserves, while prices for negative reserves were 0 EUR/MW. When evaluating the revenue potential for battery storage, I found improved economic prospects compared to 2019, with high-power battery systems performing best. While improvements in round-trip-efficiency (RTE) had a marginal impact on revenues, the DAM played an increasingly important role. Although the model was demonstrated for Germany, it is modular and adaptable to international markets, enabling comprehensive assessments of battery storage economics in diverse regions. This study offers valuable insights to a potential future role of battery storage in electricity markets.
Author Contributions: I am the lead author of this paper. I led the conception of the article, including the methodology and the experimental design. I also led the software development and created the novel implementation of the aFRR market in AMIRIS.

I carried out the experiments and compiled a comprehensive data set for analysis. In terms of visualisation, I designed several metrics and graphs to illustrate the results and communicate our findings. Finally, I was responsible for writing the original manuscript. Marc Deissenroth-Uhrig, a senior researcher at DLR at that time, contributed to both the conceptualisation and the methodology. He also contributed to software development by helping to debug certain modules in the code. Christoph Schimeczek, a senior researcher at DLR, helped to validate and investigate the results. Valentin Bertsch, Professor at Ruhr-Universität Bochum holding the Chair of Energy Systems and Energy Economics, supervised the work on the paper. All three co-authors reviewed and edited the original draft, improving the clarity and impact of the final manuscript.

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Economic evaluation of battery storage systems bidding on day-ahead and automatic frequency restoration reserves markets

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HIGHLIGHTS

- Implementation of reserves market in an agent-based electricity market model.
- Evaluation of battery storage bidding on day-ahead market and reserves market.
- Improved economic potential in German case study 2030 compared to 2019.
- Main source of revenues shifts from reserves market to day-ahead market.
- Highest revenues are found for short-term battery storages.

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ABSTRACT

In future electricity systems, not only electricity generation but also frequency stabilization must be provided by low-carbon technologies. Battery systems are a promising solution to fill this gap. However, uncertainties regarding their revenue potential may hinder investments. Therefore, we apply the agent-based electricity market model AMIRIS to simulate a day-ahead market and an automatic frequency restoration reserves market. Demonstrating the model setup, we chose a scenario with high shares of renewable energies. First, we back-test our model with historic market data from Germany in 2019. The simulation results' mean day-ahead prices of 39.20 EUR/MWh are close to the historic ones of 38.70 EUR/MWh. Second, we model both markets in a scenario for 2030. The simulated day-ahead market prices are higher on average than observed today, although, we find around 550 h/yr in which the load is fully covered by renewable energies. The variance in simulated prices is slightly higher compared to historic values. Bids on the reserve capacity market are derived from opportunity costs of not participating in the day-ahead market. This results in prices of up to 45 EUR/MW for positive reserve while the prices for negative reserve are 0 EUR/MW. Finally, we evaluate revenue potentials of battery storages. Compared to 2019, we see an improved economic potential and increased importance of the day-ahead market. High power battery storages perform best whereas improvements in round-trip efficiency only marginally improve revenues. Although demonstrated for Germany, the presented modular approach can be adapted to international markets enabling comprehensive battery storage assessments.

1. Introduction

Rising shares of fluctuating renewable energy (RE) ultimately lead to growing demand in flexibility options on various temporal scales. One prominent example is maintaining the frequency of power grids which is very sensitive to changes either in electricity demand or generation. There are various different mechanisms to ensure a stable frequency. In most countries, some kind of frequency restoration reserves markets are implemented to provide market-based system services. In Germany, for instance, the automatic Frequency Restoration Reserves (aFRR) – in combination with the Frequency Containment Reserves (FCR) and the manual Frequency Restoration Reserves (mFRR) – ensure frequency stabilization of the electricity system. At the moment, these markets are mostly supplied by conventional power plants and pumped hydro storages [1]. In future electricity systems, this may become a challenge, as

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Nomenclature

ABM	Agent-based electricity market model
AMIRIS	ABM developed at the German Aerospace Center
aFRR	automatic Frequency Restoration Reserves
BSS	Battery storage system
DA	Day-Ahead (market)
D_{spat}	Spatial differentiation
D_{tech}	Technical differentiation
D_{temp}	Temporal differentiation
E2P	Energy-to-power (ratio)
FCR	Frequency Containment Reserves
mFRR	manual Frequency Restoration Reserves
RE	Renewable energy
SOC	State of charge

there could be too little dispatchable capacity available. There are already discussions on the adaptation of the underlying power plant park and aFRR market design adjustments [2]. In theory, battery storage systems (BSS) are an attractive technology for maintaining grid frequency and participating in FCR markets and aFRR markets due to their short ramping times [3]. Hollinger, Diazgranados, & Erge [4] reviewed trends in the German FCR market concluding that the transition to distributed and renewable power plant infrastructure comes with opportunities for BSS under the assumption of higher volatility of day-ahead (DA) prices due to higher shares of fluctuating generation capacities. Nevertheless, there are currently hardly any significant BSS capacities providing balancing energy [1].

1.1. Regulatory and technical perspective

Policy-wise, the European Commission [5] provides a guideline for balancing the pan-European electricity supply system. This contains principles for reservation and accounting of several different frequency reserves. In addition, a uniform method for frequency reserve activation should be established. The regulation affects transmission system operators, distribution system operators, as well as the regulatory authorities of the EU member states. Ocker, Ehrhart, & Belica [6] modeled future auctions on balancing markets while taking into account the proposals by the European Union. The results show that those auctions with uniform pricing lead to systematic underbidding of market participants compared to the present pay-as-bid pricing due to the repetitive nature of the bidding by an invariant supplier side. Looking at the operator level, several studies have already assessed the implications and revenue potential of BSS in different energy systems and case studies. Thorbergsson, Knap, Swierczynski, Stroe, & Teodorescu [7] investigated the application of Li-Ion BSS providing FCR and compared several different control strategies varying the state of charge (SOC) set point of the BSS. A different analysis looking at the impact of multiple operation strategies for BSS providing FCR is conducted in Fleer & Stenzel [8] showing measures such as SOC limits have significant impact on the operation characteristics and therefore the expected revenues. A multi-use BSS is simulated in Zeh, Mueller, Hesse, Jossen, & Witzmann [9] calculating the economic benefits of additional aFRR market participation with only minor effects on the aging of the BSS. Braeuer, Rominger, McKenna, & Fichtner [10] conducted a comprehensive analysis of a BSS participating in the FCR market, intraday market, and DA market while providing peak shaving for small and medium sized enterprises in Germany. They found, that in all scenarios the net present values are negative concluding that it is economically not attractive under the scenario assumptions to invest and operate in BSS. Xu, Oudalov, Poland, Ulbig, & Andersson [11] looked at control strategies for BSS providing FCR and compared the situation in Germany with a selected market in the USA also finding a more profitable situation in the latter. Many more studies concerning BSS in DA markets and reserve markets exist, e.g. Tian, Bera, Benidris, & Mitra [12], Vejdan & Grijalva [13], Hu, Sarker, Wang, Wen, & Liu [14].

Flexibility cannot only be provided by BSS, but by various technologies. The most prominent one is pumped-hydro storage, such as described in Borsche, Ulbig, Koller, & Andersson [15], Doherty, Lalor, & O'Malley [16], Ela et al. [17], Kirby & Kueck [18], O'Sullivan, Power, Flynn, & O'Malley [19] and Wu, Lee, Cheng, & Lan [20]. There are studies on prosumers [21] which could also be active on reserve markets as presented in the case studies by Iria, Soares, & Matos [22] and Iria, Soares, & Matos [23]. Flexibility for the aFRR could also be made available by the aggregation of electric vehicles, as demonstrated in Ricardo J Bessa & Matos [24] and Ricardo Jorge Bessa & Matos [25] and Vatandoust et al. [26]. Other technologies are also investigated for their application for flexibility such as solar plants and BSS [27], gravity storage systems [28], hydropower [29], spinning reserves [30].

1.2. Modeling perspective

Modeling and evaluation of these applications has a long record in research. Important works have been conducted regarding the bidding on energy markets. Swider & Weber [31] present a methodology for actors bidding on multiple electricity markets under price uncertainty, explicitly including pay-as-bid reserve markets, by maximizing a stochastic non-linear objective function of expected profit. The specifics of sequential bidding in DA markets and reserve markets is addressed in Swider [32], whereas simultaneous bidding on the same markets is described in Swider [33]. Regarding the price mechanisms and interactions between DA markets and reserve markets, Chao & Wilson [34] present an assessment concluding that the separation of power bids and energy bids is essential for an efficient market design. Mazzi, Kazempour, & Pinson [35] look at bidding strategies in electricity markets where pay-as-bid remuneration schemes are implemented presenting a two-stage stochastic problem as a mixed-integer and linear problem. A fundamental analysis of the German balancing power markets is compiled in Müsgens, Ockenfels, & Peek [36] where the authors identify the scoring and settlement rules, which are based on the work of Chao & Wilson [34], as key elements of the market design. Loesch, Rominger, Nainappagari, & Schmeck [37] investigate the impact of energy prices in the German aFRR market on the probability of reserve energy activation and therefore the revenue potential based on historic market data from 2012 to 2016. Fleer et al. [38] analyze a BSS active on the German FCR market finding that the investigated bidding strategies do not have any significant influence on the profitability of BSS owners, whereas the development of FCR prices and BSS costs are crucial for the economic feasibility. The implementation of bidding strategies into models can be accomplished by several different techniques such as stochastic optimization [39], multi-stage stochastic optimization [40], probabilistic optimization [41], non-linear optimization [42], bi-level optimization [43], fuzzy optimization [44], evolutionary programming [45] and dynamic programming [46]. While most of these models apply some kind of optimization model, we use an agent-based modeling (ABM) approach. ABM puts the actors, their interactions and their environment to the center of the simulation. Thus, ABM allows for assessing the challenges of the energy transition taking the behavior of actors into account (Tesfatsion [47], Deissenroth, Klein, Nienhaus, & Reeg [48]). Additionally, ABM enables the researcher to look at the system's perspective and conduct analyses on energy system transformation pathways.

There are various studies investigating how future energy systems with a large reduction in green-house gas emissions could be achieved specifically taking into account the characteristics of BSS, such as Stiphout, De Vos, & Deconinck [49], Alqurashi, Etemadi, & Khodaei [50], Wierzbowski, Lyzwa, & Musial [51], Belderbos, Virag, D'haeseleer, & Delarue [52], Limpens, Moret, Jeanmart, & Maréchal [53].

However, they are missing the spotlight on the individual actor who is responsible for investing in new technologies, such as BSS. Investments in the energy system are characterized by significant expenditures resulting in long depreciation periods. It is therefore important to consider the perspective and revenue potential of an individual actor in order to estimate how investments in e.g. BSS could be refinanced on the markets. Existing literature mostly covers only a single market [54], small regions in remote areas [55], or peer-to-peer systems [56] when assessing the profitability of BSS. Different incentives for regulated versus market-driven BSS installations and their remuneration is described in Huang, Xu, & Courcoubetis [57].

1.3. Novelty of the present paper

The aim of this paper is to assess the economic potentials of a privately owned BSS which is active on the DA market and the aFRR market using synergies when serving both markets [58]. As described in the previous section, existing literature often applies different types of optimization models for analyzing wholesale electricity markets. In our opinion, however, such approaches cannot adequately account for the liberalized character of todays' electricity markets. Our fundamental electricity market model simulating the two markets and their interactions, therefore follows no overall objective function as used in optimization models. Instead, we can account for the outcome caused by the actions of individual actors participating in these markets which is much closer to actual market situations. Subsequently, the revenues and possible applications of a BSS operator in a future scenario will be determined and applied to a case-study simulating a whole market region rather than only a small test-region. An additional novelty of the present study is the combined modelling of the DA market and aFRR market following a model-within-model approach. This means that we integrate an optimization model for the revenue maximization of an individual BSS operator with a fundamental ABM simulation approach depicting the German electricity market. The two markets are explicitly modelled and the respective bidding and agent's behavior is implemented according to market theory described in detail in Section 2.1. Compared to the existing literature, our integrated assessment enables us to fundamentally model the market situation of future electricity markets. We derive the question of how the market situation is changing with increasing shares of RE and how it will affect the economic potential of BSS. Therefore, we set up a back-testing scenario and a future scenario in which agents participate on the DA market and aFRR market based on their marginal or opportunity costs, respectively. Hence, we simulate the prices on both markets. Subsequently, we evaluate the economic potential of BSS operators in order to assess their revenue potential. With some adaptations, the developed approach can be used to account for different market specifications and is therefore relevant for a wide international audience. The remainder of the paper is structured as follows. In Section 2, we describe our method and the data used. In Section 3, we elaborate the main findings consisting of the prices on the DA market and aFRR market as well as the revenue potential of a BSS operator on these markets. In Section 4, we compare our results with similar assessments in the literature and discuss the limitations of the presented approach. In Section 5, we conclude and give an outlook on future expansion and model developments.

2. Methodology and data

In order to investigate the market situation in a future energy system, we deploy two different kinds of models. The agent-based electricity market model AMIRIS simulating future electricity markets is presented in Section 2.1, whereas the linear optimization model depicting the BSS is described in Section 2.2. The back-testing scenario and the scenario for 2030 are outlined in Section 2.3 and Section 2.4, respectively.

2.1. Electricity market simulation model

The ABM AMIRIS [48] was developed to investigate the integration of renewable power plants in electricity markets. The behavior of individual prototyped groups of actors can be considered under different framework conditions such as varying market design or different remuneration schemes. In contrast to equilibrium and optimization models, there is no superordinate, centrally specified objective function that, e.g. minimizes system costs. Instead, the focus of the bottom-up model is on the actors of the electricity system represented as agents with their objectives and options for action. In AMIRIS, the relevant actors (e.g. direct marketers of RE plants or storage operators) are represented as prototypical agents [59]. Their microeconomic decisions are based both on the assessment of electricity market prices and generation forecasts. These are associated with uncertainties and the consideration of current support instruments for RE (variable and fixed market premiums or capacity premiums). The bids of the agents result in simulated market prices. For example, AMIRIS can be employed to examine the use of storage technologies in the electricity market from a business perspective. The central market in AMIRIS is the DA market, where an hourly market clearing of the power supply bids and demand bids is carried out resulting in simulated electricity prices. Conventional power plant owners place their bids with their marginal costs which are determined by fuel prices, CO_2 prices, technology-specific efficiencies and other variable costs. The DA electricity price results from the intersection of sorted supply bids and demand bids. A detailed description of the methodology of AMIRIS can be found in Deissenroth et al. [48] and Table A4. As elaborated in Section 1.3, we present a novel work of further developing and enhancing AMIRIS by the implementation of the aFRR market, which extends the possibility to generate revenues for the power plant operators. These actors can sell their flexible power generation either on the DA market or the aFRR market and aim to maximize their profit. The bidding behavior is fundamentally modeled and based on the technology-specific marginal costs of electricity generation. It is based on a theoretical comparison of the potential revenues on the DA market and those on the aFRR market [36]. Participation in the aFRR market is remunerated for reserving power (positive and negative) and for the actual provision of energy (positive if frequency below 50 Hz and negative if frequency above 50 Hz). The corresponding opportunity costs are calculated for the four products of the aFRR market (positive & negative power prices and positive & negative energy prices) as seen in equations (1) to (4). The calculation of the opportunity costs of the power prices requires an assessment of whether the power plant's offered output can be provided at prices less than or equal to the forecasted DA exchange price $\boldsymbol{p_{forecast}}$ (i.e. inframarginal state), or whether it must be generated at higher prices (extra-marginal state). The aFRR market bids are calculated as follows:

$$\boldsymbol{Bid_{power,pos}} = \begin{cases} \boldsymbol{p_{forecast}} - c, c \leq \boldsymbol{p_{forecast}} \\ (\boldsymbol{c} - \boldsymbol{p_{forecast}})*\dfrac{\boldsymbol{Power_{min}}}{\boldsymbol{Power_{pos}}}, c > \boldsymbol{p_{forecast}} \end{cases} \tag{1}$$

$$\boldsymbol{Bid_{power,neg}} = \begin{cases} 0, c \leq \boldsymbol{p_{forecast}} \\ (\boldsymbol{c} - \boldsymbol{p_{forecast}})*\dfrac{(\boldsymbol{Power_{min}} + \boldsymbol{Power_{neg}})}{\boldsymbol{Power_{neg}}}, c > \boldsymbol{p_{forecast}} \end{cases} \tag{2}$$

$$\boldsymbol{Bid_{energy,pos}} = \boldsymbol{c} \tag{3}$$

$$\boldsymbol{Bid_{energy,neg}} = 0 \tag{4}$$

With $\boldsymbol{Bid_{power,pos}}, \boldsymbol{Bid_{power,neg}}$ as the power bids for positive and negative aFRR in EUR/MW, $\boldsymbol{Bid_{energy,pos}}, \boldsymbol{Bid_{energy,neg}}$ as the energy bids for positive and negative aFRR in EUR/MWh, $\boldsymbol{p_{forecast}}$ as the forecasted DA market price in EUR/MWh, $\boldsymbol{c}$ as the marginal cost of generating electricity in EUR/MWh, $\boldsymbol{Power_{min}}$ as the minimum power generation of the power plant in MW and $\boldsymbol{Power_{pos}}, \boldsymbol{Power_{neg}}$ as the offered positive and negative

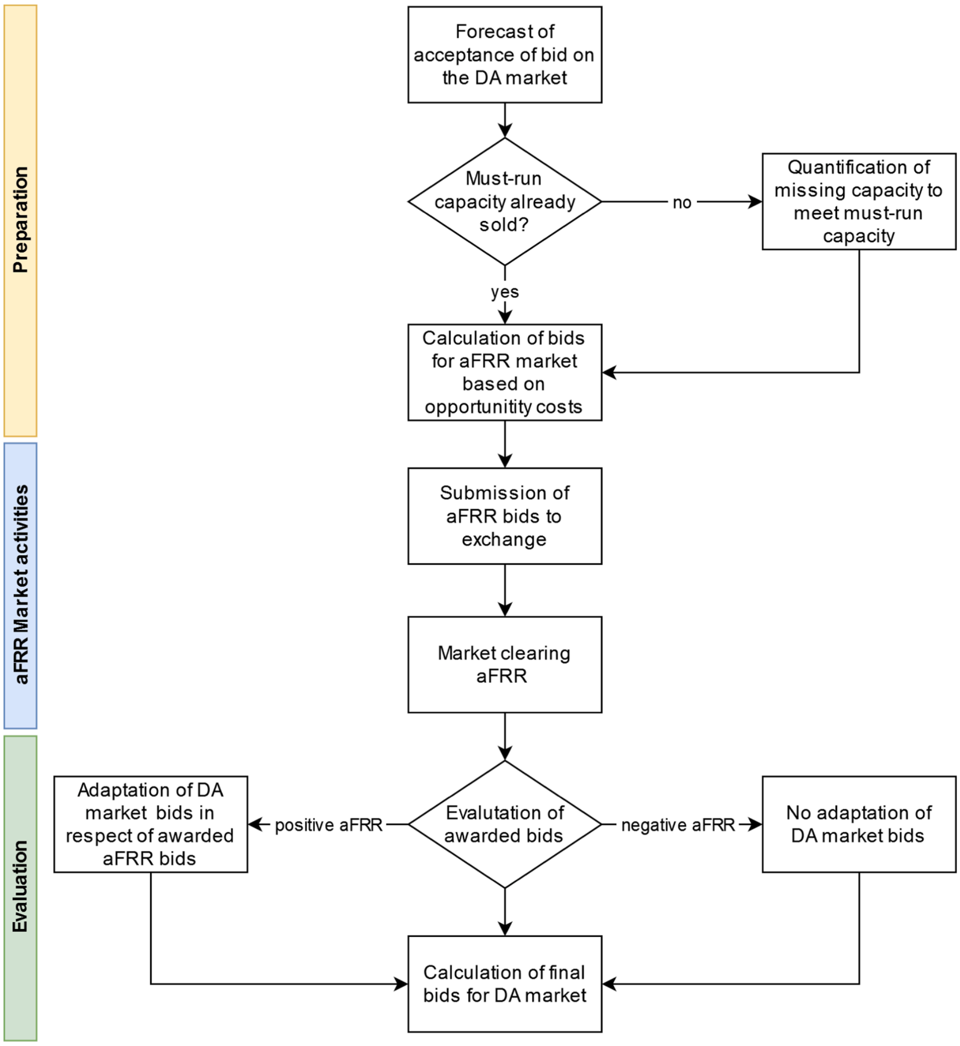

Fig. 1. Schematic bidding procedure of power plants participating in the aFRR market and DA market in the agent-based electricity market model AMIRIS.

power in MW used to determine power prices and energy prices.

The bidding logic process was implemented as shown in Fig. 1 and consists of three main phases: preparation, market activities and evaluation. In the beginning, the forecasts for the DA market are received. Based on the expected market participation, any missing capacity to achieve the must-run capacity is determined and results in bids at minimum prices to ensure that the must-run capacity is met. The aFRR bids are then formulated on the basis of equations (1) to (4). In the next phase, the market clearing of the aFRR market, both for the required positive and negative power, takes place. Once the bids are awarded on the aFRR market, they are evaluated in the final phase. This includes the adaptation of DA market bids corresponding to the awarded bids on the aFRR market in order to comply with the power plant's capacities. Final DA market bids are then forwarded to the DA market where a market clearing takes place determining the electricity prices. In the simulation, the described procedure is executed for each simulated hour.

Finally, the results of AMIRIS are price time series of the DA market and aFRR market depending on the available capacity of the technologies as well as the corresponding dispatch profiles of the power plants. These results are used in the optimization model as described in the following section. The presented electricity market model is currently representing the situation in Germany. However, it can also be applied to assess other international markets. This may necessitate minor adjustments in order to meet different market specifics, such as modifications to the market clearing mechanisms. The method of agent-based modeling and the object-oriented structure of the model enables researchers to accomplish the required changes with little effort.

2.2. *Battery storage system optimization model*

While the energy system model AMIRIS (Section 2.1) focuses on the electricity system from the system's perspective, we also set up an optimization model representing the market situation from the business perspective of a BSS operator. In other words, we apply a linear optimization model to evaluate the economic performance of a BSS in the presented scenario. The model is designed to find the optimal operation strategy of the BSS on the DA market and aFRR market under consideration of perfect foresight. The price time series are therefore used as input data in the optimization model. The BSS is constrained by technical specifications, such as charging and discharging efficiencies, ramping restrictions, and its state of charge. The optimization model is implemented as a mixed integer programming model in GAMS [60]

Table 1
Installed power plant capacities in Germany at the end of 2018 [62]

Technology	GW_{inst}
Nuclear	9.5
Lignite	20.9
Hard coal	23.8
Natural gas	23.8
Other non-renewable	10.1
Pumped hydro storage	9.7
Run-of-river	3.8
Biomass	7.7
Wind onshore	50.3
Wind offshore	5.4
PV	42.3

Table 2
Installed power plant capacities in the presented scenario for Germany derived from

Technology	Installed Power in GW
Nuclear	0
Lignite	9
Hard coal	11
Natural gas	53
Other non-renewable	5
Storage	8
Run-of-river and hydro storage	6
Biomass	6
Wind onshore	58
Wind offshore	15
PV	73

using the CPLEX solver [61]. It is assumed that the BSS is prequalified for trading on the DA market and aFRR market aiming to maximize its total revenue under perfect foresight over the observation period of one year. The function

$$Revenue_{Total} = \sum_{i=1}^{8760} Revenue_{DA,i} + Revenue_{aFRR,i} \tag{5}$$

describes the total revenues consisting of the summed revenues in hour *i* in the two markets which the storage operator tries to maximize. The revenues from trading on the DA market are defined by

$$Revenue_{DA,i} = p_{DA,i}*(Energy_{DA\_Sell,i} - Energy_{DA\_Buy,i}) \tag{6}$$

with $p_{DA,i}$ as the price at the DA market, $Energy_{DA\_Sell,i}$ as the energy sold at the DA market and $Energy_{DA\_Buy,i}$ as the energy bought at the DA market in hour *i*.

The revenues from the aFRR consist, on the one hand, of the income from the provision of power $Revenue_{aFRR,Power,i}$ in positive or negative direction

$$Revenue_{aFRR,Power,i} = p_{aFRR,Power,positive,i}*Power_{aFRR,positive,i} + p_{aFRR,Power,negative,i}*Power_{aFRR,negative,i} \tag{7}$$

which are awarded with the prices $p_{aFRR,Power,positive,i}$ and $p_{aFRR,Power,negative,i}$ assuming that the BSS places its bids at the same price as the most expensive power plant which is still in the market; on the other hand, the revenue $Reveue_{aFRR,Energy,i}$ from the actual energy flows

$$Reveue_{aFRR,Energy,i} = p_{aFRR,Energy,positive,i}*Energy_{aFRR,positive,i} + p_{aFRR,Energy,negative,i}*Energy_{aFRR,negative,i} \tag{8}$$

which is awarded with the prices $p_{aFRR,Energy,positive,i}$ and $p_{aFRR,Energy,negative,i}$ when reserve capacities are actually called.By its specifications, the BSS is equipped with technical parameters that characterize its performance. First of all, the state of charge (SOC_i) must at no hour *i* fall below the minimum SOC_{min} or exceed the maximum SoC_{max} at any time. Accordingly, the following condition

$$SOC_{min} \le SOC_i \le SoC_{max} \tag{9}$$

applies for each hour of the optimization. Participating and trading on the DA market or the aFRR market has a direct effect on the SOC_i which is represented in

$$SOC_i = SOC_{i-1} - Energy_{DA_{Sell},i} + Energy_{DA\_Buy,i} - Energy_{aFRR,positive,i} + Energy_{aFRR,negative,i} \tag{10}$$

where the SOC_i is updated every time step *i*. At the beginning of the optimization, the battery is half charged. Additionally, a ramping condition depicted by

$$\forall Energy_i \le \frac{SOC_{max}}{E2P} \tag{11}$$

applies. This means, that all energy flows $\forall Energy_i$, i.e. all purchases or sales on both markets, are subject to the maximum output rate. The energy-to-power (*E2P*) ratio indicates the charge or discharge in relation to its maximum capacity SOC_{max}. A BSS with an *E2P* ratio of 1 is fully charged in one hour from an empty state or can deliver full power for 1 hour, provided that it was originally fully charged. At an *E2P* ratio of 10, this would mean 10 h of charging or 10 h of continuous power. Therefore, the smaller the *E2P* ratio, the more suitable the storage is for short-term deployment. Battery degradation has not been considered in this model since the effect is expected to be very minor when interpreting the results of a single simulation year. Self-discharge has also not been considered in this work since the timescale of relevant self-discharge is in the order of months and thus much longer than the time interval of typical battery storage use in the order of days. A binary constraint prohibits the BSS from simultaneous charging and discharging in the same hour.

Finally, the optimization algorithm tries to find the best operating decision in each hour to maximize the operating result in the whole year

$$max\{Revenue_{Total}|conditions\ (9)\ to\ (11)\} \tag{12}$$

while considering the restrictions defined in (9) to (11). We do not consider other operational costs, taxes, costs of market participation, nor prequalification costs in the presented assessment. A description of the full parameterization of all input variables to the BSS model can be found in the Appendix in Table A7.

2.3. Back-testing scenario 2019

Back-testing is an important method for evaluating the outcome of energy systems models. That is why we have set up a reference scenario for Germany in 2019 in order to compare simulated prices to historic ones. The power plant park is listed in Table 1. Despite already high shares of RE plants in Germany, electricity generation is still dominated by fossil-based generators [62].

Historic electricity prices at the DA market, load data including imports and exports as well as RE generation are derived from the SMARD data platform which is hosted by the Bundesnetzagentur [63]. European Emission Allowances were taken from the EEX [64] and used for CO_2 price information. Fuel price indices are used from the monthly reports from the Federal Statistical Office of Germany [65]. The full list of model parameters is described in the Appendix in Table A5.

2.4. Scenario 2030

In order demonstrate the feasibility of the developed approach, we decided to define a case study for Germany in 2030. However, the model set-up can also be parameterized to serve similar international electricity markets. The presented scenario follows the results of the simulations in a study on the macroeconomic effects of the energy system transformation in Germany in Lutz et al. [66]. This study aims for an

Table 3
Capacities of technologies supplying the German aFRR market and total German aFRR demand as defined for the 2030 scenario

		Positive aFRR in GW	Negative aFRR in GW
Supply	Hard coal	0.2	0.2
	Lignite	0.1	0.1
	Gas	3.6	3.2
	Oil	0.4	0.2
	Hydro power	6.6	8.4
	RE (Wind/PV/Biomass)	7.6	7.6
Demand	Total power requested	1.7	1.7

electricity system with almost 85% CO_2 reduction in 2050 compared to 1990 and describes a pathway to this goal. The power plant park was derived from the scenario year 2030. The structure of the power plant park is listed in Table 2. There are significant capacities of photovoltaics (PV) and wind power (onshore and offshore) installed. 60% of the yearly total energy demand of 539 TWh is supplied by RE technologies. A complete nuclear-phase out is already accomplished, whereas 11 GW of hard coal and 9 GW of lignite powered plants are still in service. The price for one ton of emitted CO_2 is defined at 35 EUR/t. The market premiums for RE are assumed to be variable under the current legal framework. Accordingly, the amount of the premium is adjusted monthly according to the market values of the respective technology.

An overview of all model-related assumptions and input parameters, such as fuel prices, specific emissions, power plant availability, economic factors and storage parameters can be found in the Appendix in Table A6 for the AMIRIS model and in Table A7 for the BSS optimization model.

In the presented market model, no electricity transmission grid is considered. Therefore, the regulation of generation plants is only based on economic principles and not caused by the grid restrictions. The net frequencies and the required power for frequency stabilization are not simulated, but are exogenously derived from historic data. We estimated the demand for positive and negative aFRR with 1.7 GW each which is based on historic averages for the German aFRR market [67]. For the supply side, the total capacity of each technology which participates in

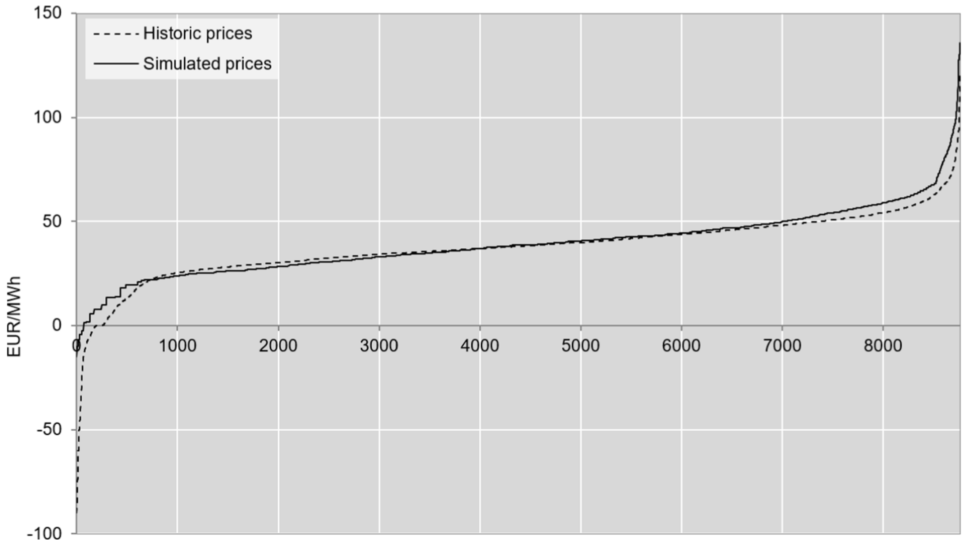

Fig. 2. Comparison of simulated and historic day-ahead price-duration curves.

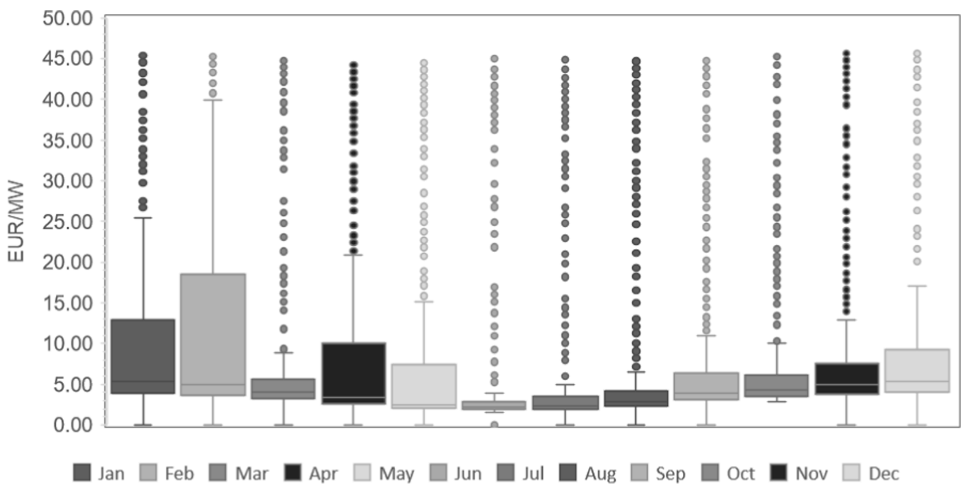

Fig. 3. Monthly positive aFRR capacity prices, showing the median, 1st, and 3rd quartile.

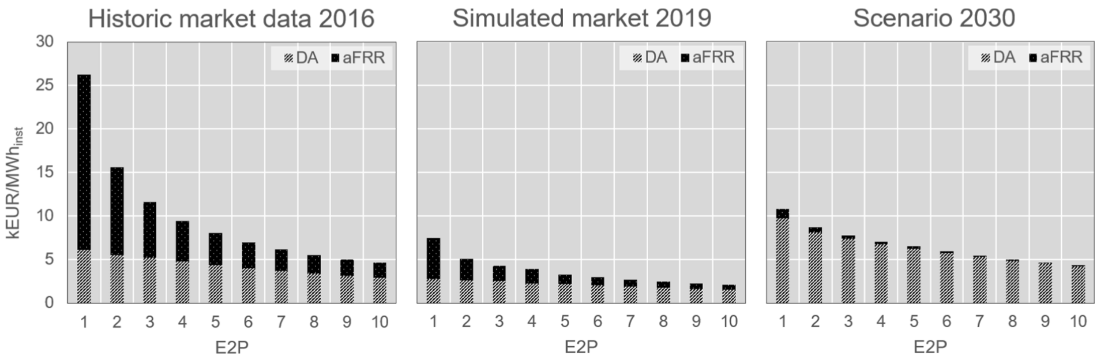

Fig. 4. Annual revenues per storage capacity of the BSS operator on the DA market and aFRR market based on 2016 historic market data (left), a simulated market for 2019 (middle) and the 2030 scenario (right).

Table A4
Model characteristics of AMIRIS; *D_{temp}, D_{tech}, D_{spat} - temporal, technological, spatial differentiation.

Model name	AMIRIS - Agent-based market model for the investigation of renewable and integrated energy systems			
Author (Institute)	German Aerospace Center (DLR), Institute of Networked Energy Systems			
Model type	Agent based electricity market model			
Technical focus	Electricity market, use of renewable energies under regulatory framework conditions at actor level			
Geographic focus	Germany			
Spatial resolution	Single bidding zone			
Temporal resolution	Hourly			
Input parameters		D_{temp}	D_{tech}	D_{spat}
	• Costs (fixed and variable) for investment operators and direct marketers	x	x	
	• Power plant efficiencies	x	x	
	• General market conditions	x	x	
	• Fuel prices and CO_2 certificate prices	x	x	
	• Load profile	x		
	• Power plant park (conventional and renewable)	x	x	
Output parameters	• Profiles of storages under different operation strategies	x	x	
	• Profiles of RE plants under different regulatory frameworks	x	x	
	• Electricity prices	x		
	• Revenues of direct marketers	x	x	
	• Operational costs and emissions	x	x	

the aFRR is shown in Table 3. We estimated the share of total installed capacities which can theoretically supply aFRR based on Hasche et al. [1] and for wind, PV and biomass from Spieker, Kopiske, & Tsatsaronis [68]. In the present market simulation, we have integrated an hourly bidding procedure. This is a simplification, since in reality on the German aFRR market, bids had to be submitted on a weekly, or – after changes in market design in 2018 [69] – daily basis. This adaptation had to be made in order to keep the problem solvable in the AMIRIS model. We expect, however, additional adjustments in the future which will likely introduce an even more short-term tender for the required aFRR.

3. Results

The following results are divided in Section 3.1 where we describe the outcomes of the back-testing of AMIRIS whereas in Section 3.2 we present the result of the scenario for 2030.

Table A5
Input parameters to the ABM AMIRIS in the back-testing 2019 scenario

	Parameter	Value	Unit	Note
Fuel prices	Nuclear	3.03	EUR/MWh	Federal Statistical Office of Germany [65]
	Gas	27.29	EUR/MWh	
	Lignite	5.00	EUR/MWh	
	Hard coal	7.86	EUR/MWh	
	Oil	30.70	EUR/MWh	
Specific emissions	Nuclear	0	tCO_2/MWh	
	Gas	0.202	tCO_2/MWh	
	Lignite	0.364	tCO_2/MWh	
	Hard coal	0.341	tCO_2/MWh	
	Oil	0.267	tCO_2/MWh	
Availabilities	Nuclear	85	%	
	Gas	97	%	
	Lignite	98	%	
	Hard coal	96	%	
	Oil	93	%	
Minimum and maximum efficiencies	Nuclear	33.0 – 33.0	%	Open Power System Data [81]
	Gas	27.6 – 61.2	%	
	Lignite	31.3 – 43.1	%	
	Hard coal	28.5 – 49.0	%	
	Oil	30.5 – 39.7	%	
Technical parameters of storage technologies	*E2P*	5	h	
	Charging efficiency	87	%	
	Discharging efficiency	87	%	
	Forecast period	168	h	
	Planning period	24	h	

3.1. Results back-testing scenario 2019

The simulated and historic DA prices are plotted in Fig. 2 for the year 2019 as price-duration curve. When comparing to historic prices, we observe a higher price level for simulated prices. The mean price is 38.70 EUR/MWh for the historic prices and 39.20 EUR/MWh for the

Table A6
Input parameters to the ABM AMIRIS in the 2030 simulation scenario

	Parameter	Value	Unit	Note
Fuel prices	Gas	27.0	EUR/MWh	Lutz et al. [66]
	Lignite	6.0	EUR/MWh	
	Hard coal	9.0	EUR/MWh	
	Oil	112.5	EUR/MWh	
Specific emissions	Gas	0.202	tCO_2/MWh	
	Lignite	0.364	tCO_2/MWh	
	Hard coal	0.341	tCO_2/MWh	
	Oil	0.267	tCO_2/MWh	
Availabilities	Gas	97	%	
	Lignite	98	%	
	Hard coal	96	%	
	Oil	93	%	
Minimum and maximum efficiencies	Gas	27.6 – 61.2	%	Open Power System Data [81]
	Lignite	31.3 – 43.1	%	
	Hard coal	28.5 – 49.0	%	
	Oil	30.5 – 39.7	%	
Technical parameters of storage technologies	*E2P*	5	h	
	Charging efficiency	87	%	
	Discharging efficiency	87	%	
	Forecast period	168	h	
	Planning period	24	h	

Table A7
Input parameters to the BSS optimization model

	Parameter	Value	Unit	Notes
Time series	DA prices, historic 2016	Timeseries	EUR/MWh	Bundesnetzagentur [63]
	DA prices, from AMIRIS	Timeseries	EUR/MWh	
	Power prices aFRR market, historic 2016	Timeseries	EUR/MW	
	Power prices aFRR market, from AMIRIS	Timeseries	EUR/MW	
	Energy prices aFRR market, historic 2016	Timeseries	EUR/MWh	
	Energy prices aFRR market, from AMIRIS	Timeseries	EUR/MWh	
Technical parameters of BSS	Minimum SOC	0	MWh	
	Maximum SOC	1	MWh	
	Initial SOC	0.5	MWh	
	E2P	1–10	h	
	Charging efficiency	[92.20, 93.54, 94.87]	%	
	Discharging efficiency	[92.20, 93.54, 94.87]	%	
	Forecast	8760	h	
	Planning period	8760	h	

simulated ones. Especially for lower prices, AMIRIS tends to overestimate the prices. This effect can be explained by the fact that AMIRIS does not incorporate ramping and start-up costs of power plants in a bottom-up manner. Prices in the mid-range are simulated more accurately. In hours of high demand we find a higher level of prices in the simulation compared to the historic observations. The standard deviation is 10.60 EUR/MWh in the historic case compared to 11.50 EUR/MWh in the simulated scenario. The remaining deviations may be caused by costs for ramping power plants or due to missing depiction of block-bids in the current AMIRIS model. The correlation of the two price time series is 0.81.

3.2. Results scenario 2030

Besides the power plant dispatch, the main outputs of the AMIRIS model are the simulated price time series. Specifically, we derive a price time series for the DA market with 8760 h. The mean simulated DA price is 63 EUR/MWh. The price deviation is 12 EUR/MWh and therefore slightly higher compared to prices from 2015 to 2019 where prices deviated with 11 EUR/MWh around the mean of 35 EUR/MWh.

Fig. 3 shows the capacity prices in EUR/MW for positive aFRR as boxplots for each month of the modeled scenario year 2030. We have refrained from comparing the simulated aFRR prices with 2019, as the recent changes in German aFRR market regulations mean that this is no longer viable. Instead, as described in Section 2.1, we have applied the theory according to Müsgens et al. [36]. A high variability of aFRR prices can be observed in January, February, and April; whereas especially the summer months June, July, and August have the lowest mean and additionally the smallest deviation of prices. This effect may be explained by the interplay with the DA market where lower prices are usually also found in summer. The maximum prices are around 45 EUR/MW.

Regarding the negative aFRR capacity prices and following the theory of equation (2) described in Section 2.1, we observe prices of 0 EUR/MW. This means, that power plants with marginal costs below the forecasted DA market price can fully supply the negative aFRR capacities leading to this result.

In additional calculations, we altered the required demand from currently 1.7 GW to 2 GW in a “High demand” scenario, and to 1.4 GW in a “Low demand” scenario. These variations should account for the uncertainty of future aFRR demand and their effect on prices. However, these alterations did not change the prices significantly since the capacities are sufficient to meet the demand for the aFRR. Therefore, these results are not described in more detail.

While AMIRIS focuses on the whole electricity system, we can get insights in the situation for the BSS operator using our optimization model, which is described in Section 2.2. We use the price time series from the AMIRIS model as input to the optimization model and calculate the optimal BSS operation strategy. We assume that the BSS, which operates under perfect foresight, calculates its bids at the same price as the highest power plant which is still in the market. This leads to the identification of an upper limit regarding the revenue potential of the BSS operator. The results in the present scenario, however, disclose a very competitive situation on the DA market and aFRR market with overall low revenue margins for the BSS operator. Fig. 4 shows the annual revenues of a BSS on both markets with *E2P* ratios between 1 and 10 and a fixed roundtrip efficiency of 85% in three different situations. We compared the results from the presented scenario 2030 to revenue evaluations based on historic market data from 2016, and to the 2019 market simulations as presented in Section 3.1.

The analysis for the historic market data 2016 shows the highest annual revenues. Although the power plant park has not significantly changed from 2016 to 2019, we observe reduced economic revenue potentials in the simulated market 2019. This indicates that prices on the aFRR market are probably not fully described by the theory as stated by Müsgens, Ockenfels, & Peek [36], see Section 2.1, and the simulation is probably lacking to account for strategic bidding. The distribution of revenues between the DA market and aFRR market, however, is very similar. When looking at the situation in the scenario 2030 we find that total revenues are higher compared to the simulated market 2019, but still considerably lower than in the historic market data 2016 situation. Yet, the revenues from the DA market increase strongly until 2030 because of higher fluctuations in DA prices, leading to a major shift for the primary source of revenues towards the DA market in the scenario 2030. In other words, we hardly see any significant revenues from the aFRR market in the scenario 2030 since the BSS is mainly active on the DA market. The revenue split between the DA market and aFRR market is therefore significantly different in the 2030 scenario compared to the historic case (2016 and 2019). In the latter, the revenue share on the aFRR market ranges between 77% (for $E2P = 1$) to 27% (for $E2P = 10$) meaning that more short-term BSS generate more revenues from providing system services such as aFRR. The picture is different for the scenario 2030 in which we observe hardly any significant revenue from the aFRR market. This is contradictory to the study by Ela et al. [70] who state that system services may become a greater proportion of revenue sources.

Generally, assuming a fixed BSS capacity, the smaller the *E2P* ratio, the higher the expected yearly revenues. This is caused by short-term fluctuations of prices which favor short-term BSS (smaller *E2P* ratio). Calculations with different roundtrip efficiency levels showed that an increase in the roundtrip efficiency of one percentage point generates approximately 2.5% additional revenue for the BSS operator when operating on the DA and aFRR market.

Our results show a very challenging situation for BSS operators in the future scenario for 2030. Although the BSS operator acts under perfect foresight, one cannot expect revenue opportunities as observed in 2016. This low expected profitability may lead to reduced private investments in BSS. In case BSS are identified as an essential part of future energy systems [71] investors would need access to additional, more profitable markets or require further incentives to build flexibility options, such as BSS.

4. Discussion

4.1. Limitations of the modeling approach

The following points should be considered when applying the presented modeling approach and drawing conclusions from the results. First, the presented analysis does not consider all possible technologies for the provision of flexibility on the aFRR market, but uses only those listed in Table 3. For example, demand response or dispatchable loads of large consumers (e.g. industry) are not modeled. Similarly, there is neither Power-to-X nor a high penetration of electric vehicles implemented. Theoretically, these technologies expand the available capacity for frequency stabilization and could thus have an impact on prices at the DA market and aFRR market. However, they may require regulatory adaptations, which would allow them to participate at ancillary markets such as the aFRR market. Second, due to the downstream setup of the optimization model, the power supply of the modeled BSS has no influence on the coverage of the required quantity for frequency stabilization in the AMIRIS model. In the presented scenario, however, the simulated BSS has no system-relevant size. Therefore, we estimate the influence of the considered BSS operator as minimal on the change of the power prices. However, we do see the necessity of additional analyses in future work addressing the interplay of actors and their feedback on the prices. Regarding the implications of strategic bidding, Maaz [72] found that market participants add markups to their bids which can deviate from their marginal costs. Ocker, Ehrhart, & Ott [73] made an analysis of bidding strategies in the German and Austrian balancing markets, finding that the expected profits of the energy bid are taken into consideration for the calculation of the optimal power bid. Also Merten, Rücker, Schoeneberger, & Sauer [74] describe a comparison of different statistical approaches taking the acceptance probability of German aFRR bids into account. These issues may be addressed in future work to investigate the impacts on the prices and revenue potentials. Third, since the future demand for balancing power is very difficult to estimate, several variations of the required reserve power were assumed. However, only the quantity of required power, both positive and negative, was changed, but not the energy actually demanded. These quantities are difficult to project fundamentally, as they are very difficult to model and would require at least a basic implementation of the electricity grid, forecasting errors regarding load and generation as well as a representation of outages of power plants and power consumers. For these reasons, historic data on called energy is used for the analysis in this study. Fourth, the BSS in our test setup has access to the DA market and the aFRR market, as described in Section 2.2. However, BSS are also suitable for use in more short-term markets such as the Intraday market or FCR market due to their very fast response time [3]. However, these markets require a very high temporal resolution which currently cannot be modeled with AMIRIS. At the moment, we can conduct calculations on an hourly basis as described in Section 2.1. For this assessment, the aggregation of short-term markets to hourly values is not meaningful and would not achieve reasonable results. Alternatively, BSS can be active on mFRR markets competing with other large-scale power plants but also more innovative solutions such as virtual power plants or load shifting technologies in industry. The lack of these potential additional sources of income (FCR, Intraday, mFRR), however, could improve the economic situation in favor of the BSS operators. Fifth, the optimization calculation of the BSS is carried out under the assumption of perfect foresight. This means that the algorithm determining the BSS operation strategy has complete information, which is not available to this extent in reality. Therefore, the solver can calculate with market prices that will later occur exactly as expected. Additionally, we do not include taxes and levies on revenues or costs of market participation (e.g. prequalification costs for the aFRR market) for the BSS. Changes regarding the efficiency of the BSS showed no significant influence on the economic potentials. Furthermore, because cell degradation is driven primarily by calendar aging rather than cycle aging [75], we do not explicitly model this effect. In a long-term analysis of BSS, however, this has to be considered as a prominent driver in the economic evaluation. In general, we interpret the presented results as an upper-limit regarding BSS revenue potentials on the modeled markets. Finally, the lacking consideration of competition among the flexibility options should be mentioned. Such competition may lead to cannibalization effects and a further decrease of revenue potentials. The Europeanization of the electricity markets could also lead to more competition and greater pressure on individual operators in the markets and subsequently reduce the revenue opportunities of individual BSS.

4.2. Interpretation of the scenario 2030

The analysis by Braeuer et al. [10] is in line with our findings, as they conclude that investing in and operating BSS is not economically reasonable from a current point of view, despite they also considered multiple revenue possibilities. Berrada et al. [28] conducted a profit comparison between different storage technologies on DA markets and ancillary markets. Although their findings also show negative profits for innovative market participants – e.g. gravity storage – a valid comparison to our approach is not possible since they model only a single day whereas we simulate a full year. The analysis by Merten, Olk, Schoeneberger, & Sauer [76] investigates the combined use of BSS on the Intraday market and aFRR market concluding a potential economic feasibility of such systems in 2025. Angenendt, Merten, Zurmühlen, & Sauer [77] state solely the provision of frequency restoration reserve by BSS is less economical than a combined use with e.g. a PV system. The declining revenue potential for BSS over the last years is also found by Spodniak, Bertsch, & Devine [78]. Regarding different *E2P* ratios, the findings by He et al. [42], Engels et al. [75] and Pusceddu et al. [58]

point in similar direction by showing largest revenue potentials for short-term orientated BSS and declining profits for BSS with higher *E2P* ratios. As Xu et al. [11] already proposed in their study, there is a need for adapting the regulations of existing ancillary markets, such as aFRR, to compensate for the specifics of BSS. Otherwise, a market-driven integration of BSS is not likely based on current regulations. Regarding the future demand for balancing power markets in electricity systems with high shares of RE, Ocker & Ehrhart [79] addressed the questions raised by Hirth & Ziegenhagen [80], concluding that the improvement of grid control cooperation can lead to significant efficiency savings. The situation in our 2030 scenario, however, is still very unclear and we cannot model the demand endogenously. According to the prequalified capacities for the aFRR market presented in Hasche et al. [1], we assume that a rising demand for aFRR could be met without any problems, even in a scenario with reduced conventional capacities. However, since the uncertainty regarding the demand remains, we investigated the effect of different demand levels for aFRR power in a sensitivity analysis. Yet, we did not find any significant changes in prices nor in the economic potential of a BSS. This is especially true for the scenario 2030, where the prevailing share is earned at the DA market. As described in Section 3.2, the technical specifications of the BSS in form of the *E2P* ratio have much greater influence on its total revenues. Therefore, we renounced to alter the scenario in this regard in more detail.

5. Conclusions

We present a novel approach for simulating the automatic frequency restoration reserves market alongside the day-ahead market in an agent-based electricity market model. For this purpose, we calculate bids based on the opportunity costs of market players in order to participate at the two modeled markets. First, the model was back-tested for Germany for the most recent available year 2019 achieving an overall good fit. Then, we have set up a scenario for 2030 according to a recently published study for a low-emission electricity system in Germany. The simulated electricity system features a significant share of renewable power plants supplying already 60% of the yearly electricity demand. From this scenario and model setup, we derive price time series for both investigated markets. We then assess the revenue potentials of battery storage system operators which are active on these two markets. In an optimization model, we calculate the optimal storage dispatch strategy and evaluate its profitability. When we compare the simulated potential revenues in the given scenario 2030 to those revenues in a simulated market 2019, we see an improved economic potential in the simulated future scenario. Additionally, in the scenario 2030 the distribution of revenues shifts towards the day-ahead market which is explained by higher price fluctuations. The technical specifications of the battery storage system are crucial for an optimal use-case. We find that the ability to provide power in the short-term leads to the highest revenues concluding that high power battery storage systems perform best in the given scenarios. Higher round-trip efficiency only contributes to minor improvements regarding the annual revenues. Additional calculations could further enhance the presented results by taking the investment and operational costs of battery storage systems into account. Future work may also improve the presented approach by including additional markets such as the Frequency Containment Reserves market or Intraday market into the model to generate a more comprehensive view of the revenue potentials. As discussed, the battery storage system operator may increase its revenue when employing a multi-use strategy to serve various markets simultaneously. While the presented modeling approach is demonstrated for the specifications of the German market, the developed methodology can be adapted to describe the situation on different national electricity markets such as North America or European countries. This enables policy makers, companies, and investors to get a better understanding of the application of battery storage systems. For this purpose, technical specifications may have to be adjusted to reflect the corresponding market design and rules. In addition, the region-specific power plant parks and market prequalification requirements to participate in the day-ahead market and frequency restoration reserves market must be considered accordingly.

Credit authorship contribution statement

Felix Nitsch: Conceptualization, Methodology, Software, Validation, Investigation, Visualization, Writing - original draft. **Marc Deissenroth-Uhrig:** Conceptualization, Methodology, Software, Writing - review & editing. **Christoph Schimeczek:** Validation, Investigation, Writing - review & editing. **Valentin Bertsch:** Writing - review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

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3.2 Paper II: The future role of Carnot batteries in Central Europe: Combining energy system and market perspective

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Executive Summary: Carnot batteries, high-temperature heat storage systems, promise an attractive solution to meet growing flexibility needs systems with high RE shares. To assess the future economic potential of such Carnot batteries, I coupled the energy systems optimisation model REMix with the agent-based electricity market model AMIRIS. REMix evaluates the least-cost infrastructure configuration of the energy system, while AMIRIS focuses on the profitability of these storage systems. I applied this modelling chain in a case study of a zero-emission energy system in Central Europe for the year 2050. To guide the development of this promising technology, I conducted a parameter scan of costs and efficiencies of Carnot batteries in this system. My findings show that the availability of a low-cost storage medium is a key driver for the use of Carnot batteries from an energy system design perspective. Additionally, combining Carnot batteries with wind energy offers benefits as a result of the potential for longer storage durations compared to electrochemical batteries. Carnot battery operators could potentially realise positive annual gross profits, depending on the system design, their role within the energy system, and importantly, their market power and bidding strategy. On the basis of these results, I conclude that to make Carnot batteries competitive with other storage technologies on a broader scale, their development potential must be fully leveraged. This work builds on the preliminary study that was published as part of the proceedings to the International Conference on Applied Energy 2022 in Bochum, Germany (Nitsch and Wetzel 2022).
Author Contributions: I am the lead author of this paper. The main research work of this paper was shared between Manuel Wetzel, a PhD student and researcher at DLR, and myself. Manuel Wetzel carried out the work on the energy system optimisation model REMix, while I carried out the work on the agent-based electricity market model

AMIRIS. I also ensured the coupling of the two models through a dedicated workflow. The analysis and visualisation were done by me and Manuel Wetzel. The original manuscript was written by me and Manuel Wetzel. The manuscript was reviewed and edited by Hans Christian Gils and Kristina Nienhaus, both group leaders and senior scientists at DLR. Hans Christian Gils and Kristina Nienhaus were also responsible for the supervision and acquisition of funding.

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Research papers

The future role of Carnot batteries in Central Europe: Combining energy system and market perspective

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ABSTRACT

Power generation from variable renewable energies is expected to dominate the future energy supply in many countries, which will lead to an increased demand for flexibility options. Carnot batteries offer the technical prerequisites for meeting this flexibility demand and are relatively easy to scale. This paper investigates the future economic potential for Carnot batteries by coupling the energy systems optimization model REMix and the agent-based electricity market model AMIRIS. While REMix evaluates the least-cost infrastructure configuration of the energy system and the role of Carnot batteries in it, AMIRIS focuses on the corresponding profitability of these storage systems. The modelling chain is applied in a case study of a zero-emission energy system in Central Europe for the year 2050. To provide guidance for a promising technology development, a parameter scan for costs and efficiencies of Carnot batteries is performed for this system. We find that from an energy system design perspective the availability of a low-cost storage medium is a key driver for the usage of Carnot batteries. In addition, the combination of Carnot batteries with wind energy provides benefits due to the possibility of longer storage durations compared to electrochemical battery systems. Carnot battery operators can potentially realize positive annual gross profits, based on factors such as the system's design, their designated role within the energy system, and notably, their market power and bidding strategy. We conclude that the development potential of Carnot batteries must be leveraged to make them competitive with other storage technologies on a broader scale.

1. Introduction

Energy storage plays a critical role in modern energy systems [2], especially in those with high shares of wind and solar power [3]. Due to the intermittent nature of variable renewable energy (VRE) sources, balancing power demand and supply requires either spatial, sectoral, or temporal flexibility. Spatial balancing can be achieved through power grids, sectoral balancing e. g. through electric heat production and cogeneration, while temporal balancing can be achieved through the use of energy storage options. There are various types of storage options available, each with its advantages and use cases [4–6]. Pumped storage potentials across Europe are limited by topography and do not offer significant options for further expansion, except for Scandinavia [7]. Likewise, cavern adiabatic compressed air energy storage requires saline rock formations in order to benefit from a low-cost storage volume [8]. Lithium-ion batteries, in contrast, are easily scalable and widely used in the transportation sector [9], but they have risks associated with increasing costs and availability due to limited annual mining of lithium [10]. Sodium-ion batteries may offer an alternative to remove the dependency on lithium, but are not yet an established technology. Another promising option are vanadium redox-flow batteries, however the current state-of-the-art systems require additional scale-up effects for both the stack and the vanadium electrolyte in order to become an economically viable alternative [11].

The choice of storage method is further influenced by the intended storage duration. To illustrate, short-term storage can be effectively achieved through battery storage, while mid-term storage can be facilitated by pumped hydro storage. For extended durations, power-to-gas and hydrogen storage are favourable solutions [12]. For such stationary applications, energy density plays a minor role and more emphasis can be put on choosing a low-cost storage medium. Carnot battery concepts [13] can provide large-scale electrical energy storage capacities. Due to their modular nature, a wide range of different technical configurations of Carnot batteries is possible [15], but the underlying working principles stay the same: Electricity is transformed into heat and stored in a storage medium such as molten salt [14]. The stored heat is then converted back into electricity when needed using processes such as the Brayton or Rankine cycle.

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Because of these advantages, we aim at analysing the potential role of Carnot batteries in future energy systems. In addition to technical challenges, such as increasing efficiency and scaling up storage systems, it is also essential to consider their economic perspectives. Investments in storage technologies require a detailed view of future profitability potentials in electricity systems with high VRE shares. A previous study indicated a significant role of generic storage systems in the overall power system design if storage technologies can achieve storage specific costs below 35 €/kWh and a competitive role against gas turbines in the range between 35 €/kWh and 75 €/kWh [16]. Similarly, Dumont et al. [17] identified the need for a low-cost energy storage medium when considering grid-scale systems with storage times between 4 and 8 h and outlined competition against lithium-ion batteries in the long run. Furthermore, the authors of [18] propose conversion of existing coal power plants to Carnot batteries with 5 h storage times and unit costs of 100–200 €/kWh$_e$, depending on the operation regime. Achieving this low-cost storage medium can therefore enable technology competitiveness for Carnot batteries against other storage technologies such as pumped hydro storage or lithium-ion batteries and be a main driver for the integration of electricity from renewable energy sources into the overall energy system. For a large-scale integration of Carnot batteries in a Danish 100 % renewable energy systems, it is imperative that the associated costs are reduced to levels below the range of 60.5 to 66.2 €/MWh$_e$ as suggested by [19]. Other studies focus more on technical optimization of Carnot battery storage but less on the integration in future energy systems and electricity markets [20–23].

While these papers provide some first indication on the potential of Carnot batteries in future energy systems, they do not provide the full picture. Various energy systems modelling studies have shown that flexible sector coupling, such as electric vehicles [24], demand response, and thermal energy storage [25], or transmission grid reinforcement [26] can have a substantial impact on the competitiveness of power-to-power storage technologies. However, flexible sector coupling is not considered in earlier studies of the economic potential for Carnot batteries [16,17]. Furthermore, the applications and profitability of Carnot batteries on electricity markets have not been assessed in this depth. Therefore, the present paper provides insight into the potential role of Carnot batteries in future sector-coupled energy systems as well as in corresponding electricity markets and helps to identify the most promising areas for further research and development. More specifically, our research addresses the following research questions:

1) What targets for techno-economic parameters need to be achieved for Carnot batteries in order to enter into the cost-optimal energy mix of a system with competing flexibility options?
2) What are promising technological niches for the future deployment of Carnot batteries if cost competitiveness for balancing power supply cannot be reached?
3) What are the economic potentials for Carnot batteries with regard to the business-oriented perspective of storage operators and different modes of operation?

To answer the first research question, the study analyses the cost-effectiveness of Carnot batteries compared to other energy storage options. The analysis considers the costs of installation, maintenance, and operation, as well as the efficiency and lifespan of the storage systems. The second research question focuses on identifying the most promising technological niches for the deployment of Carnot batteries. This involves evaluating the potential applications and benefits of the technology, as well as the technical requirements and challenges that need to be addressed. Finally, the third research question targets the economic perspectives for Carnot batteries investigating different modes of operation. These modes of operation refer to how the storage system is utilized in the electricity market, and the economic perspectives include factors such as investment costs, operation and maintenance costs, and revenues from energy arbitrage. An analysis of these factors can provide insights into the potential profitability of Carnot batteries and inform investment decisions for their deployment in future electricity systems.

By addressing these research questions, our study effectively bridges a significant research gap, providing a comprehensive system analytical evaluation of Carnot batteries. Notably, our study extends beyond a single-country focus, encompassing a comprehensive techno-economic investigation within the context of Central Europe. Our analysis is particularly concentrated on the interaction of Carnot batteries with other flexibility options and the anticipated revenue they can generate in the electricity market. Therefore, we combine a centrally planned energy systems optimization perspective with a business-driven electricity market simulation approach. By investigating these aspects, our research not only advances the understanding of Carnot battery performance on electricity markets but also contributes to the broader discourse on the integration of storage technologies into systems with high shares of VRE. This paper is a substantial extension of the conference paper [1] presented at the International Conference on Applied Energy (ICAE2022) in Bochum, Germany, Aug 8-11, 2022.

Our paper is structured as follows. In Section 2, we describe the general model setup, design of the parameter scan on techno-economic assumptions, and the selection process of the different scenarios considered in the study. Section 3 presents the results for both the cost-optimal energy system design aspect and the market simulation. The limitations of the study are discussed in Section 4, while the conclusions and outlook for future work are presented in Section 5.

2. Material and methods

The analysis is designed around a coupled modelling system, as seen in Fig. 1. We deploy the energy system optimization model REMix [27] to find cost-optimal designs under different techno-economic assumptions, and the electricity market model AMIRIS [28] to get a more detailed view into the effects of operational decisions made by Carnot batteries in the electricity market. The model coupling is implemented using iog2x [29] which is based on the workflow manager ioProc [30] and guarantees efficient data transfer from REMix to AMIRIS. This involves processing REMix results by converting them into the required format for the AMIRIS model, while also taking care of AMIRIS execution and model result evaluation.

2.1. Parametric study with the energy systems optimization model REMix

To establish a baseline on the overall energy system design and decisions on infrastructure, we use the REMix framework for optimizing energy system models [27]. The model considers both capacity expansion planning and economic dispatch in a high spatial and hourly resolution in order to find the least-cost optimal energy system design. The technology modelling in REMix is described in detail for the power generation and storage in [31], for the power grid in [32], for the heat sector in [25], for the gas sector in [33], and for electric vehicles in [34]. Previous studies have for example focussed on the impact of national political targets on the overall design of a 100 % renewable energy system [35,36], the role of green hydrogen and methane for a climate neutral energy system under different considerations regarding limited network expansion [37], or on different modelling approaches [38]. For the case study at hand, we build upon a previously published dataset for the power system and additional technologies for the consideration of sector-integration with the heat and gas sectors [39] which is linked to the case study presented in [33]. This model encompasses Germany spatially resolved into 10 partially aggregated federal states and 12 neighbouring countries as individual model regions, as seen in Fig. 2. For the temporal resolution 8760 time steps are used in order to adequately capture the variability of feed-in from VRE sources. A cost-optimal capacity expansion planning for power plants, gas pipelines, electrical grids, and storage technologies for the model year 2050 is conducted while considering the pre-existing capacities such as

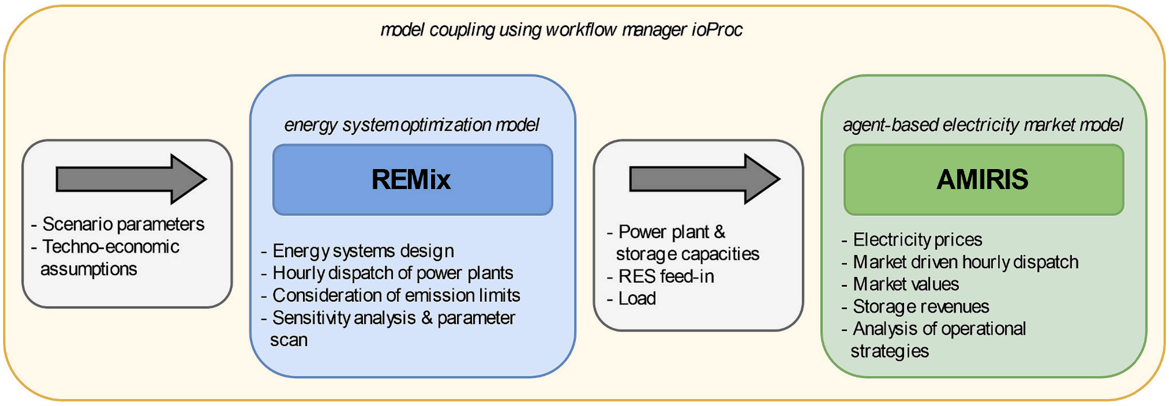

Fig. 1. Model coupling setup.

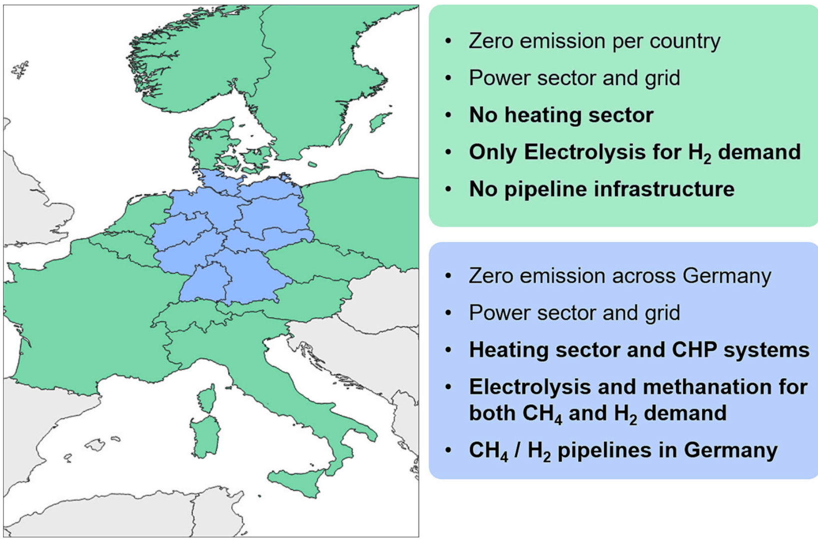

Fig. 2. Representation of the spatial scope of the case study based on [39]. While Germany is modelled as 10 aggregations of federal states and with higher sectoral detail, especially for the heating sector and the gas infrastructure for hydrogen and methane, its 12 neighbouring countries are modelled with less sectoral detail and fewer flexibility options.

pumped-hydro storage plants. In the selected case study, the main competitors for Carnot batteries are pumped hydro storage, lithium-ion battery storage technologies, and conversion to methane for subsequent reconversion to electricity. For Germany the hydrogen produced via electrolysis can be further processed via methanation units and used for electricity production in gas turbines, while in the neighbouring countries it can only be used to satisfy the exogenous demand for hydrogen. This competition is not only between different options for storing electrical energy, but also against chemical storage options in the form of hydrogen and methane, and provides a better basis of understanding on the role of Carnot batteries. In Germany, Carnot batteries are additionally competing with extended district heating networks to provide flexibility to the electricity system. By integrating thermal storage and a wide range of technologies for heat supply, including CHP plants, heat pumps, electric boilers and fuel-based boilers, district heating networks can react flexibly to the VRE supply. A detailed description of the scenario and model setup can be found in [33], the corresponding model assumptions are documented in [21].

To evaluate the efficiency and cost development required to achieve competitiveness from an energy system design perspective, we conduct a parametric variation of the techno-economic assumptions on Carnot batteries. This parametric study considers a variation of overall round-trip efficiency, capital expenditure (CAPEX) for the charging and discharging infrastructure, and CAPEX for the storage capacity. The charging and discharging capacity and energy storage volume are optimized independent from each other in order to derive the optimal design range in terms of energy-to-power (E2P) ratio.

Table 1 compares the techno-economic parameters for the Carnot batteries derived by the state-of-the-art reviews by [17,40] to those of other storage technologies considered in the case-study. Furthermore, it provides the ranges assumed in the parameter scan, which are based on the more optimistic projections on future technology development stated by [17,40]. In reality, we expect a certain correlation between the different components such as higher round-trip efficiencies leading to higher CAPEX for charging and discharging, which, for the sake of identifying ideal techno-economic configurations, is ignored in this study and all possible combinations are considered. The wide range reported in both review studies hints at the large uncertainty faced during current prototype projects and cost projections for future systems. To comprehensively reflect the uncertainty of technology

Table 1
Techno-economic assumptions for Carnot batteries and the different storage technologies in competition with each other. Values are derived from Dumont et al. [17], Vecchi et al. [40], and Gils et al. (year 2050) [39].

Storage system	Technical lifetime in years	Round-trip efficiency	CAPEX storage	CAPEX converter
Brayton Cycle, [17]	25–30[a]	60 % - 70 %	55–198 $/kWh	395–875 $/kW
Rankine Cycle (Electric heating), [17]	25–30[a]	12 % - 55 %	~94 $/kWh	~376 $/kW
Rankine Cycle (Heat pump), [17]	25–30[a]	30 % - 73 %	68–117 $/kWh	272–468 $/kW
Brayton PTES, [40]		52 % - 70 %	50–1500 $/kWh	2000–4000 $/kW
Rankine PTES, [40]		45 % - 65 %	250–1000 $/kWh	500–8000 $/kW
LAES, [40]		40 % - 60 %	400–800 $/kWh	700–3000 $/kW
Power to gas (methane), [39]	25 / 25 / 30	45 %[b]	0.2 €/kWh	350 / 800 / 850 €/kW[c]
Lithium-ion batteries, [39]	25	94 %	150 €/kWh	50 €/kW
Pumped hydro storage, [39]	60	85 %	10 €/kWh	200 / 250 €/kW[d]
Carnot battery parameter scan, [39]	25	[55 %, 65 %, 75 %]	20–150 €/kWh	90–400 €/kW

[a] Assumed lifetimes based on [41].
[b] Assumed efficiency for electrolysis 80 %, methanation 90 %, CCGT 63 %.
[c] Assumed investment costs for electrolyser, methanation plant and CCGT.
[d] Separate cost assumptions for turbines and pumps.

development, we derive a set of assumptions for each of the key input parameters. Thus, the parameter scan includes three assumptions for the round-trip efficiency (55 %, 65 %, 75 %), four for the converter CAPEX (90 €/kW, 150 €/kW, 270 €/kW, 400 €/kW), and five for the storage CAPEX (20 €/kWh, 35 €/kWh, 55 €/kWh, 70 €/kWh, 90 €/kWh).

Due to the limited potential of expansion of pumped hydro storage and methane cavern storage sites, the highest competition arises from battery systems. This also gives a rough upper limit for the allowed storage CAPEX as values above would be outcompeted in most cases due to both the higher efficiency and lower cost of the power electronics for charging and discharging. By considering all possible combinations of assumptions for efficiency and investment costs, the parameter scan includes a total of 60 REMix runs. This wide range allows the role of Carnot batteries to be assessed for scenarios where they can play a significant system-wide role, as well as for scenarios where the techno-economic data limits the deployment of the technology to a niche role.

2.2. Market analysis with the agent-based electricity market model AMIRIS

Transforming the centralized approach of cost optimal energy systems into operating energy systems, investments in technologies have to be made by individual entities. Therefore, these investments must demonstrate a favourable economic outlook in practice. In order to assess economic potentials for Carnot batteries with regard to the business-oriented perspective of storage operators, we employ the open agent-based electricity market model AMIRIS [28] to simulate the German day-ahead market. AMIRIS is implemented in the open framework for distributed agent-based modelling of energy systems FAME [42] which allows a powerful, yet flexible model parameterization [43]. AMIRIS can be utilized to explore market dynamics that arise from the interactions of market actors [44], economic assessments of battery storage [45], while also considering regulatory frameworks [46], and actors' behaviour under uncertainty [47]. AMIRIS has been calibrated and back-tested for the German day-ahead market [45] and Austrian day-ahead market [48], demonstrating a good fit in simulating historical electricity prices. All relevant configuration files and data are openly available [49]. AMIRIS represents various actors in the electricity market, including power plant operators, traders, and policy agents. We use a dedicated storage agent class who provides temporal flexibility. This agent is parameterized with techno-economic parameters such as capacity, power, charging and discharging efficiencies, availabilities, and costs. In contrast to the optimization model REMix, two distinct operational strategies for the Carnot battery agent are implemented. These strategies are described in detail in Section 2.2.1. A detailed elaboration of all other agent types can be found in [50] whereas a schematic overview of AMIRIS is found in the Appendix in Fig. 9.

2.2.1. Storage dispatch strategies

The bidding strategy of a Carnot battery as a flexibility provider is crucial for profitable operation. Various methods have been proposed in the literature to determine effective bidding strategies, including stochastic programming, game theory, and machine learning. Here, we adopt two strategies on the basis of dynamic programming that require forecasted information about the market (i.e. forecasted electricity prices) for a defined window. The algorithm evaluates the discrete states-of-charge of the Carnot battery to identify optimal charging and discharging opportunities. The resulting bids and asks are submitted to the electricity market accordingly. Specifically, we compare a system-optimal solution that minimizes system costs with a best-case, upper-limit scenario for the Carnot battery operator that maximizes profits by utilizing the market power of the total installed storage capacity and power. Both strategies optimize the operator's schedule over a 168 h window with perfect foresight.

2.2.1.1. Minimizing system costs. In order to reduce overall operational system costs associated with dispatching the power plant park, the *Minimize system costs* strategy corresponds to a flexibility provider that operates in a "system-friendly" manner. This approach minimizes the sum of the marginal costs of operating the electricity system over the forecast horizon. While minimizing system costs may not be a feasible business case for individual storage operators in reality, this approach helps to explore the potential solution space.

2.2.1.2. Maximizing profits. The *Maximize profits* strategy aims to maximize the profits of storage operators by utilizing their market power in the electricity market, especially for large-scale storage systems. Due to the assumed operator's perfect foresight and full market power, this approach represents the absolute upper limit of profits in the analyzed scenario. Typically, the storage operator seeks to charge when forecasted prices are low and discharge when forecasted prices are high. The algorithm considers the impact of the operator's own bids and asks on the merit order and its price changing effect. This effect is significant if the storage characteristics (i.e. power, capacity) are relevant to the system's total size, meaning that the storage can actually impact market prices due to its behaviour.

2.3. Scenarios and sensitivity analysis

In addition to both the parameter scan for the overall energy system design and dispatch strategies for the storage operators, several additional aspects for the energy system design can have a large influence on the role of Carnot batteries in the cost-optimal solutions. To this end we extend the "*Base*" case system of the parametric study as presented in 2.1 by three additional sub-scenarios to study the economic impacts and the sensitivity of Carnot battery expansion towards additional design objectives. The first scenario "*No Grid*" limits the available transmission lines to those planned in the ten-year network development plan from the year 2016 [51] as well as the e-Highway 2050 study [52]. This reduction in the spatial flexibility of the system is expected to lead to an increased demand for temporal flexibility options. Similarly, the second scenario "*Low Flex*" decreases the flexibility on the demand side by enforcing a capacity factor of 0.75 for the operation of water electrolysis. While technically electrolysis can be operated in a highly flexible fashion [53], this assumption emulates a hesitancy for investments into electrolysers operated solely based on surplus electricity. The third scenario "*Low Curtail*" addresses limitations in profitability for renewable energy operators by limiting the possibility for curtailment of energy from renewable sources to 5 % of their annual energy demand. This limitation of flexibility likewise increases demand for temporal storage options in the overall system design.

To further test the sensitivity of the results to the techno-economic assumptions regarding the main competing storage technologies and the composition of the VRE plant fleet for electricity generation, supplementary model calculations are carried out with REMix. Based on the parameter study, three combinations from the parameter scan in Section 3.1 are selected to test the related interactions with the techno-economic assumptions for Carnot batteries. The results of the sensitivity analysis are described and analyzed in the Appendix B.

3. Results

The analysis is presented in the order of model application. First, the REMix results on the energy systems design in the parametric study are described in Section 3.1, followed by the electricity market analysis relying on AMIRIS in Section 3.2.

3.1. Competitiveness of Carnot batteries from an energy system design perspective

In order to find the technical configurations in which Carnot batteries start entering the overall system design during a least-cost optimization, the full parameter scan using different techno-economic data is computed, see Section 2.1. Fig. 3 shows the share of Carnot battery capacity against the overall storage capacity from both Carnot batteries and battery storage systems. In addition, the most optimistic systems based on [17] are included as reference points. All of the configurations reported in the literature are not competitive against the assumed improvement in battery systems. However, both the Brayton cycle and Rankine cycle systems are close to being viable configurations due to their higher round-trip efficiencies. This leads to the conclusion that additional efforts in research and development or cost reductions by technological advancements are required if no support schemes are implemented. If sufficient cost reductions are achieved for either the power specific CAPEX or the storage specific CAPEX, both Brayton and Rankine systems could become cost competitive options. For lower round-trip efficiencies in the range of 55 % the target range for the introduction of Carnot batteries ranges between 400 €/kW at 20 €/kWh to 90 €/kW at 55 €/kWh. For higher round-trip efficiencies in the range of 75 % there is more leeway for higher investment costs between 400 €/kW at 35 €/kWh to 150 €/kW at 70 €/kWh. Overall, out of the 60 modelled system configurations, eight reach a share in combined storage capacity between 20 % and 50 %, ten a share between 50 % and 90 %, and nine a share higher than 90 %. However, the system configurations leading to high market shares would require significant progress along all three dimensions making a share above 50 % for Carnot batteries quite unlikely. Still, even with lower system wide shares Carnot batteries can fill a niche role specially if low energy specific investment costs are reached. As explained in the following, these niches arise especially in regions with a high wind energy share in power generation or limited flexibility in sector coupling.

A closer look into the spatial distribution of storage technologies shown in Fig. 4 reveals a close correlation between the installed capacities of wind onshore and Carnot batteries, photovoltaic capacities and battery storage systems, as well as offshore wind capacities and electrolysers. Especially for electrolysers there is a distinct concentration in the northern parts of Germany due to the availability of storage caverns for hydrogen and methane. As a consequence of the different approaches towards modelling sector integration in Germany and the remaining countries in Europe there is no significant investments in either Carnot batteries nor battery systems under most techno-economical parameter combinations in Germany. This can be explained by the high demand side flexibility provided from water electrolysis and, if necessary, methanation for electricity production in gas turbines. On the other hand, the exogenous demand for hydrogen and methane requiring at least some investments into electrolysers and therefore decreasing the marginal cost of using the technology as a

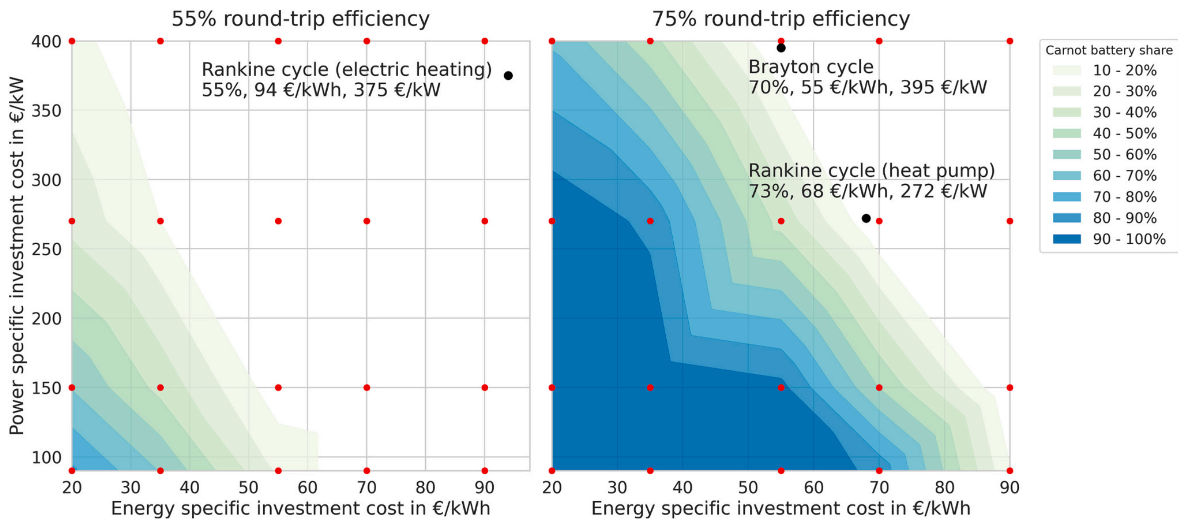

Fig. 3. Share between provided electricity from Carnot batteries and battery storage systems for the full parameter scan. Contours of the different shares are based on a linear interpolation of all points in the three-dimensional space. Red points indicate the different combinations in techno-economic assumptions, while black points indicate the most optimistic state-of-the-art system configurations identified by [17]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

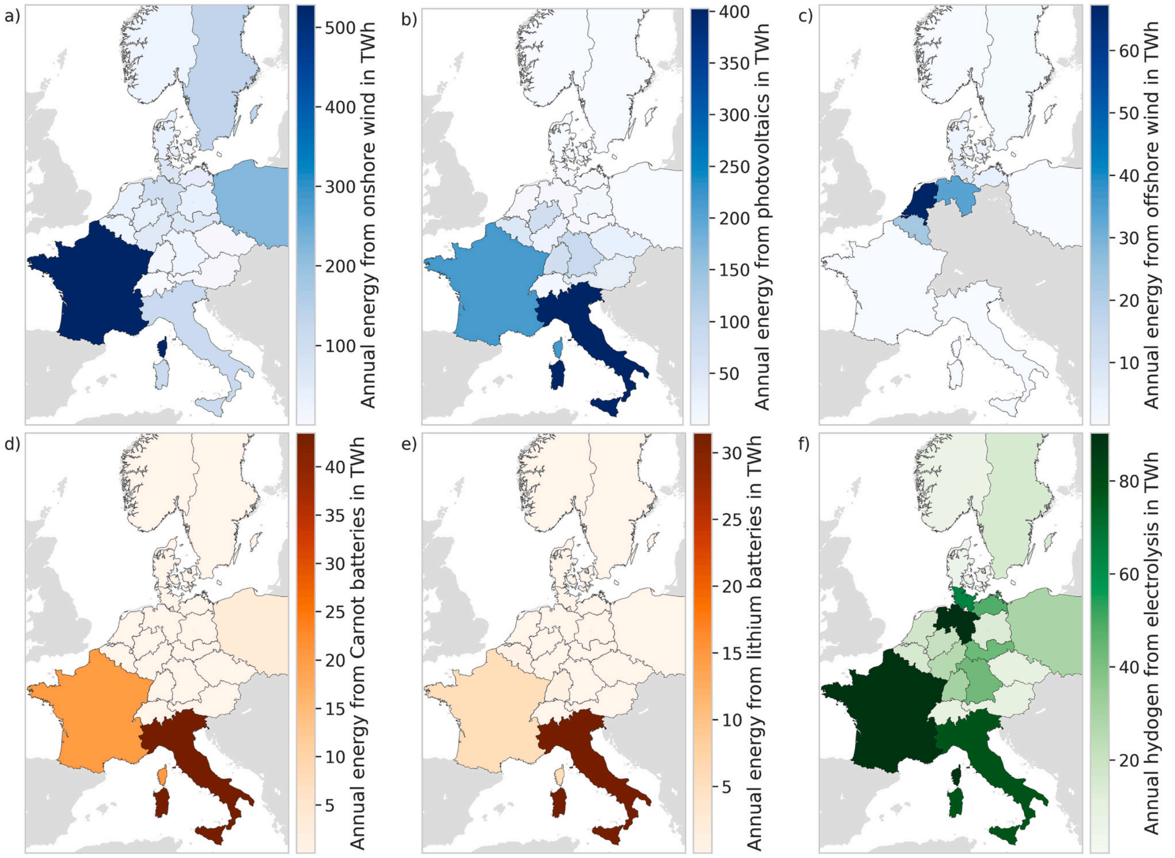

Fig. 4. Spatial distribution of annual energy generation from renewable technologies (a – c), annual energy provided from storage systems (d, e), and annual hydrogen production from water electrolysis (f). The spatial correlation indicates synergies between onshore wind and Carnot batteries as well as photovoltaics and battery storage. Values are derived from the techno-economical configuration of 65 % round-trip efficiency, 20 €/kWh storage specific CAPEX and 270 €/kW power specific CAPEX.

flexibility option. In the case of considerable optimistic technological progress for Carnot batteries (i.e. 65 % round trip efficiency, 150 €/kW, 20 €/kWh), there is some investment into Carnot batteries in Germany. This is the reason, why we focus on these cost assumptions to be further analyzed in the market assessment. The spatial distribution of Carnot batteries in Germany is presented in Appendix C.

In addition to the spatial correlation, we can consider the temporal charging and discharging pattern to further substantiate the connection between renewable technologies and storage technologies. Fig. 5 shows a clear diurnal charging pattern for battery storage systems, which matches the feed-in profile from photovoltaics and indicates most of the energy is charged during the middle of the day and discharged in the evening hours. Some additional charging and discharging at the beginning of the day allows reducing the typical electricity peak during the morning hours. In contrast, the charging of Carnot batteries has a wider band during the midday hours and is not charged every day. Storage discharging is also mainly in the evening hours, which is driven by both the exogenously provided electricity demand profile and the lack of photovoltaic generation. With respect to the storage level the clear roles of lithium-ion battery storage as a daily peak load provider and the Carnot batteries as an energy storage for multiple days can clearly be identified.

3.2. *Electricity market analysis*

In contrast to the energy systems optimization, which is performed from a central planning perspective for Central Europe, the market simulation is limited to the German market due to model constraints at time of the research design. Imports and exports to neighbouring market zones are taken as exogenous time-series from the respective REMix model runs. The Carnot battery specifications regarding power and capacity differ substantially in the investigated three scenarios (see Section 2.3), their configuration is displayed in Fig. 6. The installed power of Carnot batteries are 3.7 GW in the *Base* scenario, 15.8 GW in the *Low Flex* scenario, and up to 35.8 GW in the *No Grid* scenario. E2P ratios range from 7.4 (*No Grid*), to 8.2 (*Low Flex*). In all three scenarios, the Carnot battery's technical specifications and status as singular operator contribute to significant market influence and market power. When interpreting the following results, these characteristics are important to be kept in mind.

The profitability analysis is performed by comparing gross profits (difference between revenues from and costs for traded electricity, neglecting any other expenses) for all three scenarios and the two dispatch strategies, i. e. minimizing system costs and maximizing profits. Fig. 7 illustrates gross profits relative to the best-case scenario *Low Flex* applying the *Maximize Profits* strategy. This strategy consistently outperforms the Minimizing System Costs strategy in all regarded scenarios, attributable to the Carnot battery operator's effective utilization of its substantial market power. In all cases, positive annual gross profits can be achieved. These results represent the most upper limits of revenue potential, emphasizing the unique advantage conferred by the Carnot battery's status as the main flexibility provider. This is especially

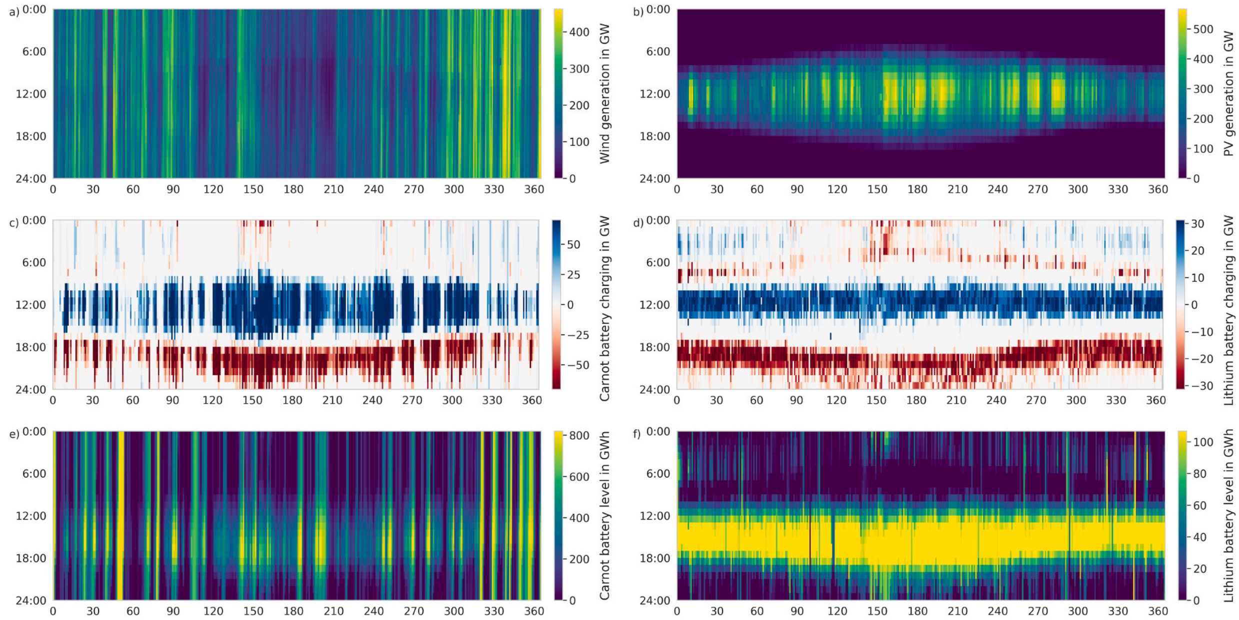

Fig. 5. Hourly feed-in from renewable technologies (top), hourly charging and discharging (middle) for batteries and Carnot batteries (middle), and storage levels (bottom) throughout the year for Carnot batteries and lithium-ion batteries. Hourly values are derived from the techno-economical configuration of 65 % round-trip efficiency, 20 €/kWh storage specific CAPEX and 270 €/kW power specific CAPEX.

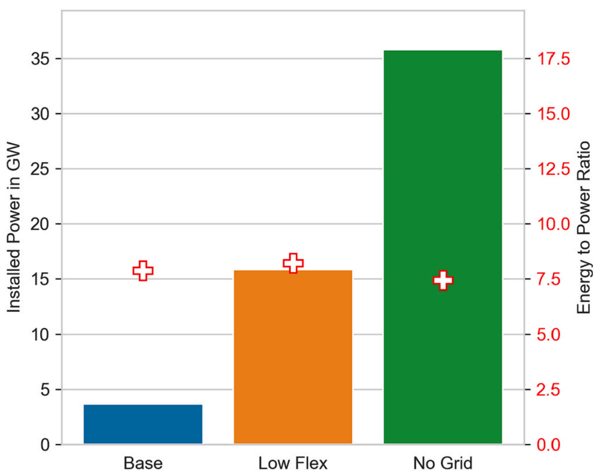

Fig. 6. Installed Carnot battery capacities and their Energy to Power ratio (red framed crosses). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

prevalent in the *Low Flex* and *No Grid* scenarios. Notably, all strategies profit from employing a rolling window of perfect foresight for arbitrage options.

Even though the Carnot battery capacity in the *No Grid* scenario is more than doupled compared to the *Low Flex* scenario, it cannot outperform the gross profits from the latter. We observe diminishing spreads in electricity prices as a consequence of arbitrage. Therefore, the increased trading capacities of the Carnot battery in the *No Grid* scenario cannot generate additional revenue potentials.

Table 2 provides additional comparative evaluation of the *Maximize Profits* and *Minimize System Costs* strategies. In this analysis, values exceeding 100 % indicate a greater impact when employing the *Maximize Profits* strategy. The *Maximize Profits* strategy also significantly influences mean prices, driving them up by at least 345 % in the *Base* scenario and as much as almost 400 % in the *Low Flex* scenario. Full cycles tend to be lower compared when aiming at maximizing profits. Total system costs (sum of all operational costs) are more than doubled (*Base* and *Low Flex*) or even tripled (*No Grid*) scenario. Regarding accumulated discharged and charged energy, the results reveal higher values in the *Base* scenario, contrasting with smaller values in the *Low Flex* and *No Grid* scenarios.

4. Discussion

The results show that with our model setup and scenarios analyzed, Carnot batteries have a limited role in the modelled optimal future energy systems for Central Europe, even with optimistic cost assumptions. This results from the extensive provision of flexibility through sector coupling technologies, such as flexible hydrogen production or advanced district heating, and from the use of battery storage, which proves to be more cost-effective for many locations. However, further development, especially based on Brayton cycles and Rankine cycles in combination with heat pumps, can make Carnot batteries a promising alternative for electricity storage. Though, the future role of Carnot batteries will likewise depend on the future development of battery storage systems and electrolysers. Both technologies can have a significant impact on the overall landscape of flexibility options. This balance may be shifted if additional factors, such as material availability or increasing prices for raw materials are considered. Therefore, additional research on the life cycle impacts of different storage technologies will be an important field of research going forward.

The REMix parameterization used here considers the power grid only in aggregate form as transmission capacities between model regions (Fig. 8). As a result, information about grid congestion within these regions is lost. Consequently, flexibility needs at the local level are partially underestimated, and so are the potentials of Carnot batteries at locations of high generation surpluses. The extent to which local wind power curtailments can be cost-effectively avoided by Carnot batteries

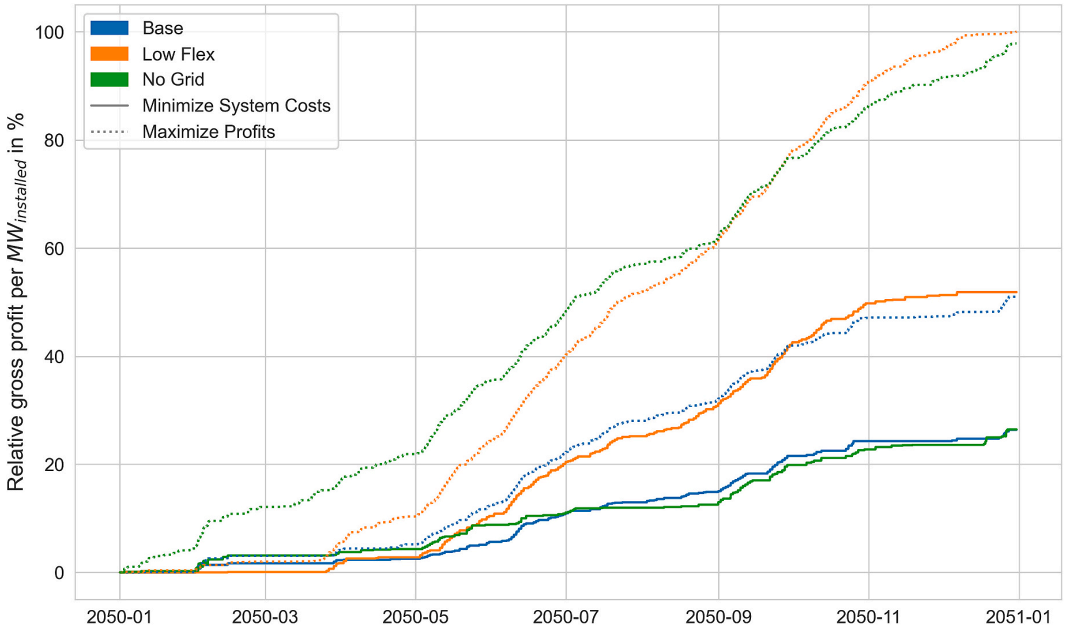

Fig. 7. Relative gross profit per $MW_{installed}$ compared to best performing combination (*Low Flex* with *Maximize Profits strategy*).

Table 2
Evaluation of the performance of the *Maximize Profits* strategy in comparison to the *Minimize System Costs* strategy, where a value greater than 100 % indicates a more pronounced impact when applying the *Maximize Profits* strategy.

	Total System Cost	Mean Price	Full Cycles	Accumulated Discharged Energy	Accumulated Charged Energy
Base	235 %	345 %	85 %	85 %	84 %
No Grid	309 %	378 %	81 %	81 %	81 %
Low Flex	262 %	395 %	80 %	80 %	80 %

thus remains to be addressed in more spatially detailed analyses.

The electricity market analysis of our study focuses on the economic analysis of Carnot batteries on the German market in future scenarios. [54] previously explored the economic viability of pumped heat electric storage on historical 2016 day-ahead prices concluding that high investment costs posed challenges for profitability. [55] simulated a Carnot battery on the scale of multiple households achieving similar results. In contrast, our results indicate positive gross profits, although with optimistic learning rates regarding CAPEX. Additionally, our work expands its scope beyond residential applications and considers Carnot batteries at a larger scale, with variations in power and capacity configurations. [56] explored the optimal sizing of Carnot batteries in combination with concentrated solar power plants, focusing on historical day-ahead prices in the Spanish electricity market and identifying E2P ratios between 5 and 10 as optimal for intraday storage purposes. Our study also suggests E2P ratios between 7.4 and 8.2 resulting in similar characteristics. Furthermore, in line with [57], who emphasized the significance of E2P ratios greater than 7 and steep electricity price increases for Carnot battery applications, our findings support the importance of the scaling of the Carnot battery for achieving profitability. In [19], the authors investigate a 100 % renewable energy system proposed for a future Danish energy system in 2045. The findings reveal that Carnot batteries have the potential to facilitate 32 annual storage cycles, in combination with significantly elevated E2P ratios. Consistent with our own results, the authors underscore the importance of decreasing storage costs to thresholds below 60.5 €/MWh_{el} and 38 €/MWhel, contingent upon the specific sub-scenario considered. When interpreting the presented results on economic perspectives the following limitations have to be considered. First, the technical assumptions and cost basis of the presented Carnot batteries follow very optimistic learning rates. The assumed storage power and energy cost assumptions of 150 EUR/kW and 20 EUR/kWh, respectively, combined with a round-trip efficiency of 65 % must be kept in mind when interpreting the market analysis results. The benefit from a more integrated system such as thermal integration of Carnot batteries with industry processes or district heating systems as well as retrofitting power plants to storage systems, or competition with other flexibility options are outside the scope of this study and may shift the conclusions on the overall energy system design and the economic profitability. Second, the scope of the electricity market analysis is limited to arbitrage trading on the German day-ahead market. This not only neglects additional revenue potentials like providing system services such as frequency restoration reserve, but also possible competition from neighbouring market zones and other flexibility providers. Third, we want to emphasize that the profitability of the *Maximize profits* strategy marks the most upper limit of possible revenues since the storage trader benefits from its total market power and makes full use of it.

5. Conclusions

We present a comprehensive analysis of Carnot batteries and assess their future role in energy systems with high shares of renewable energies. A model coupling of the energy system optimization model REMix with the electricity market simulation model AMIRIS allows an investigation on both system and market perspective. From a general energy system design perspective, we can conclude that Carnot batteries may be a promising option for mid-term energy storage if technology development makes significant progress. In terms of system parameters this translates into the need for achieving a low-cost storage medium in the range of 20–35 €/kWh. Improving the round-trip efficiency seems to be a viable secondary target, however, needs to be traded-off against increases in the capital expenditures for charging and discharging, which may increase accordingly. If this is achieved, Carnot batteries would be more viable for high energy to power ratios than lithium-ion battery storage systems. The results from the REMix model further indicate synergies between Carnot batteries in conjunction with electricity generation from wind turbines but also to a certain degree with photovoltaic and lithium-ion battery systems. However, this synergy depends on the overall need for energy storage which can be impacted by high shares of electrolysis. The results also confirm that the use of flexible sector coupling, realized through storage for heat and hydrogen, reduces the demand for electricity storage. This has a noticeable impact on the market potential for Carnot batteries. Regarding the profitability analysis, we simulate the German day-ahead market using AMIRIS identifying positive gross profits among different scenarios. We conclude that the gross profit of Carnot battery storage systems is highly impacted by their considerable size and their favourable market position. Our results indicate that profitability is strongly related to market power of the storage operator which is particularly pronounced when the profit maximization strategy is applied. Therefore, further research may focus on a more accurate simulation of the competition of flexibility options and on finding robust strategies for the storage operator considering its impact of market power. Additional revenue streams such as ancillary markets could also be integrated in upcoming studies. Additionally, we propose that future investigations should extend the scope to other regions worldwide, recognizing the potential variability in the energy landscape and market dynamics, thereby contributing to a more comprehensive understanding of Carnot battery applications on a global scale.

Author agreement statement

We declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us. We understand that the Corresponding Author, Felix Nitsch, is the sole contact for the Editorial process.

He is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs.

CRediT authorship contribution statement

Felix Nitsch: Writing – original draft, Visualization, Software, Methodology, Investigation, Conceptualization. **Manuel Wetzel:** Writing – original draft, Visualization, Software, Methodology, Investigation, Conceptualization. **Hans Christian Gils:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Kristina Nienhaus:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Overview of the model workflows

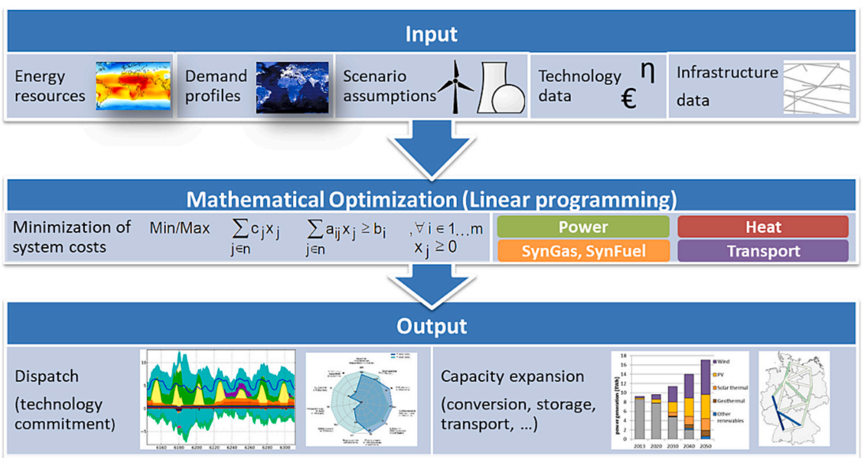

Fig. 8. Schematic overview of the REMix energy system model, from [58].

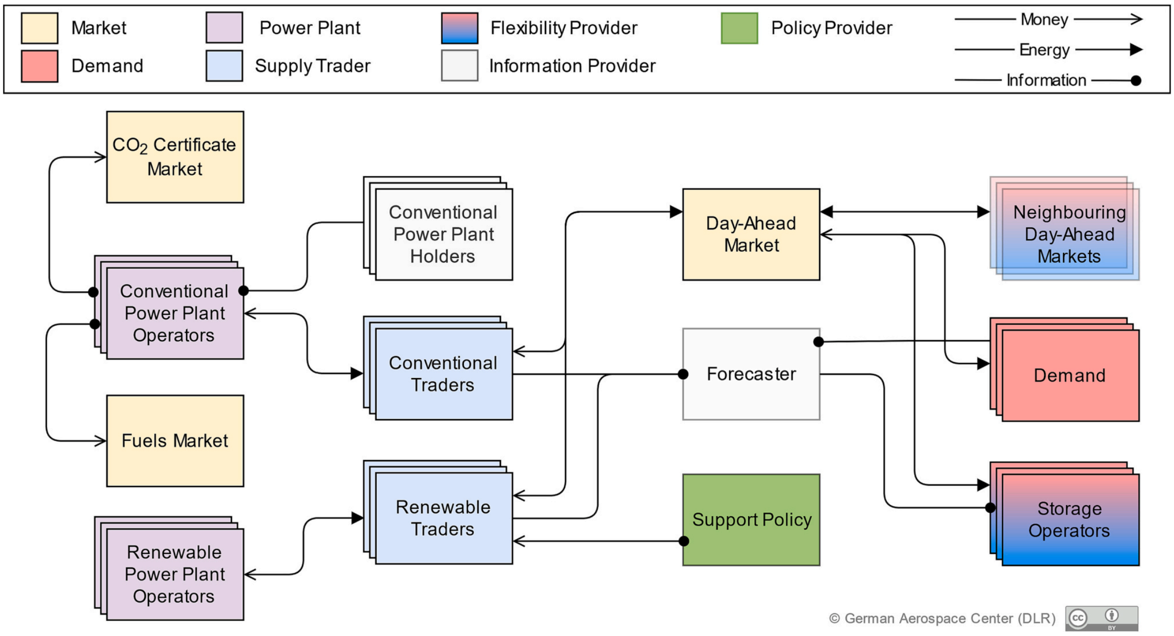

Fig. 9. Schematic overview of the electricity market model AMIRIS, see also [28].

Appendix B. Sensitivity analysis for the energy system design

As described in Section 2.3, further model calculations were carried out with REMix to examine how deviating assumptions on the composition of electricity generation and storage technology development affect the role of Carnot batteries in the cost-optimal system. This is realized by varying the cost assumptions for lithium-ion battery storage, P2G2P, photovoltaics and wind power plants. The additional assumptions used are based on values collected by the Danish Energy Agency [59] and the ranges of investment costs in 2050 mentioned therein. The resulting assumptions for battery storage costs are summarized in Table 3 and the assumptions for wind energy, photovoltaics and P2G2P in Table 4. The sensitivity analyses are carried out for the following three cases from the parameter study of technoeconomic assumptions on Carnot battery systems.

(1) 55 % round-trip efficiency, 35 €/kWh energy-specific costs and 150 €/kW power-specific costs
(2) 75 % round-trip efficiency, 35 €/kWh energy-specific costs and 400 €/kW power-specific costs
(3) 75 % round-trip efficiency, 75 €/kWh energy-specific costs and 150 €/kW power-specific cost

Table 3
Lithium-ion battery cost assumptions in the sensitivity analysis. The Base case values represent the assumptions used in the parametric study with the results presented in Section 3.1.

	base	battery++	battery+	battery0	battery-	battery–
Energy storage expansion cost (€/kWh)	75	46	78.5	111	143.5	176
Output capacity expansion cost (€/kW)	60	40	92.5	145	197.5	250

Table 4
Cost assumptions for wind energy, photovoltaics, electrolysis and methanation in the sensitivity analysis. If a field specifies no values the Base values are used. For all technologies fixed operational costs are scaled accordingly.

	base	p2g2p+	p2g2p-	pv + wind-	pv + wind+	pv-wind+
Electrolyzer expansion cost (€/kW)	350	150	500			
Methanizer expansion cost (€/kW)	800	450				
Photovoltaic expansion cost (€/kW)	518			250	250	
Onshore wind expansion cost (€/kW)	1173				800	800
Offshore wind expansion cost (€/kW)	1800				1640	1640

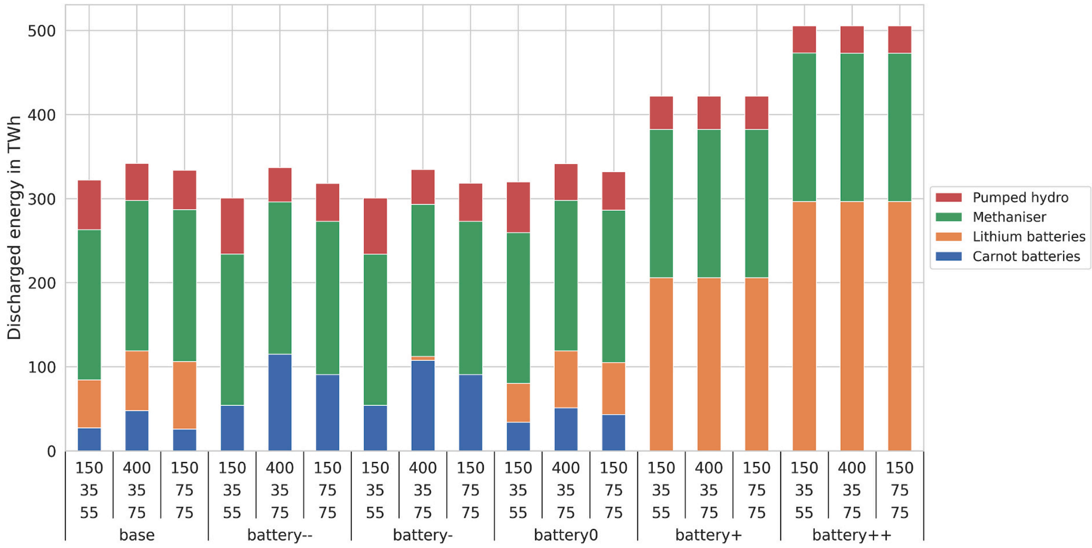

Fig. 10. Discharged energy across Europe (battery scenarios).

Varying the costs for lithium-ion batteries results in the expected effects, see Fig. 10. Thus, with higher battery costs in all three cases examined, there is almost complete substitution of lithium-ion batteries by Carnot batteries. The total capacity of the battery storage systems remains approximately constant. The effects are uniform for the three sets of assumptions analyzed for Carnot batteries. Assuming lower costs for lithium-ion storage systems, on the other hand, Carnot batteries are completely pushed out of the system and the total capacity of the storage systems is doubled or tripled. As no Carnot batteries are used anymore, the difference between the three model runs disappears.

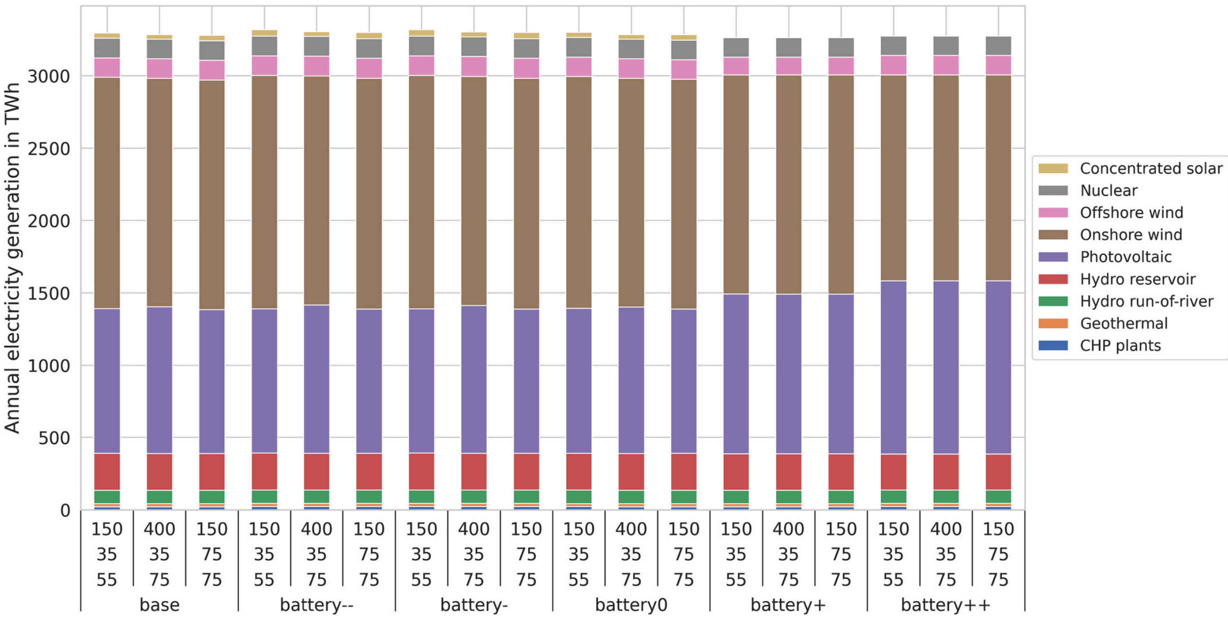

Fig. 11. Annual electricity generation across Europe (battery scenarios).

The variation in battery costs has only a minor impact on the power generation structure (Fig. 11). These are most evident in the case of lower battery costs, which lead to CSP and partly also onshore wind being replaced by PV. Higher battery costs, on the other hand, lead to a slight increase in total electricity production, as the use of Carnot batteries is associated with higher losses.

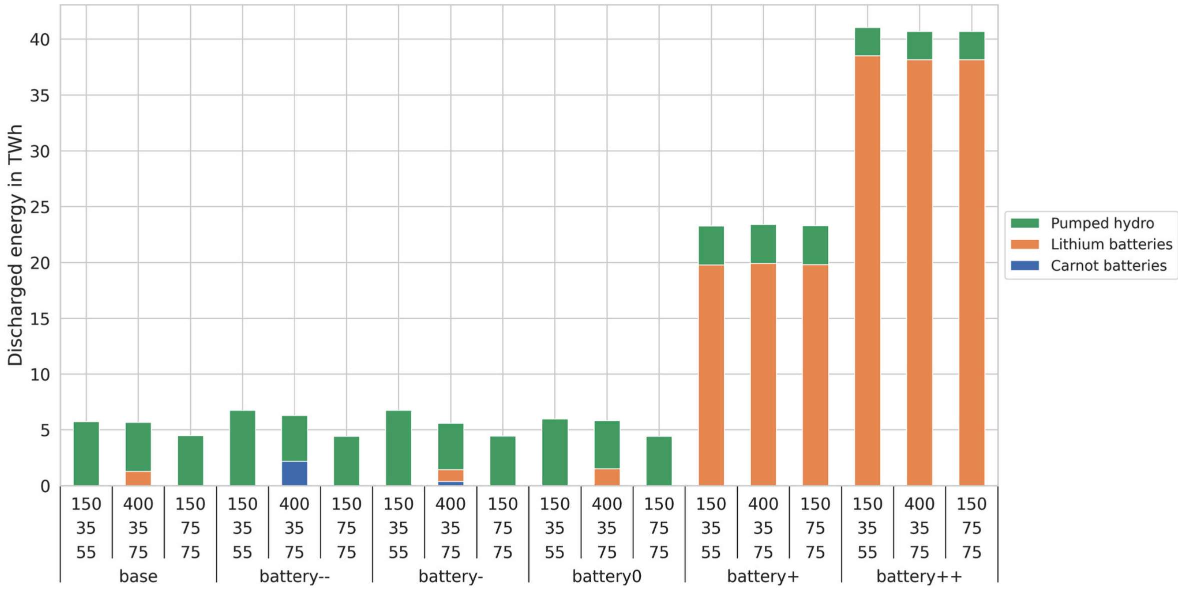

Fig. 12. Discharged energy across Germany (battery scenarios, without methanizer).

The described effect of the cost variations on the entire study area is essentially also confirmed for Germany. However, the importance of electricity storage is lower there due to the greater availability of other flexibility. This means that an increase in lithium-ion battery costs only has a very insignificant effect on the use of electricity storage (Fig. 12), although in case of a significant cost increase (battery–), lithium-ion batteries are replaced by Carnot batteries. A reduction in the cost of lithium-ion batteries, on the other hand, would mean that they would find a place in the German system and significantly increase the importance of electricity storage.

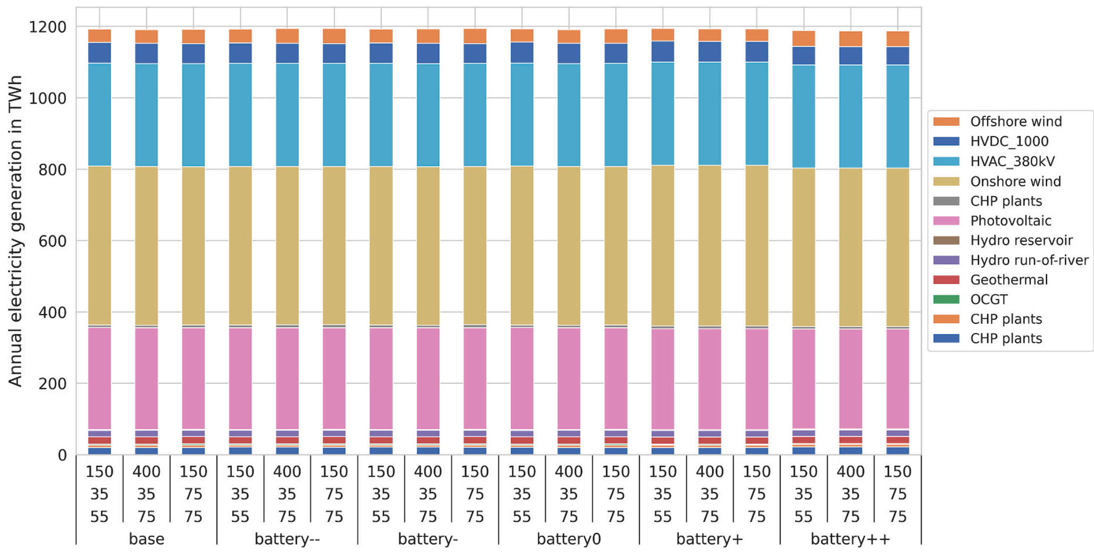

Fig. 13. Annual electricity generation in Germany (battery scenarios).

The analysis of electricity generation in Germany shows that the variation in lithium-ion battery storage costs only changes this very slightly (Fig. 13). The most relevant aspect is the slight decrease in total generation due to the reduction in renewable energy curtailment and storage losses in case of significantly cheaper chemical batteries (battery++).

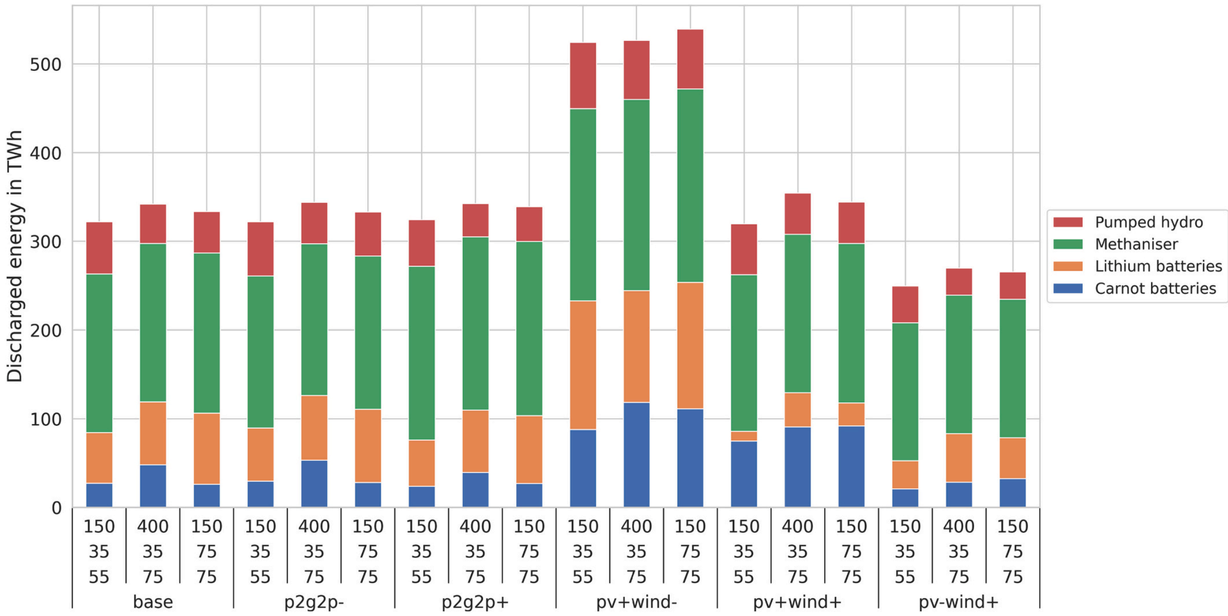

Fig. 14. Discharged energy across Europe (VRE scenarios).

The considered variations in the cost assumptions for the production and reconversion of synthetic methane only have a very weak effect on the results (Fig. 14). As the methanization plants are essentially used to cover gas demand in industry, cost changes have hardly any influence. This also applies to the other storage technologies analyzed. A different picture emerges when varying the costs of VRE technologies. Reduced PV costs significantly increase the contribution of this technology to electricity generation and push offshore wind in particular out of the system (Fig. 15). This results in a significantly higher storage requirement, which is covered disproportionately by Carnot batteries. Discharge from lithium-ion batteries also doubles. If both wind and PV costs are assumed to be lower, this has a particular impact on wind power generation, where offshore wind is replaced by onshore wind. This also results in a change in storage requirements. Although this hardly increases for the sum of lithium-ion and Carnot batteries, the latter can significantly increase their share. If a cost reduction is only assumed for wind, this again makes onshore wind generation in particular more attractive. This displaces offshore wind and PV in equal measure and also reduces the need for storage. However, lithium-ion batteries are also more affected here than Carnot batteries.

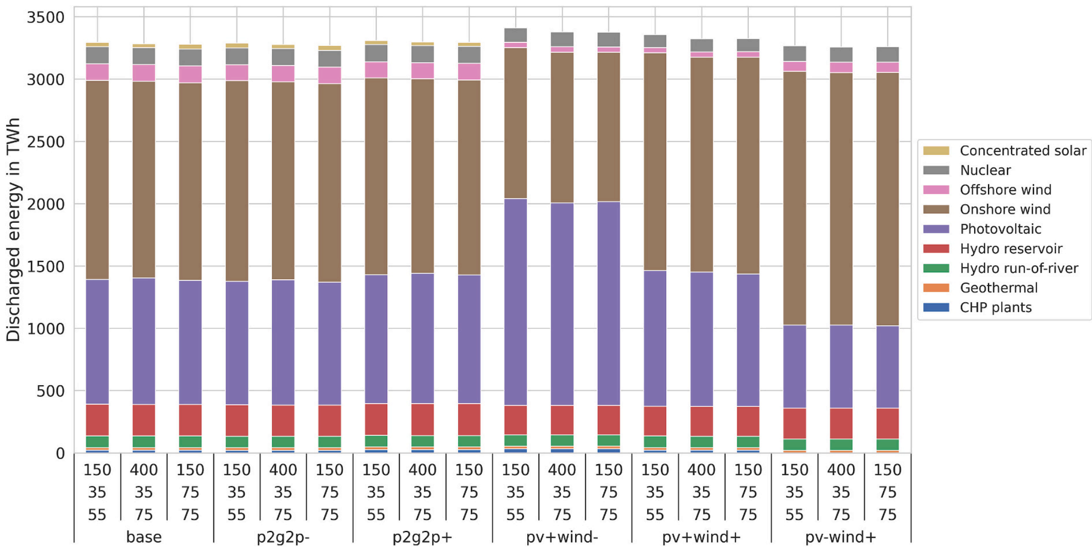

Fig. 15. Annual electricity generation across Europe (VRE scenarios).

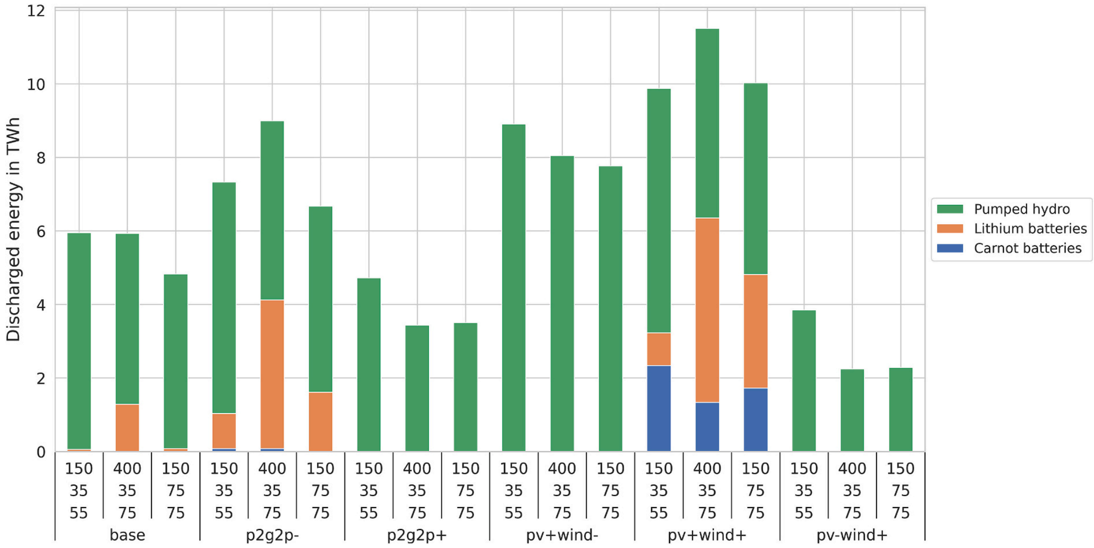

Fig. 16. Discharged energy across Germany (VRE scenarios, without methanizer).

A focused look at Germany reveals some further effects (Fig. 16). For example, the very low contribution of lithium-ion batteries in the *Base* case is significantly increased by higher costs for gas generation and reconversion, and Carnot batteries also enter the system to a very small extent. In the opposite case of lower costs, however, there is no longer any room for batteries. Lower PV costs significantly increase the use of pumped hydro storage, but battery storage is no longer part of the system. In the case of reduced wind power costs, batteries are again not part of the optimal solution, and the use of pumped storage is also reduced. At first glance, the result for the case of reduced costs for wind and photovoltaics is surprising. This leads to an even greater increase in the use of electricity storage than a cost reduction for photovoltaics alone. In addition, not only is the use of lithium-ion batteries increased here, but Carnot batteries are also used. This results from the increased use of photovoltaics and onshore wind, which are supplemented by different storage systems. In contrast, the use of offshore wind and flexible CHP plants is reduced (Fig. 17).

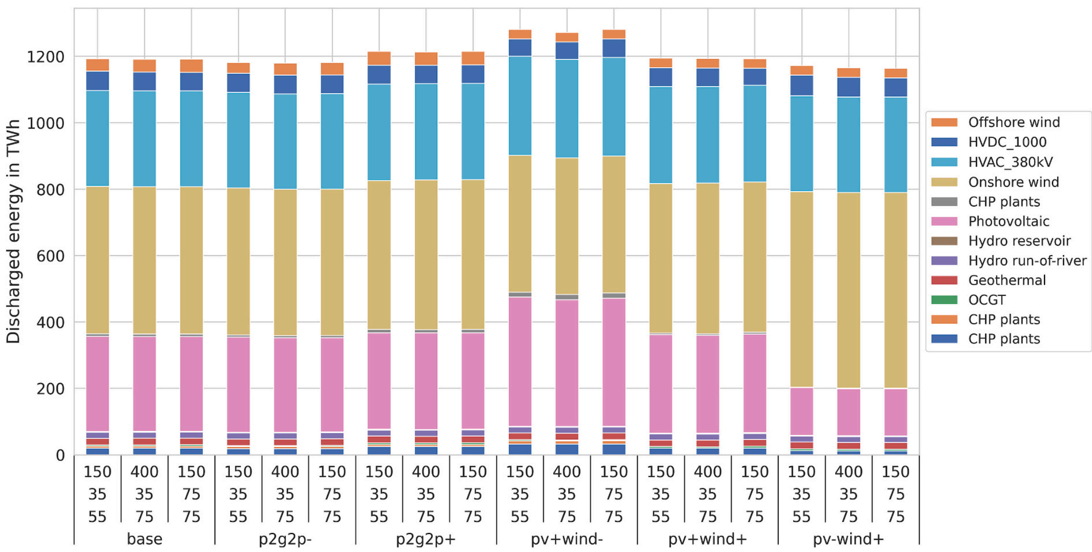

Fig. 17. Annual electricity generation in Germany (VRE scenarios).

Appendix C. Spatial distribution of Carnot batteries in Germany

In the case of Germany, the techno-economic targets for Carnot batteries need to be quite ambitious in order to arrive at relevant capacities. This effect is more prominent due to the sectoral representation with a detailed heating and gas sector. Both sectors allow for flexible demand via heat pumps, electric boilers and electrolysis, which in turn reduce the overall storage demand. In addition, due to the optimistic assumptions in the chosen techno-economic configuration lithium-ion batteries are almost completely pushed out of the system. As a result, in the *Base* case (Fig. 18a) Carnot batteries are only expanded in the Southern regions of Germany while with less flexible demand for electrolysis (Fig. 18b) and prevention of grid expansion (Fig. 18c) the overall demand for storage technologies increases and Carnot batteries are expanded in more model regions.

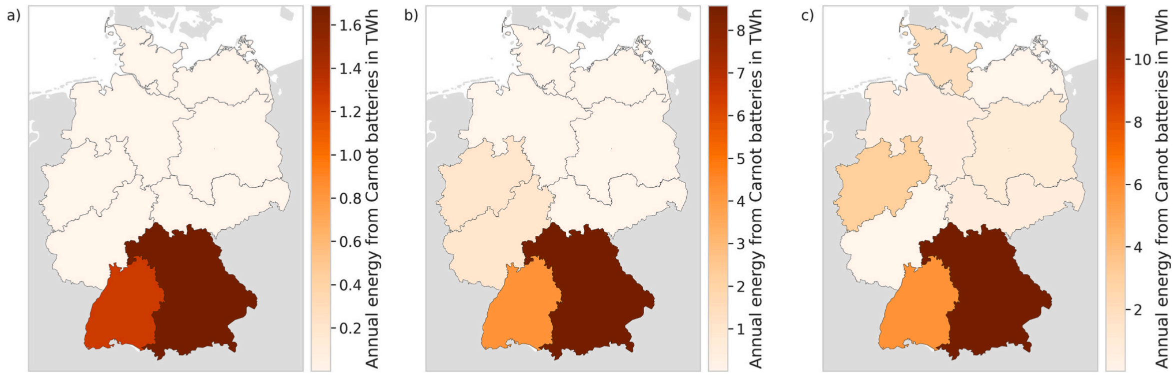

Fig. 18. Spatial distribution of annually provided energy from Carnot batteries for the three scenarios base (a), low flexibility electrolysis (b) and no additional grid expansion (c). Values are derived from the techno-economical configuration of 65 % round-trip efficiency, 20 €/kWh storage specific CAPEX and 150 €/kW power specific CAPEX.

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Glossary

ABM: Agent-based electricity market model
AMIRIS: ABM developed at the German Aerospace Center
CAPEX: Capital expenditure
E2P: Energy-to-power (ratio)
REMix: Framework for optimizing energy system models
VRE: Variable renewable energy

3.3 Paper III: Applying machine learning to electricity price forecasting in simulated energy market scenarios

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Executive Summary: The energy transition leads to several new developments, such as changing power plant portfolios, increasing flexibility demand, and thus novel electricity price dynamics. These effects can be studied using ABM, which simulates the bidding decisions of market participants and helps uncover emergent market phenomena. For accurate bidding decisions, these simulated actors, much like real-world market participants, require precise electricity price forecasts. In this context, techniques for forecasting future electricity prices must be versatile enough to handle diverse market scenarios and technology mixes without the need for scenario-specific retraining. This is a significant difference from traditional forecasting in real-world electricity markets, which typically involves minor changes in the underlying energy system. Despite the long history of market forecasting, it remains unclear which methods are best suited to predict electricity prices in simulations with varying scenarios and technology combinations. To address this gap, I assess the applicability of different forecasting methods for price time series generated by simulations of future electricity markets. Specifically, I evaluate the accuracy of two modern ML architectures, N-BEATS and Temporal Fusion Transformers, in scenarios with substantial increases in RE and FO capacity. As anticipated, ML techniques outperform naive benchmarks, particularly when future covariates, such as residual load, are incorporated. In these cases, the MAE consistently stays below 1.40 EUR/MWh, enabling precise dispatch optimisation of FOs. Beyond this forecasting accuracy, Temporal Fusion Transformers can handle disparate input data configurations making them highly adaptable to data availability constraints. The findings suggest that ML can reliably forecast electricity prices in future energy scenarios, even with significant changes in RE and flexibility capacity. Importantly, retraining may not be strictly necessary in various scenarios, making these methods particularly valuable for energy transition simulations.

Author Contributions: I am the lead author of this paper. The conceptual work of the paper was mainly done by me, with suggestions from the two co-authors Christoph Schimeczek and Valentin Bertsch. The coding and software work, from the implementation of the ML training package FOCAPY to the scenario generator AMIRIS-SCENGEN, was done by me. Christoph Schimeczek helped with guidance on these two tasks. Model execution, multi-scenario evaluation, numerical analysis and validation were done by me. All visualisations of the results were done by me and improved after discussion with the two co-authors. Acquisition of funding was carried out by Christoph Schimeczek and myself. I was responsible for writing the original draft, while both co-authors reviewed and edited the original draft.

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Research paper

Applying machine learning to electricity price forecasting in simulated energy market scenarios

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ABSTRACT

Policy packages, such as the "European Green Deal", call for a substantial restructuring of the power plant park. This, in combination with more flexible demand, will result in novel electricity price dynamics. These can be studied using, e.g., agent-based models which simulate bidding decisions of market actors, thereby uncovering emergent market phenomena. For their bidding decisions, simulated actors – just like real-world actors – require accurate market price forecasts. Techniques to obtain such forecasts need to be applicable to vastly different future electricity market scenarios, ideally without the need of scenario-specific retraining. This is a major difference compared to real-world electricity market forecasting, which is based on minimal variations in the underlying energy system. Despite the long track record in this field, it is not sufficiently clear which methods are suitable for forecasting simulated future electricity markets in greatly varying scenarios and technology mixes. To address this gap, we assess the applicability of different forecasting techniques to price time series generated by simulations of the future electricity market. We then evaluate the forecast accuracy of two recent machine learning architectures, namely N-BEATS and Temporal Fusion Transformers, based on parameter combinations with significant expansions of renewable energy and flexibility option capacity. As expected, the results demonstrate that machine learning exhibits superior accuracy compared to naïve benchmarks. Particularly, when future covariates, such as residual load, are employed, the mean absolute error consistently remains below 1.40 EUR/MWh. This may be attributed to reduced inner complexity of simulated electricity prices compared to real-world market dynamics. Our findings demonstrate that machine learning can provide reliable forecasts of future electricity prices and that retraining may not be necessary even with widely varying shares of renewable energy and flexibility capacity. These forecasting methods could therefore be effectively employed in electricity market simulations in the context of the energy transition.

1. Introduction

In order to make well-informed decisions and to develop effective legislation, investors and policy makers require a comprehensive understanding of the electricity market, including its future developments. This is particularly important in the context of significant changes being introduced by the ongoing energy transition. New legislation, exemplified by the "European Green Deal" (European Commission, 2021), defines a transformation of the energy system that will diverge from the status quo in a number of significant ways. These changes include a transition towards high shares of variable renewable energy (RE) sources and a substantial increase in flexibility options such as battery storages and demand-side flexibility technologies. These developments are already influencing the current market environment and will also have an increasing impact on future electricity markets, resulting in novel price dynamics (Haugen et al., 2024).

Scenarios of the energy transition can be simulated by applying, e.g., agent-based modeling (ABM), which is a promising approach in this field of study (Pfenninger et al., 2014). ABM enables researchers to identify and analyze the market dynamics that result from the decisions of individual market actors. In order to formulate these decisions and optimize their operational schedules, agents require forecasts of

Abbreviations: ABM, Agent-based modeling; LSTM, Long short-term memory model; MAE, Mean absolute error; MAPE, Mean absolute percentage error; ML, Machine learning; NN, Neural network; PV, Photovoltaics; RE, Renewable energy; RMSE, Root mean squared error; TFT, Temporal fusion transformers.

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electricity prices. This problem falls within the domain of time series forecasting, a well-established area of research with a rich history. A considerable body of research and the increasing computational power have led to the development of a wide range of approaches, from simple techniques to highly sophisticated machine learning (ML) methods (Petropoulos et al., 2022). However, existing studies have largely focused on past and present energy systems, and there is a clear need for research that explicitly integrates the significant changes associated with the energy transition.

What is therefore required is a robust and comprehensive approach to forecasting electricity prices that can be applied across diverse energy transition scenarios. This solution must ensure accuracy and consistency, while maintaining a reasonable level of preparation and execution time. For this purpose, we investigate and combine two areas of research, electricity market simulation and time series forecasting, with a particular focus on ML. This integration is intended to facilitate the generation of robust results even in scenarios characterized by a significant increase in RE sources and novel price dynamics.

1.1. Related works

A comprehensive review on electricity price forecasting was carried out in Weron (2014) describing the special nature of electricity as a commodity. Especially in the recent past, an extensive number of reviews has been published (Jiang and Hu, 2018; Jedrzejewski et al., 2022; Tschora et al., 2022; Heidarpanah et al., 2023; Xiong and Qing, 2023; Jiang et al., 2023; Lehna et al., 2022). Probabilistic electricity price forecasting is extensively reviewed in Nowotarski and Weron (2018). The recent work of Beltrán et al. (2022) proposes a framework for day-ahead electricity price forecasts using statistical methods and neural networks (NN) enforcing the human-machine collaboration. In Beran et al. (2021), hybrid models, specifically combined fundamental and econometric models, are found to be best suitable for day-ahead to week-ahead electricity prices, the relevant range for most operational decisions and strategy optimization. Transfer learning is tested in Gunduz et al. (2023) demonstrating an improved performance compared to a single-market procedure. Besides standard statistical methods (e.g., autoregressive moving-average models), NN and especially deep learning are gaining more popularity due to higher availability of computational power (Akhtar et al., 2023).

As the shares of RE in the electricity mix increases, the electricity price is increasingly influenced by fluctuations in solar irradiation and wind speed (Alkhayat and Mehmood, 2021; Meng et al., 2022). This highlights the need for adaptations in forecasting approaches to account for these variables (Nyangon and Akintunde, 2024). Expected load and RE generation are highly relevant for accurate electricity price forecasts (Billé et al., 2023; Bai, 2024; Da Silva and Meneses, 2023; Alhendi et al., 2023; Bashir et al., 2022). Regarding solar irradiation time series, the application of neural networks is prominent by applying long short-term memory (LSTM) networks (Cheng et al., 2021), hybrid deep NN combing multivariate inputs (Huang et al., 2021). Further, the solar power generation potential is also of high interest to market participants and modelers (Ledmaoui et al., 2023). For this, also LSTM networks are applied to forecast the expected generation by integrating domain knowledge explicitly for photovoltaics (PV) (Qu et al., 2021). Forecasting approaches are developed to be used even when no sufficient meteorological data is available by using data from other surrounding PV stations (Zhen et al., 2021). Looking at the area of wind forecasts, we also find a wide range of approaches (Arslan Tuncar et al., 2024), such as combining statistical methods with NN (Camelo et al., 2018) or temporal-based transformer (Mo et al., 2024). Nazir et al. (2020) give an extensive overview of different wind forecasting methods with increasingly popular NN integrations. Sewdien et al. (2020) identified critical parameters in NN for wind generation forecasting concluding that longer forecast periods require larger and more layers in the NN. Focusing on the trading aspect of wind generation, Fan et al. (2009) apply a two-stage NN, whereas Cruz et al. (2011) confirm an influence of wind generation forecasts on price forecasts when analyzing the situation in Spain. Fraunholz et al. (2021) combine forecasts based on ML within an ABM demonstrating that the NN approach outperforms linear regression and naïve benchmarks in a European case study from 2020 to 2050. In Shimomura et al. (2024), explainable artificial intelligence is employed to evaluate the impact of RE sources on electricity prices in Japan. In Castilho Braz et al. (2024), the Brazilian electricity markets are the subject of a detailed analysis, with forecasts of price trends for both the day-ahead and Intraday markets. Walter and Wagner (2024) present a generative time series simulation for day-ahead electricity prices on an empirical study on the EPEX spot market in Europe in the years 2020–2023. In order to forecast electricity prices in the Hungarian market, an extensive data set comprising more than 40 years of meteorological data has been applied in Mayer et al. (2023).

The majority of these studies share a common characteristic: they present extensive training, testing, and validation of their models on rich historical data, but with little variation in the underlying electricity system. This represents a significant limitation in the analysis of energy transition scenarios, given that electricity price dynamics will be fundamentally different in future electricity markets with high shares of variable RE.

1.2. Novelty

In order to address the shortcomings of existing research, which is closely associated with past and current energy system dynamics, we propose a novel assessment of various forecasting techniques. The approach is based on the combination of advanced ML with an ABM capable of generating electricity price training data sets for a range of potential future electricity systems. This setup allows us to investigate novel electricity price dynamics. Notably, RE technologies are progressively replacing conventional power plants, with fuel-based technologies projected to be gradually phased out in the coming years. The rising prevalence of RE is expected to have considerable influence on electricity prices, given that RE are characterized by almost negligible marginal costs and that conventional power plants are losing their role in price formation. Moreover, the expanded integration of flexibility options, such as battery storage, will significantly impact the energy system. Consequently, we employ the state-of-the art ABM electricity market simulation AMIRIS (Schimeczek et al., 2023a). Specifically, AMIRIS is parameterized to simulate a range of potential future electricity market scenarios which are then transformed into extensive training and testing data sets. While we acknowledge that simulated data cannot fully replicate all nuances present in measured data, it is recognized that it offers a valuable and innovative additional perspective. For example, Frey et al. (2020) have already identified the emergence of new price dynamics resulting from transformative shifts observed in such electricity market simulations. The objective of our research is, therefore, to gain a more comprehensive understanding of the accuracy and performance of varying electricity price forecasting methods in evolving renewable-based electricity markets.

1.3. Paper structure

The paper is structured as follows. In Section 2, we present an overview of agent-based energy market simulation and describe the open electricity market model AMIRIS in. In Section 3, we provide background information on electricity markets. Subsequently, five forecasting methods are described, ranging from naïve benchmarks to advanced ML methods. The necessary training and testing data is generated by AMIRIS. In Section 4, we assess the implemented approaches in terms of their quantitative forecasting accuracy. In Section 5, we discuss the practical applications and constraints of the aforementioned methods, with particular consideration given to the perspective of electricity market simulation models. Finally, in Section

6, we give a summary of the findings and outline remaining open questions.

2. Material and methods

In this Section, we argue why ABM is a powerful method to investigate future electricity markets. Subsequently, we present the ABM AMIRIS, which is applied in this study, and we provide an overview of the model design and architecture. Finally, we argue the suitability of AMIRIS for generating training and testing data for the ML networks.

2.1. Agent-based energy market simulations

The liberalization and the growing complexity of energy markets over the last decades brought new challenges to energy systems modelers (Pfenninger et al., 2014). The growing field of ABM can help researchers to find answers to pressing questions of today's and tomorrow's complex energy systems (Klein et al., 2019). Especially when simulating electricity markets, ABM have proven to be a well suitable method (Farmer et al., 2015; Ringler et al., 2016; Deissenroth-Uhrig et al., 2017; Barazza and Strachan, 2020). Firstly, by incorporating the perspective of individual actors, researchers gain insight into possible emergent effects stemming from individual agents' actions causing macro-level phenomena (Frey et al., 2020). Secondly, employing heterogenous agents in an ABM simulation allows for the representation of diverse actor characteristics, including their objectives, risk profiles, information levels, and interactions with their environment (Kraan et al., 2018). Thirdly, the practical applicability of ABM in addressing real-world energy transition challenges, while maintaining computational feasibility, stands as a significant advantage over game theoretical approaches, which may become intractable when parameterized for tackling substantial real-world problems (Hansen et al., 2019). It is highly important to accurately represent agents and their environment in an ABM. Besides detailed actors' studies (Reeg, 2019), the agent's interactions have to be modelled with a high level of detail. The central element of these economic models is the simulated day-ahead electricity market where a market clearing is carried out periodically. In order to participate in the market, an agent has to submit its bids and asks to the market. To this end, the agent is equipped with decision making mechanisms that account for different qualities of strategic decisions (Guerci et al., 2010; Li, 2012). Since agents typically act on expected prices, accurate electricity price forecasts are critical for the simulation and performance of such agents.

In the realm of energy systems analysis, models must acknowledge the complex interplay of social, technological, economic and environmental dimensions (Bale et al., 2015). ABM are well-suited in examining the interactions and behaviors of diverse actors, accounting for market imperfections (Weidlich and Veit, 2008; Ragwitz et al., 2007). Notably, there are several (open) ABM, such as AMIRIS (Schimeczek et al., 2023a), ASSUME (Harder et al., 2023), BSAM (Kontochristopoulos et al., 2021), EMLab-Generation (Chappin et al., 2017), MASCEM (Vale et al., 2011), and PowerACE (Sensfuß, 2008).

2.2. Electricity market modelling using AMIRIS

We deploy the open ABM AMIRIS which is the "Agent-based Market model for the Investigation of Renewable and Integrated energy Systems" (Schimeczek et al., 2023a). AMIRIS has been developed since 2008 and was published open source[1] in late 2021 (Nienhaus et al., 2021). It is a powerful simulation tool based on the framework FAME (Schimeczek et al., 2023b; Nitsch et al., 2023a) and it is used for the analysis of energy policy instruments and market integration of RE and flexibility options. The heart of the model is the simulation of the day-ahead electricity market revealing market dynamics and agent interactions (Nitsch et al., 2021a) while considering different policy frameworks (Frey et al., 2020). In Klein et al. (2019), a detailed comparison of AMIRIS with two other ABM contrasting a state-of-the art optimization model is carried out. AMIRIS has been back-tested for the day-ahead electricity markets of Germany (Maurer et al., 2024) and Austria (Nitsch et al., 2021b) which resulted in a good fit of simulated and historical electricity prices. Fig. 6 in the Appendix provides an overview of the agents represented in AMIRIS (i.e. power plant operators, traders, flexibility marketers, markets, and regulators) and their interactions via information, energy, and money flows. Users have to define and provide the input data, keeping feature selection and the identification of relevant time series in mind (Müller, 2021). In the context of AMIRIS this translates to power plant park structure, RE generation time series, demand data, and operational cost data. Flexibility options apply one of two distinct strategies when participating in the day-ahead electricity market: maximizing their own profits or minimizing system dispatch costs (Nitsch et al., 2024). These strategies represent a business-centered optimum or a system-friendly approach to dispatch the storage. Further revenue streams for flexibility options, such as Intraday markets, are currently under development.

In our analysis, we will use data derived from AMIRIS to test different forecasting approaches. This offers many key advantages: i) we generate training and testing data matching our needs to feed the NN, ii) we are in full control over the level of complexity in each scenario by defining agents and their properties individually, iii) we are able to assess the impact of changing power systems on price dynamics and test the suitability of different forecasting methods, iv) we demonstrate the use-case of applying different ML architectures in an electricity market simulation model, and v) we extract the key learnings of integrating the presented ML approaches in order to provide benefits for other electricity market simulation model in the field. The detailed procedure of the scenario definition is described in Section 3.2.

3. Theory and calculation

We present the theory behind wholesale electricity markets in Section 3.1. This includes a brief summary of changing price dynamics introduced by growing RE shares and impacts by large flexibility option capacity which will likely be installed in the (near) future. Based on the theory, Section 3.2 outlines our scenario definitions while Section 3.3 describes the models tested to forecast electricity prices.

3.1. Fundamental aspects of electricity markets

Wholesale electricity prices are the market result of matching supply of producers (i.e. power plant operators) and demand of consumers in a dedicated market zone. Besides trading at the power exchange, consumers and producers can also agree on individual over-the-counter trades. Although, these trades are usually non-transparent and bilateral, we assume them to be mostly aligned with wholesale prices, since larger price spreads would resemble arbitrage opportunities. Beyond that, there are also dedicated markets which are designed for ancillary services, e.g., frequency restoration reserves, usually with pay-as-bid schemes (Aussel et al., 2017). In reality, these markets do have implications on the wholesale markets since they impact the available capacity, however, they are currently not in the focus of the AMIRIS simulation. Consequently, similar to futures and forwards markets, they are not included in our day-ahead electricity price forecasting process but may be considered in extensions to our work. The main instrument to determine electricity prices is the day-ahead spot market where a market clearing is carried out (Martin et al., 2014). Bids and asks are sorted resulting in a merit-order. In Central Europe, a uniform pricing mechanism is established in the day-ahead electricity markets (Zakeri et al., 2023). Our model is therefore also based on this form of pricing. For the clearing, a congestion-free nature of the market and

[1] https://gitlab.com/dlr-ve/esy/amiris (accessed on 30 October 2024)

decentralized dispatch are assumed.

In accordance with economic theory, market participants define their bids according to their marginal cost. This mainly includes operational costs, fuel costs, and emission certificate costs. In reality, non-convex costs (Makkonen and Lahdelma, 2006) can lead to uplifts, i.e. markups to marginal costs accounting for ramp-up costs (Liberopoulos and Andrianesis, 2016), and downlifts, i.e. markdowns accounting for ramp-down costs (Pape et al., 2016). AMIRIS can also consider such markups or markdowns.

3.2. Energy transition scenarios

We define two main sets of scenarios. Firstly, we vary the storage capacity within four distinct electricity market configurations, reflecting different degrees of market influence by these flexibility options. Secondly, we examine the expansion of RE in terms of PV and wind onshore installations. This approach is designed to yield insights into forecasting accuracy in scenarios with different combinations of RE shares. It is essential to note that both sets of scenarios should be viewed as parameter variations rather than being interpreted as definitive, sophisticated scenarios, roadmaps, or guidelines for shaping future electricity markets.

Regarding the variation of flexibility option capacity, such as battery storage systems (Divya and Østergaard, 2009), we define four distinct scenarios in Table 1. "*No Flex*" describes an artificial electricity system where the power plant park solely consists of controllable conventional power plants and fluctuating renewable power plants. Due to the idealized way of modelling renewable power generation by applying exogenously defined time series, we expect a highly correlated situation between residual load (i.e. load which has to be met by dispatchable and typically conventional power plants) and the day-ahead electricity price. This is also the reason why we do not consider a conventional-only scenario.

When we introduce flexibility options, see "*Little Flex*", we expect to observe a more complex pattern due to the impacts of flexibility options. Initially, we will keep their share relatively small and increase it in "*Mid Flex*" up to "*High Flex*" so that we can evaluate the capabilities of the forecasting algorithms. Simple forecasting methods most likely will not perform well in the latter two settings, because the operational decisions by flexibility options decouple the idealistic residual load and price relationship. The remainder of the system consists of a load agent fulfilling its electricity demand, a day-ahead electricity market agent performing an hourly market-clearing, as well as supply traders offering their generation capacity at their marginal costs. The installed power plant capacity is approximately aligned with the German market in 2019 (Nienhaus et al., 2023) whereas load and RE generation potential are derived from 2018 and 2019 (SMARD, 2020). In all four scenarios, the RE capacity is identical and based on historical values. This implies that potential future scenarios with higher RE shares and potentially different price dynamics are currently not considered.

While the scenarios presented so far only consider different shares of flexibility options, we also compile scenarios of RE expansion which provide additional insights of forecasting performance. For this purpose, the AMIRIS scenario generator *scengen* (Nitsch et al., 2023b) was used to generate more than 100 scenarios which are processed to training and testing data sets. In each scenario, PV and wind onshore capacity is randomly chosen within a predefined range. All other parameters roughly correspond to the German electricity system in 2019 (Nienhaus et al., 2023). All input data undergoes a thorough check for outliers and is subsequently normalized to facilitate the ML process.

Table 1
Overview of scenarios distinguished by different flexibility option capacity.

Scenario / Parameter	*No Flex*	*Little Flex*	*Mid Flex*	*High Flex*
Electricity demand	527 TWh/a			
Conventional capacity	77 GW			
Renewable capacity	120 GW			
Flexibility options	0 GW	4 GW	20 GW	80 GW

3.3. Investigated forecasting methods

In total, we compare five forecasting methods with varying levels of complexity, two comprehensive ML architectures and three benchmarking methods. N-BEATS (Oreshkin et al., 2019) is a NN for time series forecasting by applying deep learning. It is well tested on data sets used in forecasting competitions and is said to be applicable on a wide range of domains. Temporal fusion transformers (TFT) (Lim et al., 2021) allow to integrate past and also future covariates in their training. This is a significant advantage over many other methods promising better forecasting performance. Seasonal and trend characteristics can be embedded by temporal features within the input data and the model's ability to encode such information directly. In our application, integrating covariates into the training process is expected to enhance forecasting performance, see also Fig. 1. Past and future covariates describe time series that are available for the past and future, respectively. Examples of such time series include time and calendar information. Additionally, historical covariates, which are only available for past time steps, may be included in the model. These could include, for example, actual renewable energy generation. A detailed preliminary study on feature selection was carried out in Nitsch and Schimeczek (2023). The impact of varying train-test splits, ranging from 75 % to 25 % and 25–75 %, was evaluated.

In order to quantify the accuracy, a set of commonly used day-ahead electricity price forecasting methods is employed as a benchmark (Hyndman and Athanasopoulos, 2018). Namely, we apply the naïve benchmark

$$\hat{p}_{T+h|T} = p_T \tag{1}$$

where the forecasted day-ahead electricity price $\hat{p}$ at the time $T+h$ is set equal to the day-ahead electricity price p at time T (Hyndman and Athanasopoulos, 2018). A slight modification involves setting

$$\hat{p}_{T+h|T} = p_{T+h-24} \tag{2}$$

where the forecasted day-ahead electricity price is derived from the day-ahead electricity price p at time $T+h-24$, taking into consideration the daily price patterns (Hyndman and Athanasopoulos, 2018). Additionally, we deploy an Exponential Smoothing (Winters, 1960; Holt, 2004) as

$$\hat{p}_{T+h|T} = \alpha p_T + \quad \alpha(1-\alpha)p_{T-1} + \quad \alpha(1-\alpha)^2 p_{T-2} + \dots \tag{3}$$

with the smoothing operator α, a parameter with values in the range $[0, 1]$, which is a simple yet well-proven time series forecasting method applying exponentially decreasing weights over time.

Hyper-parameters were optimized using the state-of-the-art framework Optuna (Akiba et al., 2019). The model code and documentation can be found in the open repository *focapy* (Nitsch, 2023). For error metrics, we calculated mean absolute errors (MAE) as

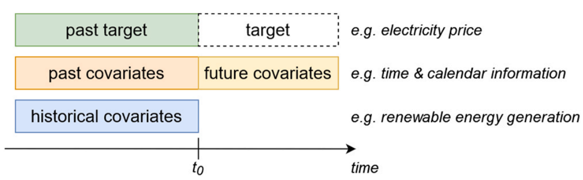

Fig. 1. Past and future covariates as time series inputs to TFT.

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|a_t - \hat{p}_t| \quad (4)$$

where a and $\hat{p}$ represent the actual and forecasted prices, respectively, with a total length of T. We chose an absolute error metric, such as MAE, given the potential for target values (electricity prices) to be (close to) zero or even negative, making the use of mean absolute percentage errors (MAPE) problematic. Additionally, we calculated root-mean-squared errors (RMSE) as

$$RMSE = \sqrt{\{\frac{1}{T}\sum_{t=1}^{T}(a_t - \hat{p}_t)^2\}} \quad (5)$$

4. Results

We begin by examining the results of the AMIRIS scenarios with different shares of flexibility options followed by the results of forecasting accuracy in scenarios of RE expansion.

4.1. Different shares of flexibility options

Prior to presenting the results of the forecasting methods in Section 4.1.2, we analyze the simulation runs of the four scenarios. These results offer valuable background information that aids in interpreting the forecasting accuracy.

4.1.1. Impact on market dynamics

Fig. 2 shows day-ahead electricity prices as simulated by AMIRIS over a 168-hour period, with each line representing one of the four scenarios (essentially varying the amount of flexibility options available). Increasing storage capacity generally has a dampening effect on electricity prices. In particular, price peaks can be flattened by discharging storage, while valleys can be raised by charging storage. It is important to note that the storage operator aims to maximize its profits, while taking into account its impact on electricity prices when optimizing its bidding schedule. As a result, there are certain time periods when all four curves are aligned, indicating that during these hours the storage operator either has no significant impact on the resulting electricity prices, or is simply inactive.

The statistics in Table 2 provide an understanding of the variability of electricity prices under different assumptions of storage installations, highlighting the impact of flexibility on pricing dynamics. In "*No Flex*", there is a relatively wide dispersion of prices, as indicated by the standard deviation of 15.27 EUR/MWh. The minimum price[2] is −63.51 EUR/MWh, while the maximum is 116.83 EUR/MW. Moving to "*Little Flex*", the mean price increases slightly to 38.49 EUR/MWh, accompanied by a lower standard deviation of 13.75 EUR/MWh, indicating a narrower spread of prices compared to "*No Flex*". In "*Mid Flex*", the mean price rises further to 38.80 EUR/MWh, with a continued decrease in the standard deviation to 12.07 EUR/MWh, suggesting the previously described price dampening effect. Finally, in "*High Flex*", the mean price reaches 38.96 EUR/MWh, accompanied by the lowest standard deviation of 11.17 EUR/MWh among all scenarios. The results from the year 2018 demonstrate similar overall trends as found for the year 2019. However, differences arise in the weighted mean electricity prices amounting to 43.50 EUR/MWh in 2018 and 38.50 EUR/MWh in 2019.

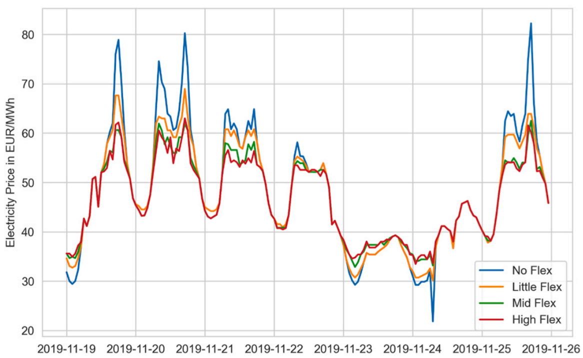

Fig. 2. Price dampening effect of different flexibility capacity in the four scenarios on simulated electricity prices over a one-week period in November 2019.

4.1.2. Electricity price forecasting accuracy

The two ML methods N-BEATS and TFT are trained on 2018 and tested on 2019. For the evaluation of the forecasting accuracy, a full year is chunked in roughly 500 samples, each with 168 hours of past covariate data and 24 hours to forecast. Forecasted values are then tested against actual values from the simulation. Table 3 lists MAE of all forecasting methods in the four scenarios.

The MAE provide insights into the forecasting capabilities of each method within different shares of flexibility options. Notably, the TFT trained with future covariates (expected load and RE generation) shows the lowest MAE values, suggesting its superior accuracy in forecasting electricity prices across a spectrum of scenarios. The benchmark methods are performing worse in every scenario, but are much cheaper to apply, since they do not require to train a model. Further, the presented results clearly demonstrate a consistent trend of improved accuracy across the scenarios of "*No Flex*" to "*High Flex*". We conclude that this effect is likely due to the price flattening effect of increasing market impact of flexibility options, see also Fig. 2.

Fig. 3 displays an exemplary forecast made by the TFT model in "*Mid Flex*". Overall, the forecast aligns well with the actual price dynamics. Nevertheless, there is a slight deviation as the model fails to accurately forecast the first valley underestimating actual values. This can likely be attributed to price dynamics caused by charging actions of flexibility options. Forecasting errors also exhibit a temporal dependency that correlates with the load pattern. Consequently, accuracy tends to be best at night, with errors peaking during the day (Nitsch and Schimeczek, 2023). In the context of the German case study presented, local weather effects, including short-term fluctuations in renewable energy generation, generally have a limited impact on the day-ahead market zone and are therefore not of great influence to this particular forecasting procedure.

4.2. Forecasting accuracy in future energy scenarios

As elaborated in the Introduction in Section 1, the energy transition will bring very different market dynamics compared to historical observations. Besides the expanding flexibility potential, as presented in Section 4.1, we expect considerable impacts by the expansion of RE leading to novel price dynamics of electricity markets. Therefore, we investigate the effects on forecasting accuracy in such scenarios. For this we have created unique training and testing data, as described in Section 3.2. Due to high computational costs of ML training, we have limited this analysis to TFT, the best performing method so far. Fig. 4 shows the results of different train-test splits in two model configurations (without future covariates and with future covariates). All six models are trained and evaluated independently. The left column shows the available training data to the TFT model and their weighted mean average prices

[2] Periods of high inflexible generation and low demand can lead to negative prices in electricity markets.

Table 2
Descriptive statistics on simulated electricity prices in the four scenarios.

Year	2018				2019			
Scenario	*No Flex*	*Little Flex*	*Mid Flex*	*High Flex*	*No Flex*	*Little Flex*	*Mid Flex*	*High Flex*
Metric								
Std. dev.	15.48	13.56	11.95	11.07	15.27	13.75	12.07	11.17
Minimum	−35.21	−22.11	−17.18	0.00	−63.51	−52.49	−37.73	0.00
Maximum	115.96	103.38	95.16	94.78	116.83	102.15	96.33	96.33

Table 3
Mean absolute error (MAE) in EUR/MWh of forecasts in four different scenarios.

Scenario / Metric	*No Flex*	*Little Flex*	*Mid Flex*	*High Flex*
Naïve t_1 (1)	9.29	7.78	6.76	6.45
Naïve t_{24} (2)	8.57	7.54	6.27	5.91
Exponential Smoothing (3)	8.06	6.70	5.73	5.46
N-BEATS (Oreshkin et al., 2019)	7.15	6.24	5.38	5.12
TFT (Lim et al., 2021)	4.11	3.90	3.20	3.26
TFT with future covariates (Lim et al., 2021)	3.12	3.45	3.26	2.86

of the scenario marked with ‘x’. Values in between are interpolated by a cubic method. It is evident that as RE capacity increases, electricity prices tend to decrease – a trend consistently observed across all three rows representing different numbers of scenarios and train-test splits (10 scenarios, 30 scenarios, and 90 scenarios). The middle and right column show the forecasting accuracy evaluated as MAE over all errors of the forecasted electricity prices against the actual electricity prices as calculated by AMIRIS. In the middle column, the TFT relies solely on past covariates, while in the right column, the TFT also incorporates future covariates, such as calendar information, expected load, and RE generation.

Notably, we observe a robust results with MAE values ranging from 2.25 to 3.25 EUR/MWh when at least 30 scenarios are employed as training data (middle and bottom rows). However, when restricting training data to only 10 scenarios (top row), forecasting accuracy deteriorates significantly, with MAE doubling, when assessing scenarios that fall well outside the range of known training data. This strongly suggests that the selection of training data is important for the performance of the model. Moreover, the TFT model equipped with future covariates (right column) consistently outperforms the version relying solely on past covariates (middle). Errors are reduced by approximately an order of magnitude, which holds promise for applications in energy system models, particularly ABM. Moreover, in the bottom row, where the train-test split is 75 % and 25 %, the results are similar compared to the middle row, where the split is reversed at 25 % and 75 %.

Additionally, we can observe that MAE generally exhibits a downward trend as onshore wind capacity increases, except for the segment of high wind power capacity, which lacked sufficient training data, as indicated in the top row of plots in Fig. 4. A similar trend is also evident when considering different error metrics like RMSE.

The histograms in Fig. 5 illustrate the distribution of errors for training with 30 and 90 scenarios. It can be observed that an increased number of training scenarios leads to a superior fit when MAE is employed as the error metric. However, the addition of future covariates – a common practice in such forecasting problems (Ozyegen et al., 2022) – improves the accuracy in our analysis even more than the quantity of available training data. Specifically, with such covariate data, MAE remain consistently below 1.40 EUR/MWh.

5. Discussion

As suggested in Haugen et al. (2024), the formation of electricity prices in energy market models represents a significant factor influencing the analysis of actors’ behaviour, ranging from the operation of flexibility options to investment decisions. The use of simulated and synthetic data as a complement to historical data is an attractive approach, particularly given its current deployment in the context of creating energy generation and load profiles (Mayer et al., 2023). Consequently, the presented methodology in this paper contributes valuable insights to the currently limited field of such day-ahead electricity price forecasting in high RE penetration scenarios. However, given the inherent complexity and non-linearity of energy markets (Castilho Braz et al., 2024), it is essential to consider that our general conclusions should not be interpreted as individual predictions on market results. Rather, they should be regarded as projections contributing towards a better understanding of potential market dynamics in systems with high shares of RE. Despite the presentation of a comprehensive range of potential scenarios, uncertainty remains to scenario definition and model formulation. Future research should investigate

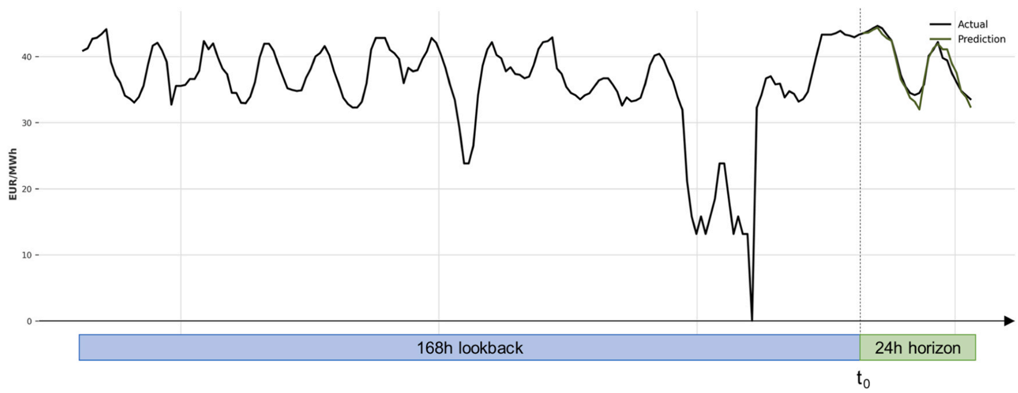

Fig. 3. Exemplary forecasted prices for the next 24 hours (green) by the TFT model in “Mid Flex” with 168 hours of past covariates plotted against actual prices (black).

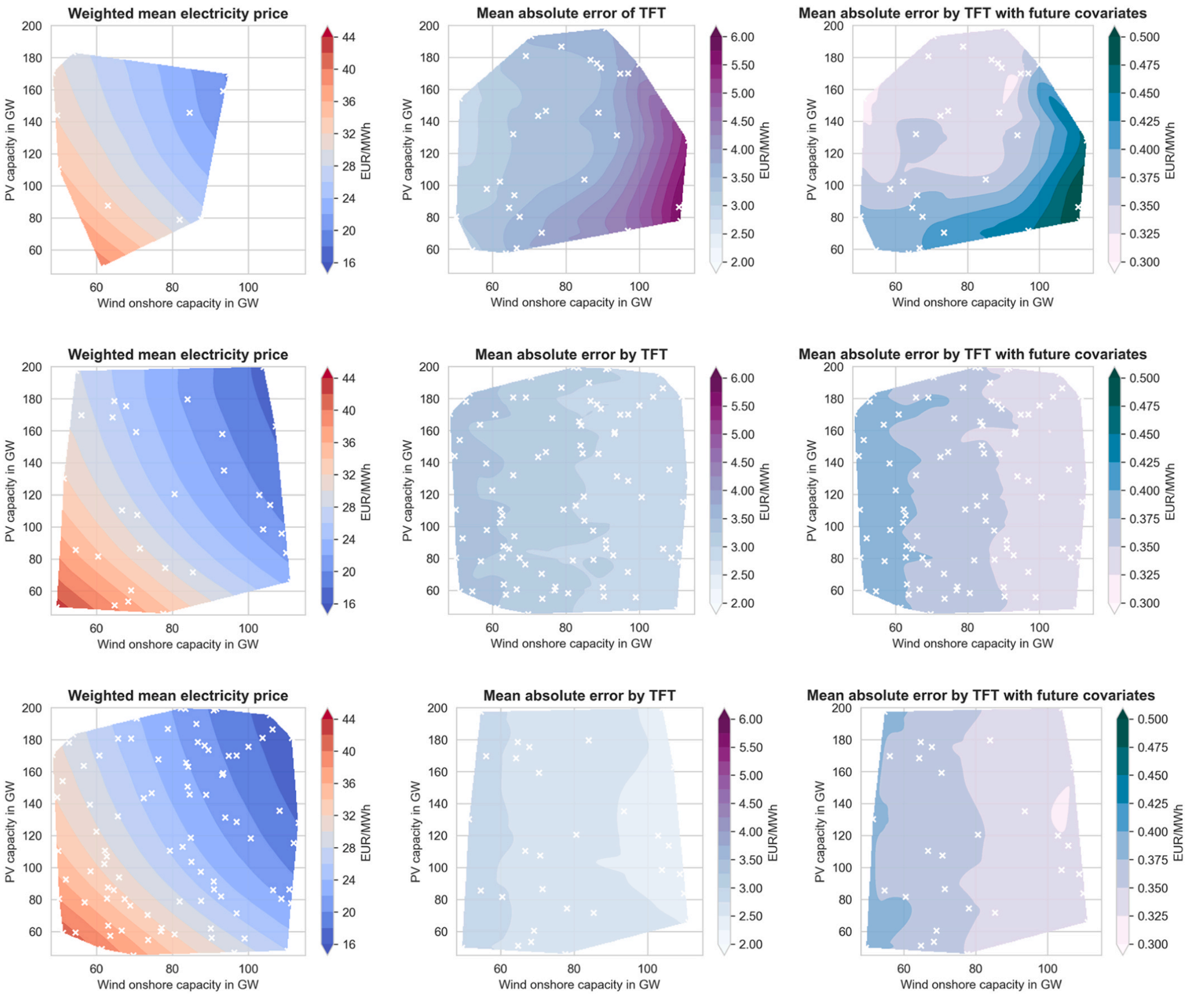

Fig. 4. Simulation of PV and onshore wind expansion scenarios (marked by white 'x' markers) using AMIRIS. Values in between are interpolated using a cubic method. The left column represents the training data, while the other two columns illustrate forecasting accuracy in terms of Mean Absolute Error (MAE) in EUR/MWh. The middle column shows the accuracy based on past covariates alone, whereas the right column includes additional future covariates to the forecasting procedure. Note: Scenarios are considered as parameter variations and shall not be interpreted as definitive and complete future electricity systems, see also Section 3.2.

the influence of changes in market and policy design, unforeseen events with significant impact on energy markets, and the manner in which market actors respond to forecast uncertainty. In addition, we wish to highlight the following limitations.

In the realm of analyzing various flexibility option shares in Section 4.1, it is important to acknowledge a potential limitation related to model training. A possible enhancement lies in the inclusion of a more diverse set of training data to refine the robustness of our models. The analysis of RE expansion in Section 4.2 underscores the considerable impact of the training data selection on results. Future analyses should therefore diligently consider this important aspect. Similarly, within the analysis of RE expansion scenarios in Section 4.2, a notable limitation lies in the missing variability of weather conditions. Periods of low wind and solar generation may substantially impact results, particularly as RE capacity increases. The use of NN with future covariates (as demonstrated in Fig. 4) might mitigate this impact since the network is aware of the short-term residual load. However, without these future covariates, variations in weather years could exert a greater influence on the results. To ensure that our results are easily transferable and understandable, our presented scenarios assume no variation in parameters aside from wind and PV capacity. As already described in Section 3.2, this assumption does not fully capture the real-world dynamics of the energy transition missing the evolution of flexible demand and generation capacity. It is evident that additional markets, which are currently under discussion but not yet implemented, such as capacity or flexibility markets, would influence market dynamics and necessitate further analysis. However, an examination of these points is beyond the scope of the present manuscript.

Beyond these specific limitations, broader considerations should be mentioned. The computational resources and training data allocation significantly affect the time required for training NN. While the initial effort to train models and optimize hyperparameters is substantial, transitioning to the utilization of pre-trained models with optional fine-tuning in production settings could significantly alleviate this workload. When experimenting with a wider array of input features, the explainable feature of TFT could help identify the most influential factors governing forecast accuracy. Additionally, the incorporation of TFT's capability to provide probabilistic forecasts holds the potential to

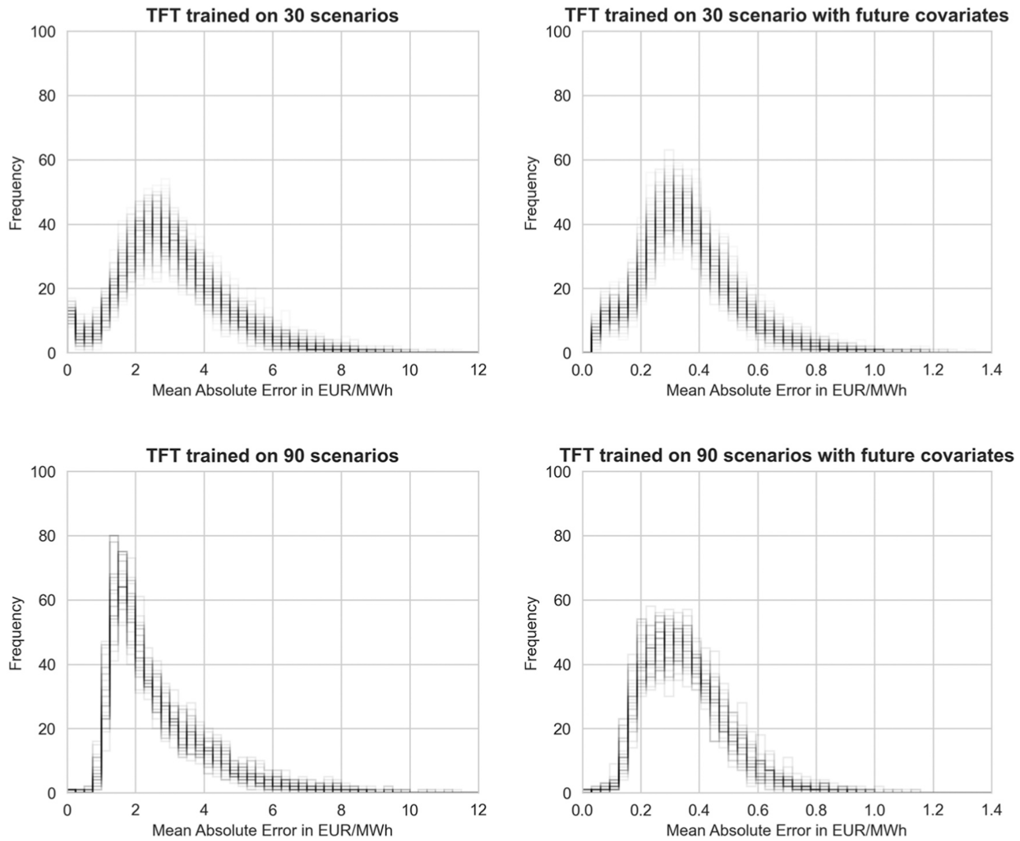

Fig. 5. Distribution of mean absolute error (MAE) in EUR/MWh for different training sets and TFT configurations. Note: Different scaling of x-axis for runs with future covariates.

broaden the applications within energy market simulation models.

In terms of our findings, they align with existing literature as follows: Lago et al. (2021) conducted an extensive review of day-ahead electricity price forecasting, also concluding that deep neural NN, such as TFT, tend to outperform Lasso Estimated AutoRegressive methods, albeit with increased computational costs. Fraunholz et al. (2021) found that NN outperform regression and naïve benchmarks when applied in an ABM. However, the choice of specific architecture significantly influences the results of the ABM, underscoring the need for a careful assessment. Trebbien et al. (2023) presented an analysis of day-ahead electricity prices from 2017–2020, identifying load, wind, and solar generation as key features for an explainable ML model, aligning with our findings regarding input data selection. While our study focuses on TFT networks in a similar domain, it is worth noting that they are often employed in forecasting load (Nazir et al., 2023) or renewable energy generation (López Santos et al., 2022). In contrast to the original N-BEATS architecture (Oreshkin et al., 2019), which does not allow future covariates, the N-BEATSx (Olivares et al., 2023) offers this extension.

Numerical test results show MAE of around 3.30 EUR/MWh on historical German market data. Azam and Younis (2021) conduct load and price forecasting using a novel hybrid deep learning approach demonstrating achieving MAE of around 5.20 USD/MWh on the ISO New England energy market in 2018 and 2019. In Ziel and Weron (2018), twelve distinct historical datasets of day-ahead electricity prices are evaluated, revealing a MAE in the German market zone of approximately 5 EUR/MWh. Fraunholz et al. (2021) perform a scenario analysis of ten interconnected market zones in Europe from 2020 to 2050 with MAPE forecasting errors between 0.10 and 0.39.

6. Conclusion

The findings of our study demonstrate a powerful approach that combines agent-based electricity market simulation and time series forecasting based on machine learning to provide forecasts for energy transition scenarios. Past and present market data, which are widely used in forecasting studies today, do not account for the novel price dynamics of future highly renewable electricity markets. In contrast, we explicitly incorporate foreseeable changes in energy systems resulting from the ongoing energy transition. In particular, we investigate energy transition scenarios with significant expansion of flexibility options and renewable energies, which are used to train and test different forecasting methods. We then use an open state-of-the-art agent-based electricity market model and open data to generate market results in these scenarios that differ significantly from today's energy system. We then assess the accuracy of different electricity price forecasting methods in the context of these widely varying scenarios. In our assessment, comprehensive machine learning methods, namely Temporal Fusion Transformers, demonstrate superior forecasting accuracy for future electricity markets compared to naïve benchmarking methods. Mean absolute errors decrease by approximately one order of magnitude when future covariates are accessible and understandable to the model. In addition to the demonstrated precision, even in environments characterized by significant change, the examined methodologies offer several key advantages over conventional forecasting techniques. Some machine learning-based methods, including Transformers, are capable of handling disparate input data configurations, thereby facilitating their adaptation to evolving settings. Moreover, scaling is readily achievable from simple proof-of-concepts to comprehensive modelling suites. In order to apply our results to other electricity market simulations, modelers need to apply their domain knowledge when defining training data and selecting input features. As machine learning-based methods can be computationally expensive, adequate resources are required, at least during the initial training stage. Our results are relevant not only to agent-based electricity market modelling but also to the broader field of electricity price forecasting. The presentation of quantitative results on forecasting accuracy contributes valuable insights to the general understanding of modeling electricity markets affected by the energy transition. Furthermore, they can be employed to supplement existing assessments of investment decisions within the industrial sector. From a technical perspective, modular, open, and comprehensive software packages facilitate the transferability of our approach to other applications and more in-depth analyses. Future research may address broadening the scenario space, with specific attention to the incorporation of diverse storage agents, varying technological considerations, the influence of potential market powers, and the impact of different agents' operational strategies. It would also be valuable to investigate the uncertainty of future electricity market scenarios in terms of market design and agent behaviour. Furthermore, the presented forecasting technique could also be applied to additional markets, such as Intraday markets. This would facilitate a more comprehensive analysis of the interplay between multiple markets.

CRediT authorship contribution statement

Felix Nitsch: Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Christoph Schimeczek:** Writing – review & editing, Supervision, Funding acquisition. **Valentin Bertsch:** Writing – review & editing, Supervision, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author agreement statement

We the declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed.

We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We understand that the Corresponding Author, Felix Nitsch, is the sole contact for the Editorial process. He is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs.

Appendix

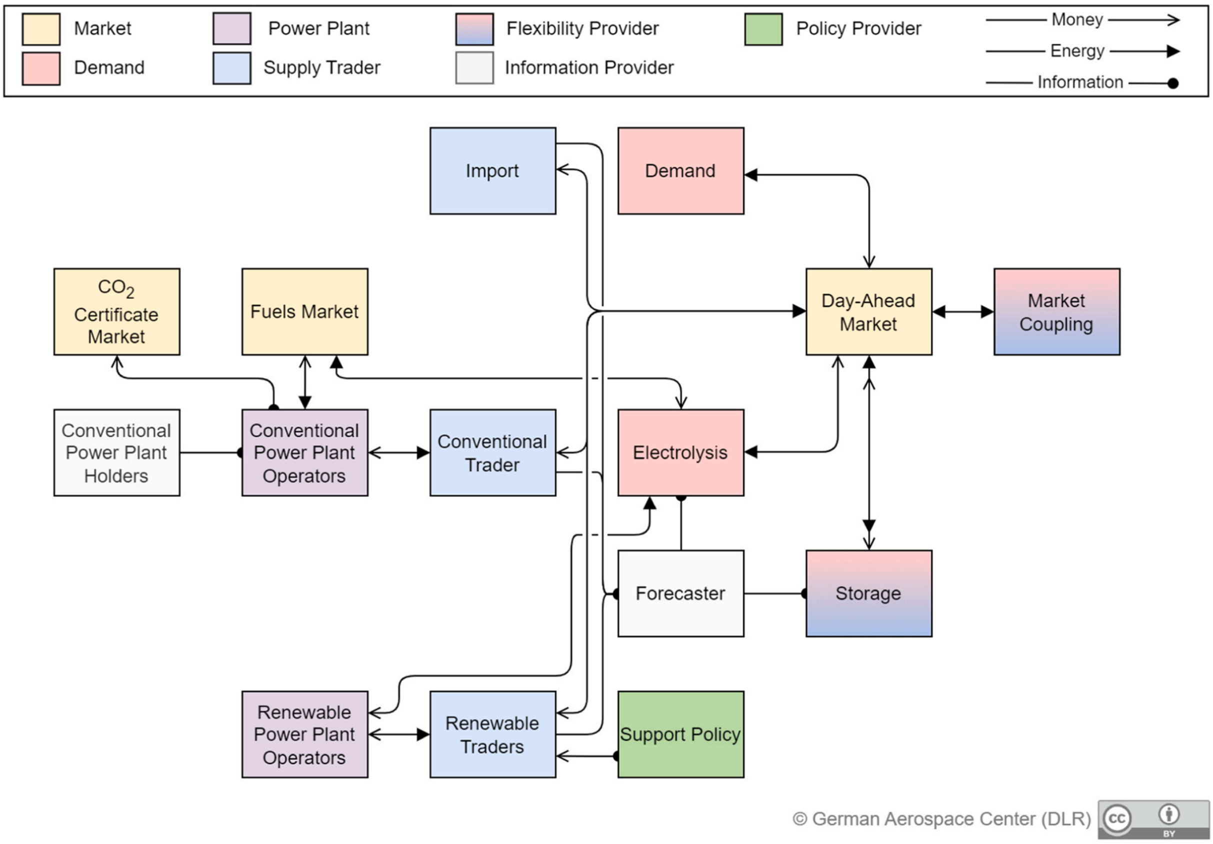

Fig. 6. Schematic overview of the agents and their connections in the agent-based electricity market model AMIRIS (Schimeczek et al., 2023a).

Data Availability

All code used to run this analysis is openly available in Schimeczek et al. (2023a), Nitsch et al. (2023b), Nitsch (2023). The data is based on Nienhaus et al. (2023).

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3.4 Paper IV: Profitability of competing flexibility options in renewable-dominated energy markets: Combining agent-based and machine learning approaches

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Executive Summary: Growing electricity price volatility has attracted significant investor interest in FOs, evidenced by over 226 GW of battery storage connection requests submitted to German transmission system operators in 2024 alone. Conversely, arbitrage by FOs tends to reduce price spreads as high prices are reduced by discharging and low prices are increased by charging. Thus, substantial uncertainty persists regarding how large-scale storage deployment will affect DAMs and individual economic viability under competitive market conditions. I address this problem by calibrating the AMIRIS model to a 2030 energy scenario for Germany, as defined in the Ariadne report[2]. My key methodological contribution extends AMIRIS with ML-based price forecasting capabilities that enable realistic simulation of competing FOs, thereby addressing a significant limitation of previous modelling approaches. With this ABM framework, I simultaneously capture individual FO economics and system-wide market dynamics through endogenous price formation. My analysis examines how forecasting accuracy influences operational decisions and competitive profitability. I find that imperfect ML forecasts can substantially reduce FO revenues, while operational strategy choices create significant performance differentials. Under accurate forecasting conditions, "risk-taking" strategies generate higher revenues than "risk-averse" approaches, although at the cost of increased cycling frequency. System-level analysis reveals a profitability plateau for homogeneous storage deployments between 4 to 8 GW installed capacity and 32 GWh total energy capacity. With favourable installation costs, annual returns can reach approximately 20% through DAM arbitrage alone. However, while heterogeneous storage technologies initially preserve their rev-

[2]The Ariadne report is widely recognised for its comprehensive analysis of potential pathways for the German energy transition towards climate neutrality by 2045 (Luderer, Kost, and Sörgel 2021).

enue shares, individual profitability declines significantly once critical market penetration thresholds are exceeded. My findings indicate that current battery connection requests in Germany may exceed economically viable deployment levels in current market frameworks. The open-source modelling toolchain supports future research extensions which may focus on additional revenue streams such as ancillary services and cross-market optimisation strategies.

Author Contributions: I am the lead author of this paper. The conceptual work was predominantly carried out by me, with input from my co-authors, Christoph Schimeczek and Valentin Bertsch. I was also responsible for software development, including implementing the AMIRIS extension package AMIRIS-PriceForecast. Together with Christoph Schimeczek, I developed the agent class PriceForecasterApi, which interfaces with the external forecasting model AMIRIS-PriceForecast via an application programming interface (API). I handled data curation, model execution, results validation, numerical analysis, and sensitivity analysis. All result visualisations were created by me and refined through discussions with my co-authors. Christoph Schimeczek and I were responsible for acquiring funding. I wrote the original draft, while both co-authors reviewed and edited it.

Profitability of competing flexibility options in renewable-dominated energy markets: Combining agent-based and machine learning approaches

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Highlights

- In 2024, German TSOs received 226 GW in battery storage connection requests
- Agent-based electricity market simulation assesses competing flexibility options (FO)
- Risk affinity impacts both revenues, but also number of full charge cycles
- Homogeneous FO are most profitable with energy-to-power ratios between 4 to 8
- Heterogeneous competition reduces FO revenues once total capacity reaches saturation

Abstract

Rising price spreads on the electricity market have sparked the interest of investors in flexibility options. German transmission system operators received over 226 GW of battery storage connection requests in 2024. However, some uncertainty remains regarding the impact of large-scale storage deployment on electricity markets and their economic performance under competition. To address this, we use the open agent-based electricity market model AMIRIS, calibrated to a 2030 scenario based on the Ariadne report. We extend AMIRIS with a state-of-the-art machine-learning-based routine to provide agents with electricity price forecasts during runtime. These forecasts enable AMIRIS to model competing flexibility options. We evaluate the forecast accuracy and analyze its influence on the operation and profitability of competing flexibility options. Our results show that imperfect forecasts created by, e.g., machine learning algorithms, may reduce the revenues of flexibility options and that operational strategies significantly affect the revenues. Given sufficiently accurate forecasts, "risk-affine" strategies yield higher revenues, but also yield more full charge cycles than "risk-averse" strategies. At the system level, we identify a profitability plateau for homogeneous storage systems with installed power between 4 to 8 GW and total capacity of 32 GWh. Depending on installation costs, annual return on investment can reach around 20% through day-ahead market arbitrage. While heterogeneous storage technologies initially maintain their revenue shares, individual profitability declines significantly beyond critical capacity levels. These findings suggest that the volume of current German connection requests may exceed economically sustainable deployment levels under current market structures. Future research can build on our open modelling tool chain to integrate additional revenue streams, such as cross-market participation or system services remuneration.

Keywords: agent-based modelling, energy systems analysis, flexibility options, electricity market, energy transition, AMIRIS

Abbreviations

ABM	Agent-based modeling
BSS	Battery storage systems
DAM	Day-ahead market
E2P	Energy-to-power ratio
FO	Flexibility option
ML	Machine learning
RE	Renewable energy
RTE	Round-trip efficiency
TSO	Transmission system operator

1 Introduction

The integration of renewable energy (RE) technologies introduces substantial fluctuations in electricity generation. Flexibility options (FO) have emerged as attractive solutions to balance this variability [1]. These options encompass a range of technological concepts and applications, with battery storage systems (BSS) representing a particularly promising approach [2, 3]. For instance, German transmission system operators received an unprecedented number of battery connection requests totaling more than 226 GW in 2024 alone [4]. Even if only a fraction of this is realized, it is a clear indication of the growing importance of BSS as an essential component to the energy transition. Investments in such FO require adequate planning and comprehensive economic analysis to ensure their viability and effectiveness [5]. This has to be done from the single-units perspective, but also considering their potential system impact. As large-scale electricity storage deployment accelerates, it will inevitably transform spot market dynamics, creating both challenges and opportunities for market participants [6]. According to fundamental market mechanics, buying electricity when prices are low tends to increase prices because there is more demand to cover. Similarly, high prices are expected to drop when many sell orders are received. As a consequence, large FO capacity will likely have an impact on electricity price formation. This can ultimately lead to potential cannibalization effects, where FOs are hampered in exploiting electricity price spreads due to their high market penetration. This is an important aspect to consider when evaluating the profitability of FOs. Therefore, applied models used to analyze these dynamics must be capable of accurately simulating such interactions.

1.1 Related works

Existing literature covers a broad range of FO assessments. Many studies focus on different levels of application ranging from behind-the-meter to front-of-the-meter. While the first group investigates FO applied by individual consumers and businesses [7], the latter are large-scale units which may also contribute to several ancillary services, such as frequency restoration reserve [8], black start capabilities [9], or congestion management [10]. In this paper, we focus on the economical and operational part of large-scale FOs. We limit our analysis on the day-ahead market (DAM) with uniform pricing, such as in place in the current German market design [11].

Detailed projections of future levelized cost of different FOs provide relevant information both in business and academic contexts [12]. Therein, BSS appear to be one of the most promising solutions when compared with eight other FO technologies. The costs of storing electricity, however, is still strongly linked to the storage operation and the setup of the whole system [13]. Other research examines, which technical specifications, such as power, capacity, efficiency, are ideal for refinancing FOs [14–16]. However, they rarely explicitly simulate the market impact of FOs or the competition among FOs.

Besides costs, FO investors also look out for attractive market signals, such as arbitrage potentials which incentivize the investment in FOs. Most existing studies rely on historical electricity market data to assess the operation and economic performance of FOs. These approaches fail to capture future scenarios which are significantly shaped by the energy transition, including changes in the power plant mix and evolving market dynamics [17]. Price formation is more and more influenced by heterogeneous market actors, particularly the growing share of RE technologies with low marginal costs and conventional peak power plants with reduced operation hours. As these price dynamics shift, so does the economic potential of FOs which engage in electricity market arbitrage [18]. This issue is becoming increasingly important as both energy systems and FOs continue to evolve rapidly [19].

As the share of wind and photovoltaic generation increases, wholesale electricity prices tend to drop, especially during periods of high production, thus reducing revenue potential for all market participants in these hours of high RE generation. This phenomenon of declining market values of RE has been extensively analyzed in the literature [20, 21] and is also considered in recent RE investment analysis [22]. FOs are often assumed to play an essential part in mitigating such cannibalization of RE [23], thus making higher shares of RE in energy systems feasible [24]. Another aspect of large-scale deployment of FO are so-called “avalanche effects” [25] where multiple actors react on the same (price-) signal, thus creating adverse effects. This effect is found in, e.g., heat pump operation [26], electric vehicle charging [27], and household load management [28]. Therefore, assessments of FO have to especially consider both individual actors’ perspective as well as the effects induced to the whole system.

The cannibalization of FOs itself is a relatively new challenge and has not received as much attention in current research [6]. Therefore, the price impacts of FOs should be endogenously captured in the applied models, thus providing more accurate simulation of energy transition scenarios and allowing the consideration of cannibalization effects [29]. [30] use an equilibrium model to assess long-term profitability of FOs. The authors find that in a French scenario, increased FO penetration reduces revenue potential, but increased uncertainty due to higher RE penetration compensates for this effect. A Greek case study also found reduced FO market values with rising competition which can, depending on the scenario assumptions be compensated by increased fluctuation by RE [31]. In contrast, a study on community electricity storage revealed substantial losses caused by FO cannibalization when competing with sector coupling and demand response [32]. However, this research optimizes community electricity storage settings, not accounting any FO system impacts or application. Reserves markets which are already dominated by FOs do no longer yield any significant revenue, and thus do not contribute to FO refinancing [33]. In a case study of the Portuguese energy system, FO competition leads to substitution effects among different FOs, however, the applied optimization model does not provide individual profitability assessments of FOs, but describes a central-planner approach [34]. A case study applying proprietary energy system optimization software investigating a Finish island also reveals cannibalization among three distinct FO technologies [35].

From a methodological perspective, the competition between FOs can also be addressed using game theoretical models. Such a case study examined homogeneous FO investors and found that rising market competition led to reduced profits [36]. [37] used deep reinforcement learning to simulate FOs in electricity markets. Although they provide an architecture enabling the simulation of competing FOs, their method does not account for price impact by FO actions and the case study provided focuses on a historical time span.

Still, several critical gaps remain in our understanding of FOs under high RE penetration.

1. FO competition: Many existing studies treat electricity market prices as exogenous model input and thus neglect FOs affecting market dynamics. While some studies examine FO cannibalization effects, they predominantly use central-planner optimization approaches or analyze homogeneous FOs. Heterogeneous FO competition capturing the interactions between different types of FO operators should be addressed.
2. Technical specifications: The optimal technical specifications identified in isolated optimization may not hold when competitive effects and market feedback are endogenously modeled. It is therefore important to assess optimal power, capacity, and efficiency parameters also from the perspective of the investors.
3. Price forecasting impact on profitability: Since real-world FO dispatch planning relies on electricity price forecasting, it is important to also address this aspect in the applied model. Current literature lacks analysis of how electricity price forecasting quality affects FO activity, particularly in competitive scenarios where avalanche effects may occur.

1.2 Novelty

To date, a comprehensive analysis is missing that addresses these interconnected challenges simultaneously. Such an analysis should cover not only individual FO operation, but also the emerging electricity market dynamics in scenarios with high RE and FO penetration. The impact of electricity price forecasting quality and technical FO parameters on the revenues should be assessed as well for such scenarios with high FO competition. Our work addresses these three specific gaps by providing a market-driven, multi-scenario assessment of FOs using an agent-based modeling (ABM) approach that overcomes the computational limitations of game-theoretical models while avoiding central-planner assumptions of optimization models. We extend and apply an ABM to analyze heterogeneous FOs and their economic performance in future electricity market scenarios characterized by high RE penetration. The research includes economic potential assessment for different cost assumptions and technical specifications, enabling more robust investment decision-making under competitive conditions. Furthermore, we ensure full reproducibility through an open modeling tool chain.

This integrated approach allows us to investigate how competition, technical specifications, and forecasting quality interact with FO performance while also accounting for changes introduced by the energy transition. Specifically, this research seeks to answer the following questions.

1. How are FOs affected by increasing competition on electricity spot markets?
2. Which technical parameters provide sufficient revenue potential for FOs?
3. What role does the quality of electricity price forecasting play in determining profitability of FOs in competitive markets?

This paper is structured as follows. In Section 2, we present our material and methods, including the applied ABM. In Section 3, we describe the findings derived from our electricity market simulations. In Section 4, we discuss the results and identify important limitations. In Section 5, we give a summary of the findings and provide an outlook on potential future research avenues.

2 Material and methods

In our analysis, we extend and apply the open electricity market model AMIRIS [38] to simulate the DAM over one year in hourly resolution, see Section 2.1. Electricity price forecasts are provided by a dedicated ML (machine learning) algorithm, thus enabling the simulation of competing FOs. The model parameterization is based on an Ariadne scenario [39], see Section 2.2, for which we systematically vary technical parameters of FOs using the scenario generator AMIRIS-Scengen [40]. We provide a fully automated, open modeling toolchain, see also Figure 1, to ensure transparency and reproducibility.

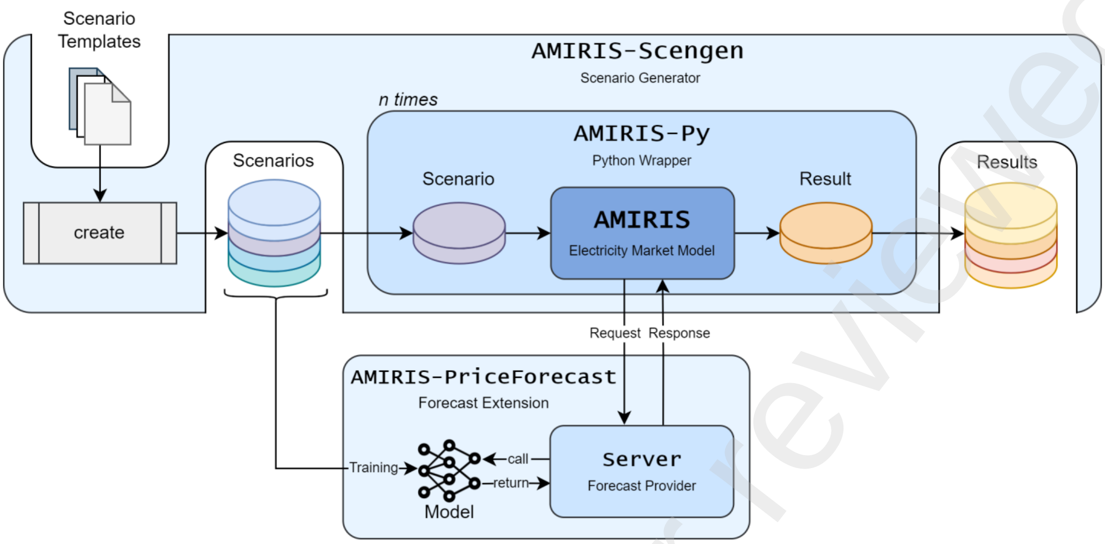

Figure 1: Modelling setup enabling agent-based electricity market analysis of competing flexibility options.

2.1 Electricity market modelling using AMIRIS

AMIRIS is the *A*gent-based *M*arket model for the *I*nvestigation of *R*enewable and *I*ntegrated energy *S*ystems [38]. The electricity market model has been developed since 2008 and was published open source[1] in late 2021 [41]. It is a powerful simulation based on the flexible framework FAME [42, 43]. The heart of AMIRIS is the simulation of the DAM revealing market dynamics and agent interactions [14] while considering different policy frameworks [44] and effects due to coupling of neighboring market zones [45]. AMIRIS has been back-tested for the German [46] and Austrian [47] DAM, which resulted in a good fit of simulated and historical electricity prices. Figure 12 in the Appendix provides an overview of the agents represented in AMIRIS (i.e. power plant operators, traders, flexibility operators, market operators and regulators) and their interactions via flows of information, energy, and money. Similar to other energy system models, users define and provide relevant input data [48]. In the context of AMIRIS this translates to power plant park structure, RE generation timeseries, demand data, and operational cost data. Central modelling outputs of AMIRIS are DAM electricity prices, as well as costs and revenues of market participants. FOs can choose between a “risk-taking” or more “risk-averse” bidding strategy when performing arbitrage at the DAM[15]. The consideration of further revenue streams for FOs, such as intraday markets, is not yet available.

[1] gitlab.com/dlr-ve/esy/amiris (accessed on 20th June 2025)

Realistic analysis of FO competition requires modeling how operators make dispatch decisions under uncertainty, which fundamentally differs from optimization approaches that assume perfect market information. In DAM, FO profitability depends not only on actual price dynamics but on operators' ability to anticipate and respond to these patterns. When multiple FOs compete, superior forecasting capabilities can lead to competitive advantages by better timing charge/discharge cycles. In contrast to energy optimization models where a central planner optimizes all units simultaneously, ABMs like AMIRIS require individual agents to make decisions based on imperfect information. This creates a critical need for electricity price forecasts provided to FO operators. This was previously addressed through simplified “naïve” forecasts eligible only for a single FO [49]. To address Gap 3 and thus enable FO competition (Gap 1), we substantially extended AMIRIS with a sophisticated forecasting system. Our key methodological contribution is the development of AMIRIS-PriceForecast [50], a dedicated machine-learning based forecasting module which runs in co-simulation with AMIRIS. As these algorithms have proven to deliver robust forecasts, even in future energy transition scenarios [51], we apply ML to derive accurate time series forecasts during AMIRIS runtime. This represents a significant advancement over both central-planner optimization models that assume perfect foresight and previous ABM studies that used oversimplified forecasting assumptions.

The forecasting workflow, see also Figure 2, operates as follows: FO agents request price forecasts from a centralized forecasting agent (PriceForecasterApi) delivering the same forecast to each client. To reduce the number of calls to the external AMIRIS-PriceForecast, PriceForecasterApi retrieves cached forecasts meeting predefined accuracy criteria. When the accuracy of previous forecasts is insufficient or forecasts for uncovered time periods are needed, AMIRIS-PriceForecast loads a pre-trained model and generates time series predictions based on the specific forecast request. The coupling between the two components AMIRIS (Java based) and AMIRIS-PriceForecast (Python based) is accomplished using a standardized interface based on FastAPI[2]. The modular architecture and open-source implementation also ensures that researchers can extend the available forecasting algorithms to keep pace with advances in time series forecasting.

[2] github.com/fastapi/fastapi (accessed on 20th June 2025)

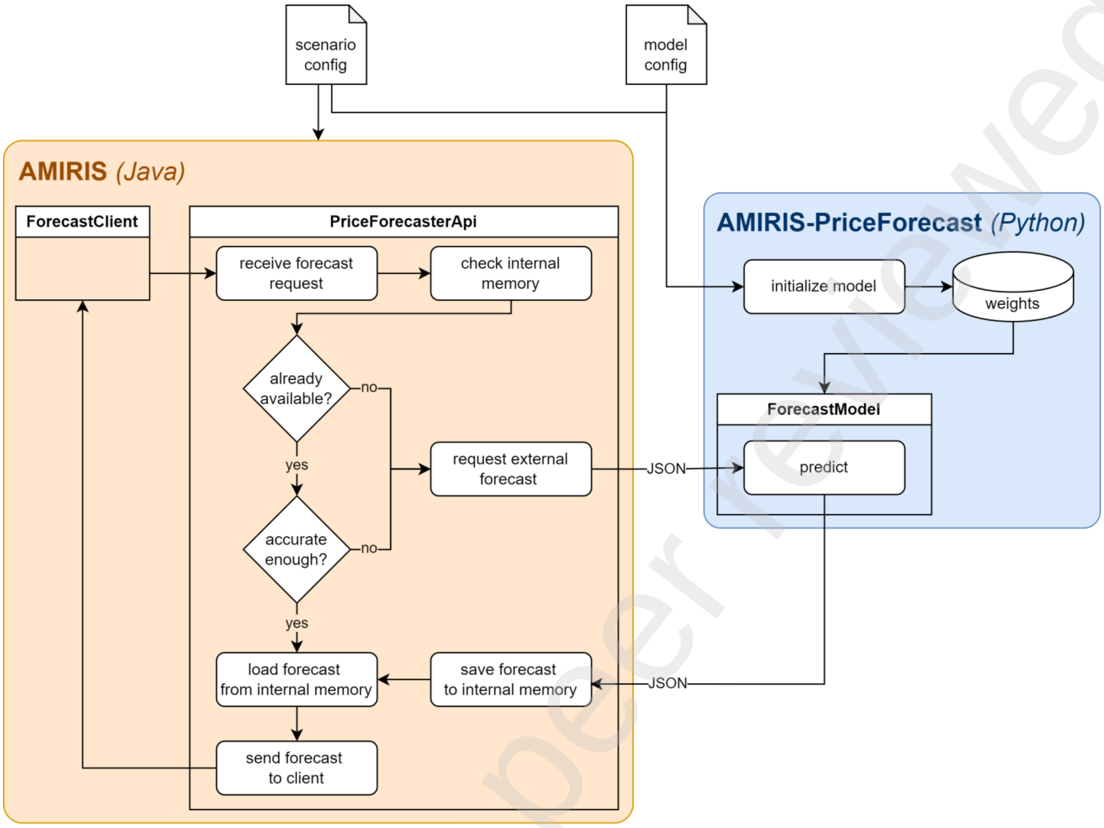

Figure 2: Workflow of electricity price forecasting in AMIRIS and AMIRIS-PriceForecast.

2.2 Energy transition scenario

Our study focuses on the German DAM zone. The data is based on the Ariadne scenario report [39], which is widely recognized for its comprehensive analysis of potential pathways for the German energy transition toward climate neutrality by 2045. The Ariadne project[3], funded by the German Federal Ministry of Education and Research, employs multiple integrated modeling approaches to assess the feasibility, costs, and sectoral implications of different transformation pathways, making it a particularly robust foundation for energy system analysis. The economic and demographic assumptions underlying the Ariadne scenario report are based on the so-called "Middle of the Road" scenario among the Shared Socioeconomic Pathways as defined in [52]. The scenarios contain detailed assumptions about RE expansion, sector coupling mechanisms, hydrogen deployment strategies, and the systematic phase-out of fossil fuels across all economic

[3] ariadneprojekt.de (accessed on 24th May 2025)

sectors. Specifically, we utilize the “mix” subscenario, which assumes the use of a mixed energy carrier portfolio (electricity, hydrogen, and synthetic green fuels) in final energy consumption, see also Table 1. This subscenario reflects a diversified approach to decarbonization where different sectors employ the most suitable clean energy carriers based on technical and economic considerations. We selected the year 2030 as our temporal focus, as many of the storage connection requests under consideration aim to be realized within this timeframe. Flexibilization of demand is already inherently integrated in the load profiles, reflecting the scenario’s consideration of demand-side management and behavioral adaptations. Thus, we add additional flexibility to the system which should represent the recent connection requests received by the German transmission system operators, thereby capturing the dynamic evolution of grid infrastructure requirements. Figure 3 provides an overview of the scenario projections on electricity supply and demand, illustrating the fundamental shifts in generation mix and consumption patterns anticipated for 2030.

Table 1: Scenario parameters derived from Luderer et al. [39].

Parameter		Value	Unit
Capacities	Nuclear	0	GW
	Lignite	0	GW
	Hard coal	0	GW
	Natural gas	30.0	GW
	Hydrogen	15.3	GW
	Biomass	15.7	GW
	Run-of-river	12.6	GW
	PV	218.4	GW
	Wind onshore	127.2	GW
	Wind offshore	25.0	GW
	Other non-renewable	0.9	GW
CO_2 certificate costs		200.0	EUR/t
Load		615.8	TWh/a
Greenhouse gas reduction compared to 1990		65	%

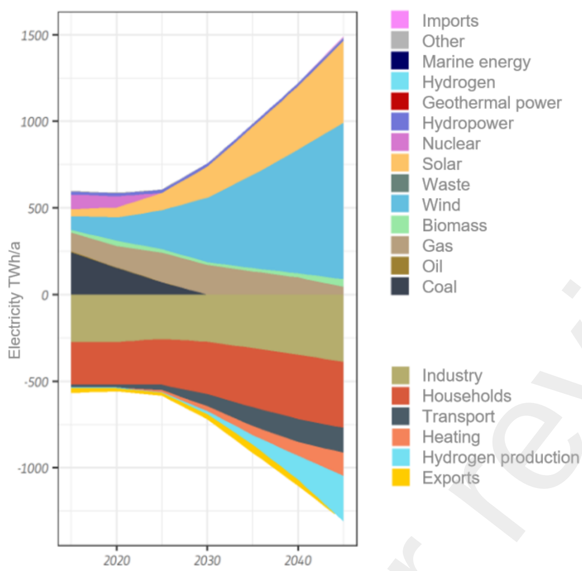

Figure 3: Electricity generation and consumption for Germany according to the Ariadne scenario; adapted with permission from Luderer et al. [39].

3 Results

The results are organized in two main sections. Section 3.1 presents the methodological advancements developed to close gap 3, demonstrating the performance of our enhanced analytical framework. Section 3.2 examines the profitability of FOs in the future energy system scenario, providing insights to gap 1 and 2.

3.1 Methodological advances

To analyze FOs in future electricity markets, we first evaluate the methodological improvements to AMIRIS. For this, we assess the accuracy of electricity price forecasts generated by the AMIRIS extension AMIRIS-PriceForecast. Typically, the FOs require at least 24 hours of electricity price forecasts to optimize their bidding schedule. Our approach employs a Temporal Fusion Transformer algorithm [53] for electricity price prediction. This architecture has demonstrated strong performance in forecasting electricity prices within future energy system scenarios [51]. The forecasting model integrated into AMIRIS-PriceForecast is iteratively called during AMIRIS runtime, generating DAM electricity price forecasts p_{t0} to p_{t23} based on previous electricity prices p_{t-24} to p_{t-1} and the residual load rl_{t-24} to rl_{t23}.

Figure 4 illustrates cumulative storage revenues achieved using different forecasting approaches, revealing the direct impact of forecast accuracy on FO performance. Perfect foresight represents the theoretical maximum revenue potential, while the baseline, a “naïve” TimeShift method using the previous 24 hours as a forecast [54], captures less than 40% of this potential. Our analysis of various hyperparameter configurations demonstrates that model architecture significantly influences revenue outcomes. The optimal ML based prediction incorporates future covariates, achieving nearly 80% of potential revenues. This finding aligns with recent research showing substantial error reduction when integrating future covariates in time series forecasting [55]. While this enhanced performance requires significantly higher computational training[4] costs, four to five times greater than alternative models, the training effort can be considered uncritical since the trained model is applicable to a wide range of simulation scenarios [51]. Each prediction call accounts for approximately 0.1 seconds including negligible overhead by the model coupling via FastAPI.

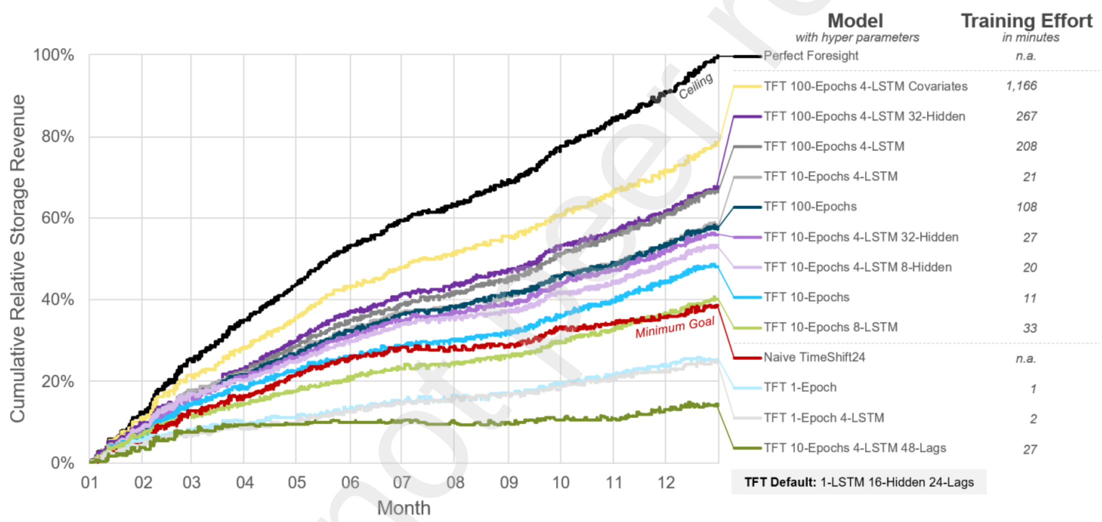

Figure 4: Impact of forecasting model on cumulative storage revenue and required training effort.

To examine how forecasting quality affects FO operation, we analyze a 1 MW, 5 MWh price-taking BSS with a round-trip efficiency (RTE) of 80% under two forecasting modes: perfect foresight, representing ex-post optimal operation, and model-endogenous ML based price forecasts. Each forecasting mode is combined with two operational strategies: risk-taking, which exploits all profitable price spreads, and risk-averse, which acts only on significant expected spreads.

[4] Model training was performed on a system equipped with an Intel® Core™ i7-11850H processor (2.50 GHz) and 32 GB of RAM.

Figure 5 illustrates the operational differences during a representative week. Perfect foresight enables optimal operation under the risk-taking strategy (Figure 5a), capturing all profitable arbitrage opportunities. The risk-averse strategy with perfect foresight (Figure 5b) results in reduced activity as some smaller price spreads remain unexploited, leading to missed charging and discharging opportunities (compare situations 5aI/5bI, or 5aII/5bII). ML based forecasting introduces prediction errors that create suboptimal storage patterns. Following the risk-taking strategy (Figure 5c), forecasting errors generate additional, often unprofitable charging and discharging events (compare situations 5aI/5cI). The risk-averse strategy with ML based forecasting (Figure 5d) leads to extended idle periods where profitable opportunities are missed due to forecast uncertainty (compare situations 5bI/5dI). As with perfect foresight, the risk-averse operation results in less activity compared to the risk-taking approach (compare situations 5cII/5dII).

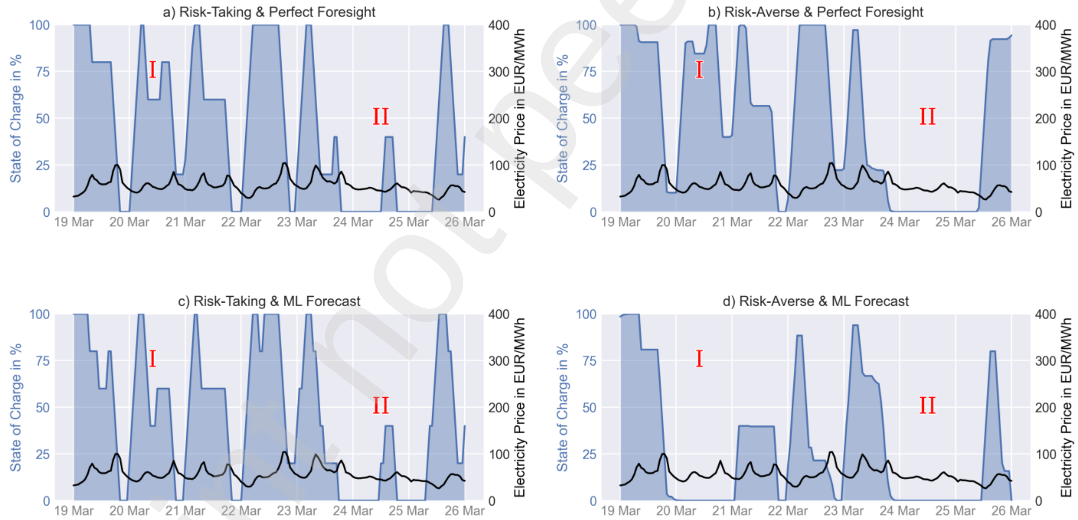

Figure 5: State of charge (blue area) and electricity price (black line) during a single week revealing the impact of storage strategy and electricity price forecast type.

While Figure 5 provides a detailed view of a single week, Figure 6 reveals systematic patterns across all combinations by presenting an annual perspective in hourly resolution. Storage charging (red areas) occurs primarily during nighttime and midday low-price periods, while discharging (blue areas) results from peak prices during morning and evening. ML forecasting errors create noticeably noisier activity patterns, which are particularly evident in the risk-taking strategy (Figure 6b). The revenue analysis demonstrates substantial impacts from both strategy choice and forecasting accuracy. Using perfect foresight as the baseline (risk-taking strategy, Figure 6a), the risk-averse strategy achieves approximately 79% of maximum revenues (Figure 6b). ML based forecasting reduces performance to 73% for risk-taking (Figure 6c) and 62% for risk-averse strategies (Figure 6d), see also Figure 13 in the Appendix. Cycling behavior also varies significantly across scenarios. Perfect foresight with risk-taking strategy results in 359 full charge cycles[5] over the simulation year (nearly one per day). In contrast, the risk-averse approach reduces this number to 227 cycles. The risk-taking strategy joined with ML forecasting produces 381 cycles (indicating increased cycling due to forecast errors). This increased number of cycles could further impact profitability if cycling costs were considered. 207 cycles result when the risk-averse strategy is combined with ML forecasts, strengthening the earlier finding that forecast errors can lead to missed opportunities depending on the operational strategy employed.

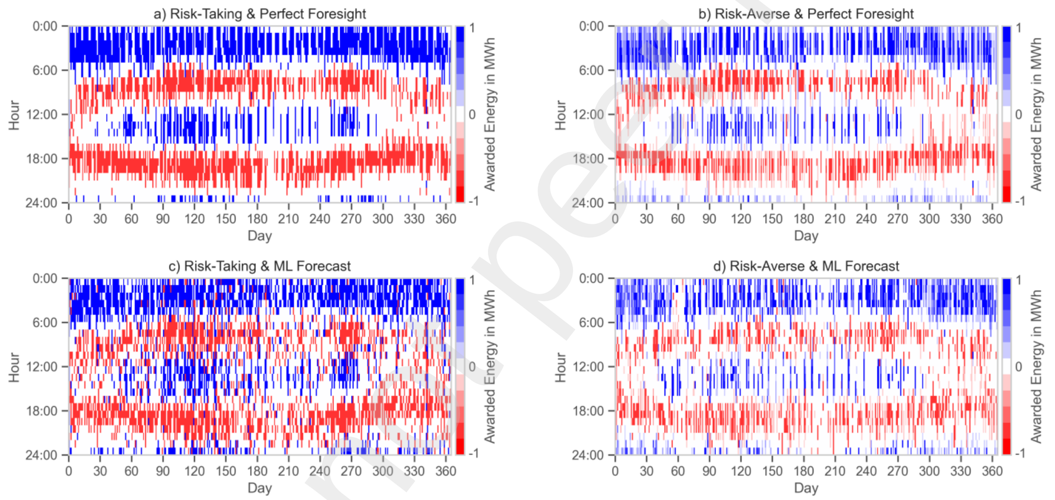

Figure 6: Storage activity, blue areas indicate charging, whereas red areas indicate discharging, during a full model year revealing impact by storage strategy and electricity price forecast type.

3.2 Profitability of flexibility options

This section aims to identify optimal technical parameters for FOs, thus addressing Gap 2, and then examining how competitive dynamics affect profitability, which addresses Gap 1. To compare the profitability of differently scaled FOs, particularly BSS, we compute the return on investment (ROI), similar to the definition in [56]. ROI, see Equation (1), is calculated as the ratio of net

[5] One full charge cycle indicates a complete charge and discharge of the storage, whether it occurs all at once or is accumulated over multiple partial cycles.

cashflow CF_t for year t from earnings e_t minus costs c_t from (dis-)charging, see Equation (3), to the total installation costs $Cost_0$, see Equation (4). The installation costs include the power-based converter costs $c_{converter}$ and the energy-based storage cost $c_{storage}$. The result is expressed as a percentage where high values express superior profitability. This metric provides a quick payback-oriented perspective for initial investment screening. As ROI does not cover annualized capital costs, we solve Equation (2) for the Internal Rate of Return (IRR), as also used in [57] assuming an estimated operational lifetime and constant cashflow to provide an additional financial performance metric.

$$ROI = \frac{CF_{t=1}}{Cost_0} \times 100 \tag{1}$$

$$NPV = CF_{t=1} \times \sum_{t=1}^{n} \frac{1}{(1 + IRR)^t} - Cost_0 = 0 \tag{2}$$

$$CF_t = e_t - c_t \tag{3}$$

$$Cost_0 = power \times c_{converter} + capacity \times c_{storage} \tag{4}$$

Figure 7 presents ROI for homogeneous large-scale BSS in the 2030 scenario with fixed power at 8 GW and varying storage capacity (8 GWh to 64 GWh) under different cost assumptions. Figure 8 shows ROI when the capacity is fixed at 32 GWh and the storage power is varied from 1 GW to 12 GW. In all cases, converter costs range from 50 EUR/kW to 200 EUR/kW [58] while the storage costs range from 100 EUR/kWh to 400 EUR/kWh [59], and RTE is at 80%. The analysis reveals that annual ROI can exceed 18% under favorable cost conditions, with optimal performance occurring at 32 GWh total capacity and 4 to 8 GW installed power. Systems with low energy-to-power (E2P) ratios, e.g., 8 GW/8 GWh, or very high E2P ratios, e.g., 1 GW/32 GWh, show significantly lower ROI, indicating the importance of technical specifications adjusted to the energy system scenario. This can be explained by novel electricity price dynamics. Figure 15 in the Appendix provides a comprehensive scan of different storage systems and their resulting activity and price impact. We note that systems with low E2P ratios can charge and discharge rapidly, but cannot benefit from longer-duration price changes whereas systems with larger E2P generally profit from these periods. In these cases, however, storage costs represent the major share of total installation cost, thus causing maximum profitability at an intermediate E2P configurations. In contrast, specific system combinations, i.e., high-capacity and/or high-power systems, impact market prices by elevating low prices during charging and suppressing high prices during discharging, thereby cannibalizing their collective revenue potential. A crucial distinction of our methodology is the endogenous modelling of electricity market prices, explicitly capturing how individual FO behavior influences market dynamics. This contrasts with studies such as [60], that treat prices as exogenous inputs, enabling us to identify saturation points where collective FO impacts reduce overall profitability. The impact of the ML training volume on ROI calculation is described in Figure 14 in the Appendix[6].

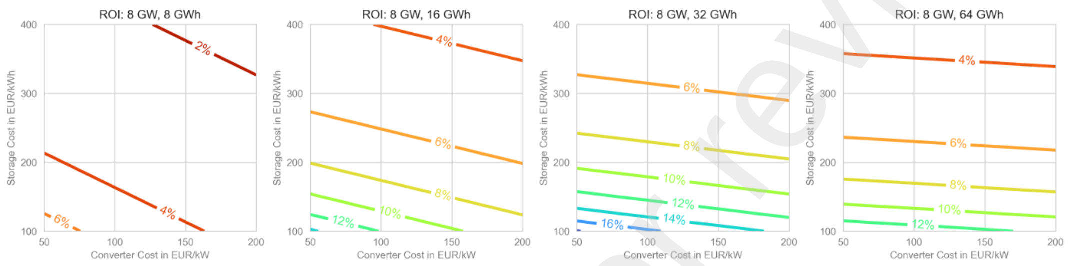

Figure 7: Return on investment (ROI) for homogeneous battery storage systems with fixed power (8 GW) and varying capacity.

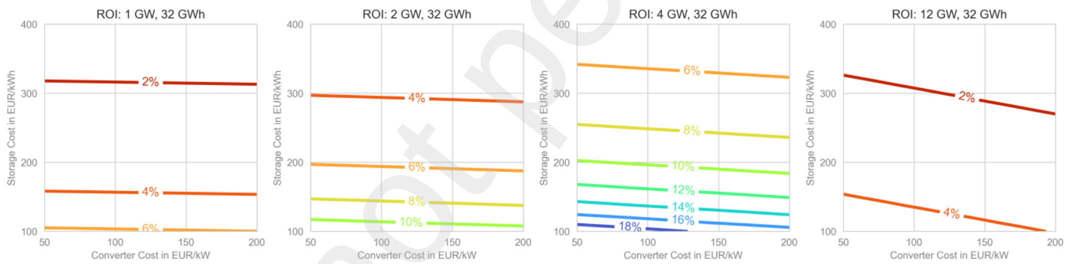

Figure 8: Return on investment (ROI) for homogeneous battery storage systems with fixed capacity (32 GWh) and varying power.

To complement our profitability analysis based on ROI, we calculate the IRR for one of the best performing technical configuration, 6 GW/32 GWh. The IRR accounts for the time value of money

[6] Figure 14 in the Appendix shows the effect of training length on ROI for BSS. When increasing training epochs from 1 to 50, we observe that the applied Temporal Fusion Transformer does not significantly improve if trained for more than 10 epochs. Compared to the analysis in Figure 4, we have increased the training data available to the model by a factor of five, thus resulting in 30 training scenarios with 8760 time steps each. Together with the used hyperparameter settings[6], this allows the model to converge quickly.

and financing considerations that the ROI does not capture, providing an additional metric for such a long-term investment. We examine IRR across operational lifetimes ranging from 10 to 20 years, applying the same cost assumptions used in the ROI analysis (converter costs: 50-200 EUR/kW; storage costs: 100-400 EUR/kWh). Figure 9 presents the resulting IRR values, where positive results indicate profitable investments assuming constant annual cash flows from DAM arbitrage throughout the operational period. In general, longer operational lifetimes and lower capital costs yield higher IRR values. Under moderate cost assumptions, BSS require minimum operational periods of 10 years to achieve profitability, with IRR values reaching approximately 20% for systems operating over 20-year lifetimes and with optimistic cost assumptions. The IRR analysis reinforces that the 6 GW/32 GWh configuration represents a robust investment opportunity as long as cost assumptions are favorable.

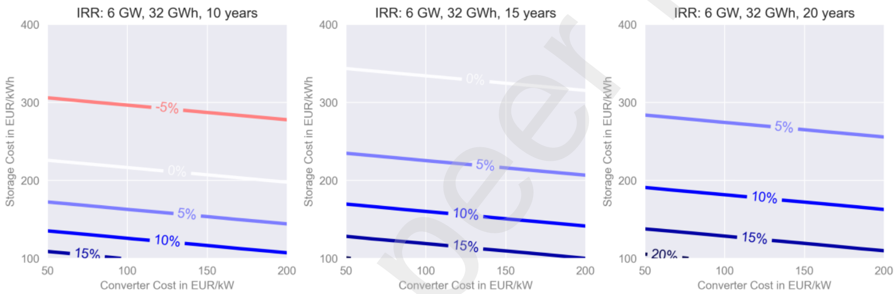

Figure 9: Internal rate of return (IRR) for homogeneous battery storage systems under different assumed lifetimes.

To provide more granular insights for the impact of BSS technical parameters on profits, we conduct detailed analysis varying E2P ratios and RTE. Maintaining fixed installed capacity at 6 GWh, we examine temporal characteristics ranging from short-term storage, E2P ratio of 1, to more medium-term storage, E2P ratio of 8, with RTE values spanning from 60% to 95% to represent different storage technologies. They all operate under the “risk-taking” strategy with ML based price forecasts. Figure 10 illustrates annual storage revenue excluding investment costs. The E2P ratio emerges as the dominant factor in revenue maximization, with best performance occurring between ratios of 3.5-7.5 for the analyzed energy scenario. This reflects electricity price dynamics in the Ariadne scenario, where high RE shares lead to extended periods of very low prices when demand is fully met by renewable generation, followed by periods requiring expensive conventional peak generation. FOs with intermediate E2P ratios most effectively exploit these price spreads. Higher RTEs consistently improve revenue potential. It is worth to note that RTE can also be interpreted as operational cost where low efficiency translates to high cycling costs. Surprisingly, short-term storage systems with E2P ratios below 1.5 generate losses rather than profits. Since capacity is fixed at 6 GWh, low E2P ratios correspond to high-powered systems which significantly impact electricity prices, undermining performance under “high-risk" strategies. This is in contrast to other studies, such as [14, 60], that identify high-power storage as optimal. This fact can be explained as these studies do not account for FO price impacts. Importantly, our results do not suggest high-powered FOs cannot be profitable in the studied scenario, but rather that they require enhanced operational strategies accounting for their market price influence. This sensitivity analysis also reveals that revenue per installed MWh, as well as ROI follows the same structure to the shown total revenue, while revenue per installed MW increases with higher E2P ratios.

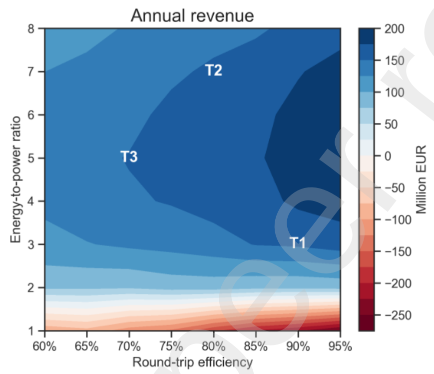

Figure 10: Variation of E2P ratio and RTE for different battery storage system and their annual revenue. Markings T1–T3 represent specific combinations used in subsequent analysis.

We then select three distinct combinations, T1, T2, and T3, from the presented analysis, each achieving roughly equivalent total revenue but representing different technical niches. T1 represents a highly efficient FO, with an RTE of 90% specialized for more short-term operations with its E2P ratio of 3. T2, with an E2P of 7 and an RTE of 80%, targets medium-term applications. T3, with an E2P of 5, falls in between the other two in terms of the E2P ratio, but is defined by a lower RTE of 70%. We investigate economic performance for these three technologies operating individually and in competitive scenarios. Figure 11 shows annual total revenue, as well as revenue per installed MW and revenue per installed MWh. In the competition case with 2 GWh each, the total revenue across all storages remains similar to the individual cases. T1 accounts for 37% of total revenue, while T2 and T3 achieve 32% and 31% respectively. This suggests that, in a competitive case, T1 can increase its revenue share by exploiting its short-term flexibility niche, which remains unaffected by the more medium-term orientated T2 and T3. When total capacity triples to 6 GWh, market dynamics shift substantially affecting all technologies. T2 takes the largest share at 36%. However, all three technologies, T1, T2, and T3, earn reduced specific annual revenues compared to the 2 GWh scenario. This reflects cannibalization effects between

FOs, as total revenue increases by only a factor of 2.1 despite tripled capacity. These effects are clearly visible when looking at revenue per installed MW and revenue per installed MWh. In general, competition between FOs has limited impact on individual technologies when total capacity remains relatively small, allowing T1 to improve its position. However, once total capacity increases significantly, revenue potential decreases sharply, with T1 experiencing the greatest relative losses compared to its competitors T2 and T3. This analysis demonstrates the critical importance of market saturation effects in determining FO profitability under competitive conditions.

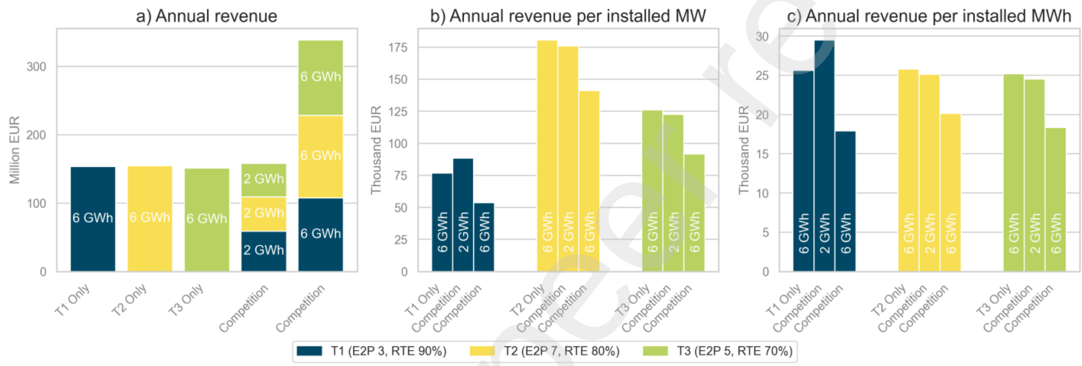

Figure 11: Annual revenue for each technology across individual scenarios ("T1 Only", "T2 Only", "T3 Only") and two "Competition" scenarios. Storage capacity varies between 2 GWh and 6 GWh, as indicated by the labels on each bar.

4 Discussion

The following elaboration on limitations provide the necessary context for interpreting the findings presented, while establishing a foundation for future research to build upon this analytical framework. Our study focuses exclusively on DAM revenues without considering additional revenue streams for the FOs or comprehensive cross market optimization strategies [61]. In our analysis, the DAM serves primarily as a benchmark rather than providing a complete profitability assessment, this approach may underestimate total FO revenue potential. However, as FO capacity increases, additional revenue streams like intraday and reserves markets may also be impacted by cannibalization effects once dominated by FOs [33, 62]. The ongoing transition of the European Day-Ahead Market (DAM) to 15-minute intervals may create additional arbitrage opportunities, however, since it is not yet implemented, there is currently no data or experience available for the German market zone.

Our findings both complement and challenge existing research. [30] identify increasing revenue potential for systems with an E2P ratio of 1 in French scenarios using equilibrium modeling with price-taker assumptions, suggesting that RE variability compensates for price dampening effects from multiple FOs. However, our endogenous price modeling reveals that high-powered systems, i.e., low E2P ratios, can face significant profitability challenges due to market price impacts, contradicting studies that ignore these feedback effects. While [62] also employ ML for electricity price prediction followed by dynamic programming for pumped hydro storage dispatch optimization, they neglect system-wide impacts of storage operation. Our integrated approach captures these crucial feedback mechanisms, revealing how individual FO decisions collectively influence market dynamics and profitability. Other literature suggests BSS costs remain too high for widespread deployment, with profitable operation limited to approximately 4% of peak demand [63]. In our study investigating the German market zone in a 2030 scenario, this constraint would translate to about 4.7 GWh total capacity. Our analysis reveals scenarios where FOs are profitable beyond this point, indicating that cost reductions and favorable market conditions could enable larger-scale deployment. However, we clearly observe cannibalization effects in scenarios with FO capacities well below the recent levels of storage grid connection requests sent to the German TSOs.

Our presented workflow couples ML with electricity market modelling, and confirms that incorporating future covariates significantly improves prediction accuracy, thus increasing storage revenue potential, consistent with findings by [51]. The selection of input data and hyperparameters proves essential for forecast accuracy [64], while the choice of the actual forecasting method clearly impacts simulated electricity prices, storage activity, and resulting profits [65]. These insights underscore the critical importance of high-quality price forecasting for optimal FO operation, though comprehensive analysis of forecasting quality and its impact on competitive FO performance remains an area for future enhancements.

As with other studies on energy systems analysis [66], significant challenges stem from uncertainty regarding future system design and scenario parameters. Our analysis employs a full simulation year capturing hourly to seasonal variability while neglecting inter-annual weather variations, limiting the robustness of our profitability assessments. Furthermore, no variations of other parameters that impact the electricity prices were performed here, e.g., emission allowance prices, fuel prices, electricity demand, hydrogen demand, the power plant park, or market designs. For a comprehensive investment assessment, appropriate variations of these parameters should be considered. Regarding the market design, some studies suggest that RE and FO-dominated markets can function within energy-only market designs [67], others argue that wholesale revenues alone may inadequately incentivize necessary FO capacity expansion [68]. It is important to keep future studies up to date with market design developments. The dynamic nature of energy system transformation necessitates continuous model development [69]. To address this requirement, we have put strong efforts in research software development by adhering to FAIR principles (Barker et al. 2022). Our open modelling workflow enables further expansion and adaptation by the research community, promoting reproducibility and facilitating extensions.

5 Conclusion

This paper advances the understanding of flexibility option profitability in future energy systems through a novel methodological approach that addresses critical gaps in existing literature. By coupling machine learning based electricity price forecasting with agent-based electricity market simulation, we provide a new assessment technique of flexibility option profitability that endogenously captures market price impacts and competitive dynamics. Our analysis, based on the Ariadne scenario targeting the German market zone, reveals several key insights for flexibility option deployment and investment opportunities. We demonstrate that the most profitable energy-to-power ratios for homogeneous battery storage systems fall between 4-8, differing from ratios identified in studies that treat electricity prices as exogenous inputs. This finding highlights how market price feedback fundamentally affects technical specifications, making operational strategies which account for price impacts necessary, especially for high-powered systems. The investigation of heterogeneous flexibility option competition reveals critical saturation effects where increased deployment leads to revenue cannibalization. When total flexibility option capacity triples from 2 GWh to 6 GWh, total market revenue increases by only a factor of 2.1, demonstrating diminishing returns that could significantly impact investment viability. Risk affinity when optimizing operational schedules influences revenue generation and charge cycle frequency, thereby affecting both profitability and storage lifetime considerations.

Beyond addressing the methodological limitations outlined previously, future research should prioritize two critical areas to enhance model comprehensiveness. First, incorporating intraday market representation would enable comprehensive cross-market revenue assessment for flexibility options. Current focus on day-ahead markets provides valuable baseline insights but may underestimate total profitability by neglecting shorter-term trading opportunities where flexibility providers can capitalize on real-time supply-demand imbalances. This extension would be particularly relevant as intraday markets grow in importance within high renewable energy systems, where forecast errors and variability create additional arbitrage opportunities. Second, expanding the analysis of competitive dynamics between heterogeneous flexibility options represents an important research avenue. Extended analysis incorporating diverse operational strategies, energy system variations, and inter-annual weather time series would yield deeper understanding of future market dynamics. This would contribute to how different flexibility technologies, including battery storage systems, pumped hydro storage, demand response, and sector coupling, interact, compete, and potentially create synergistic effects under varying market conditions.

Acknowledgements

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Code and data availability

All code used to run this analysis is openly available in [38, 42, 43, 50]. The data is based on [39].

Appendix

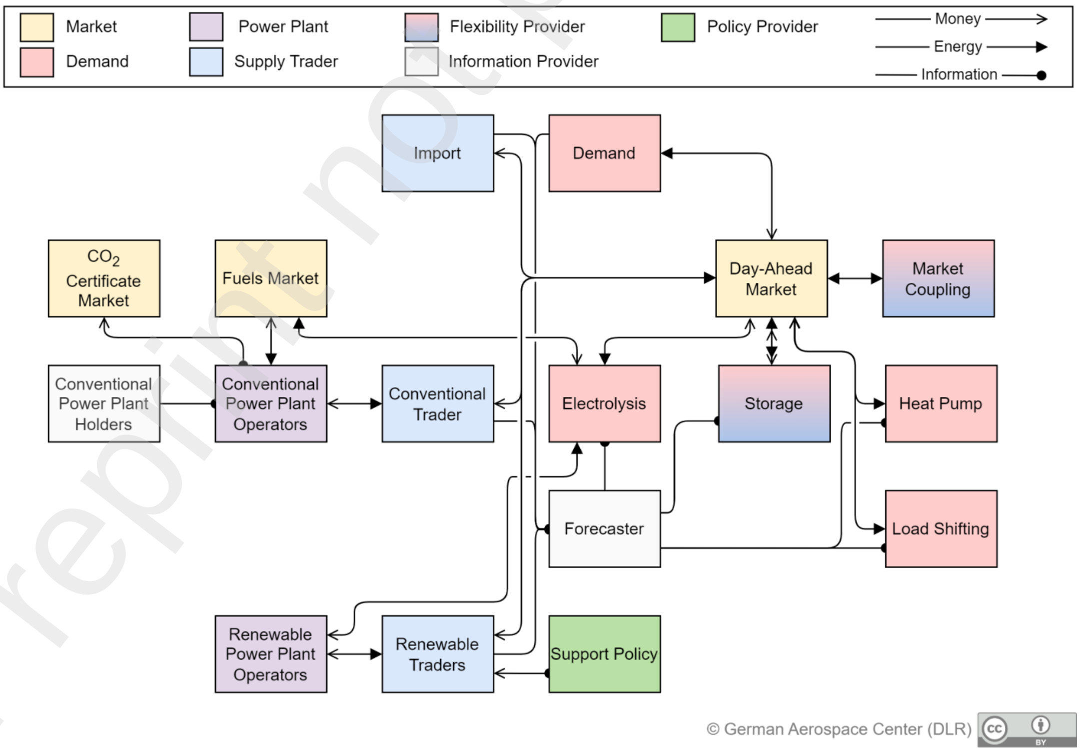

Figure 12: AMIRIS electricity market model.

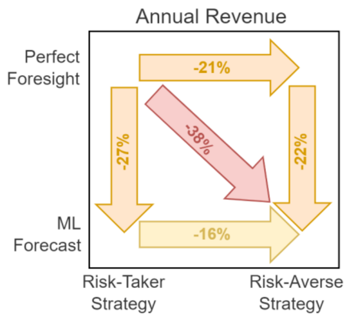

Figure 13: Storage revenue change based on applied strategy and forecast type.

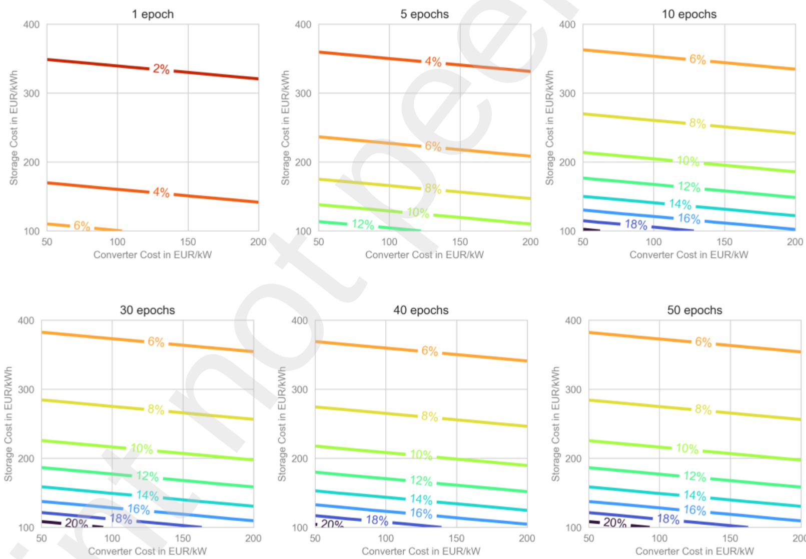

Figure 14: Impact of training length on return of investment for a 6 GW, 32 GWh battery storage system.

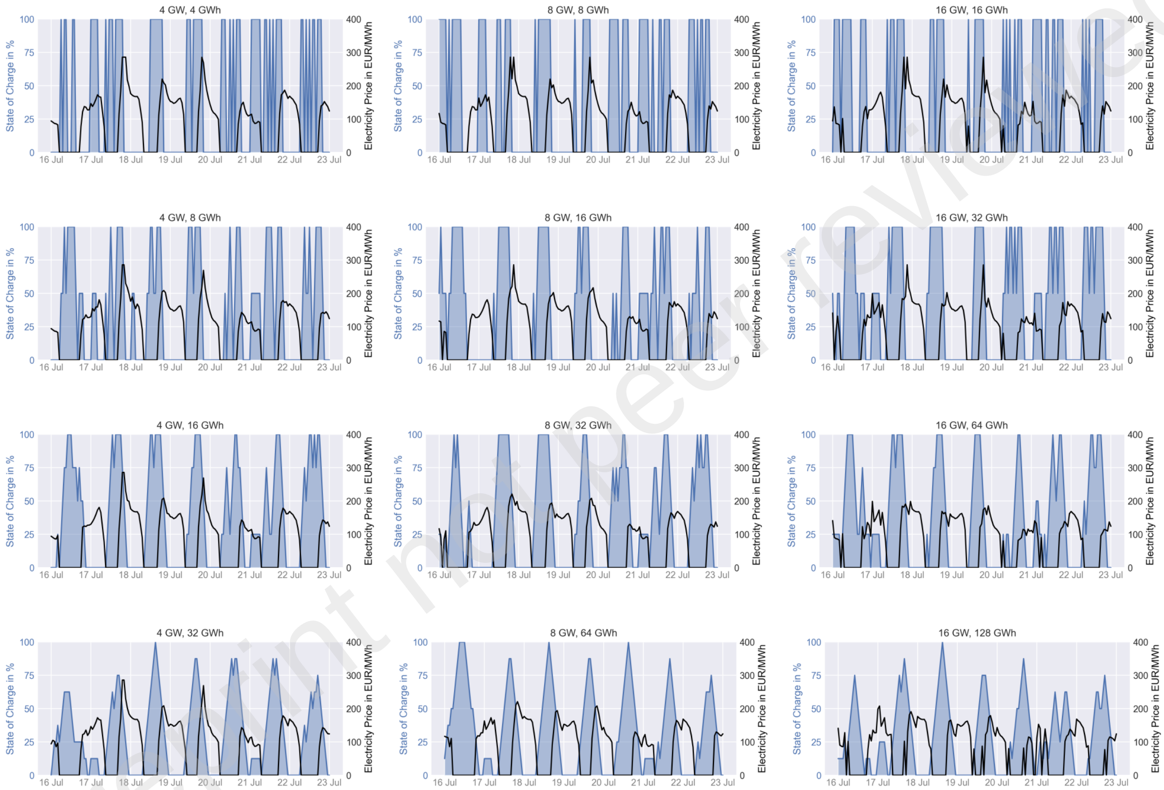

Figure 15: State of charge (blue area) and electricity price (black line) during a single week revealing behavior and impact of different storage systems.

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3.5 Synthesis

The presented publications form a coherent body of research that systematically investigates the economic feasibility of FOs from multiple complementary perspectives. This research progresses from an initial exploration of individual technologies to comprehensive analyses that include system-wide competition effects. Each publication addresses the limitations identified in previous work, while pursuing the overarching research targets defined in Section 1.2. The publications are divided into "main papers" (Sections 3.1 to 3.4), "supplementary papers" (Appendix A), and "supplementary non-peer-reviewed papers" (Appendix B). Table 3.1 shows the individual contributions of each paper to the research targets. This section also places the presented publications in context and demonstrates their systematic contribution to a unified research narrative.

Table 3.1: Contribution of publications to research targets.

		Main paper				**Supplementary Paper**						
		Peer-review									**None**	
	Target	I	II	III	IV	A1	A2	A3	A4	A5	B1	B2
1.1	*Strategies*[3]		x		x					x		
1.2	*Parameters*[4]	x	x		x					x		
1.3	*Competition*[5]			x	x							
2.1	*Features*[6]	(x)	x	x	x	x	x		x	x		
2.2	*Open science*[7]		x	x	x	x	x	x	x		x	x

[3]Identify reliable operational strategies for FOs in future electricity market scenarios.
[4]Evaluate how technical specifications influence FO refinancing potential.
[5]Quantify the impact of FO competion on their profitability.
[6]Expand ABM to capture individual FO economics and impact on system dynamics.
[7]Develop modular open-source software packages.

3.5.1 Individual technology analysis

In Paper I, I introduced a representation of the aFRR in AMIRIS, allowing a battery storage operator to generate multi-market revenues beyond DAM arbitrage. This work investigates the influence of storage parameters on the revenue potential for a future energy system. I found that revenues for FO operators across the two simulated markets are highest for short-term orientated systems. However, explicit feedback from FO operation on the overall energy system was not considered, a major limitation addressed in subsequent papers. Back-testing was performed for the German market zone in 2019 achieving good agreement with historical market data. This paper allowed for identifying the most promising technical specifications that provide the highest revenue, directly contributing to research target 1.2. It also advances target 2.1 by extending AMIRIS with a mechanism to include revenues from the aFRR market.

Paper II focuses on high-temperature heat storage, namely Carnot batteries, rather than battery storage systems. To extend the analysis to endogenously modelled system-scale storage systems, I linked the ESOM REMix (Wetzel et al. 2024) with AMIRIS. The optimised power plant park from REMix is used as scenario parameterisation for AMIRIS to investigate the economic potential of a Carnot battery storage. For this model coupling, I developed the open workflow iog2x (Nitsch, Schimeczek, Wetzel, et al. 2023), a tool based on the open workflow manager ioproc (Fuchs et al. 2020). Like the first main paper, this work adds insights to research targets 2.1 and 2.2. However, this research focuses on energy system with much higher RE shares and concentrates on Carnot battery storage systems providing flexibility. By revealing how the operational strategy and technical specifications of Carnot battery storage impact revenue potential, this paper advances research targets 1.1 and 1.2 respectively.

3.5.2 Methodological innovation for competition analysis

While these first two main papers (Section 3.5.1) provide valuable information on the operation of two dedicated FO technologies, battery storage and Carnot battery storage, they share important limitations. Both model only a single FO in the system, a small-scale single battery storage (Paper I), or a large-scale Carnot battery storage (Paper II). Additionally, I did not explicitly model competition among FOs, thus neglecting potential cannibalisation effects that can limit the profitability of such systems. Endogenous competition between agents is challenging to model in ESA, see elaboration to Figure 2.6, but provides a critical factor for better assessing the FO performance in future energy systems. Therefore, I worked to represent such competing behaviour on DAMs by enhancing the internal price forecasting mechanism in AMIRIS. Specifically, I first conducted methodological advances in the field of time series forecasting (Paper III), and then applied the newly developed methodology in a highly relevant case study for Germany in 2030 (Paper IV).

Paper III addresses novel electricity market dynamics introduced by changing power plant portfolios in future ESA scenarios. It advances the field of time series forecasting, which is essential for investigating potential cannibalising effects in ABM ESA models. In particular, the electricity price forecasts used by FOs for dispatch planning are improved to reflect future energy systems dominated by REs. I developed the scenario generator AMIRIS-Scengen (Nitsch, Frey, and Schimeczek 2023) to generate a wide range of future electricity market scenarios. These serve as synthetic training data for the newly developed ML package focapy (Nitsch 2023b). My results demonstrate that ML-based electricity price forecasts are highly capable of being used in energy transition scenarios with changing DAM price dynamics. Therefore, this paper contributes to research target 1.3 by enabling simulation of FO competition. It also brings new features and open software to ESA (research targets 2.1 and 2.2) with AMIRIS-Scengen and focapy, powerful tools enabling comprehensive analysis of current and future energy systems.

3.5.3 Integrated dynamics, flexibility competition and saturation effects in future electricity markets

Finally, Paper IV combines the previous works. It applies the enhanced electricity price forecasting from Paper III and combines it with the approach to assess economic potential used in the first two papers (Section 3.5.1). To achieve this, I extended AMIRIS with a new forecasting agent PriceForecasterApi (Nitsch 2025b) and linked it to the new external forecasting model AMIRIS-PriceForecast (Nitsch and Schimeczek 2025a). Then I assessed the economic potential of various FOs under different storage strategies (research target 1.1), technical parameters such as power and capacity (research target 1.2), while also accounting for competition effects by other FOs (research target 1.3). The results demonstrate that competitive FOs can be modelled using ABM. I quantified the cannibalisation among various homogeneous and heterogeneous FOs while explicitly considering their price impacts on the DAM. This represents a substantial advancement compared to the existing literature, as it not only contributes to improved ESA modelling capabilities, but also addresses pressing energy transition challenges by investigating FO market potential. Through open software packages, I also provide valuable extensions to the field in line with research targets 2.1 and 2.2.

3.5.4 Supplementary research contributions

In addition to these four main papers, my work resulted in seven supplementary research papers, five of them peer-reviewed publications and four of them lead authored by myself.

The first supplementary paper in Section A.1 is a journal article (Schimeczek, Nienhaus, et al. 2023) on AMIRIS, which is the central ESA model applied and extended in this thesis. The publication includes not only a manuscript describing the main features and scope of AMIRIS, but also peer review of the source code. The comprehensive functionality of the model combined with high software development standards contributes directly to research targets 2.1 and 2.2.

Similarly, the second supplementary paper (Nitsch, Schimeczek, Frey, et al. 2023) in Section A.2 features FAME-Io, an essential package of the simulation framework FAME (Schimeczek, Nitsch, et al. 2020), which is the foundation of AMIRIS. FAME-Io can be used to parameterise ABM in the ESA domain. It compiles binary input files for FAME-based simulation models and converts binary output files to human-readable CSV files. As the previous publication on AMIRIS, this publication includes peer-reviewed source code. Modular design, state-of-the-art software development principles, high test coverage, and extensive documentation contribute significantly to research targets 2.1 and 2.2.

The third supplementary paper (F. Maurer et al. 2024) in Section A.3 compares AMIRIS and ASSUME (Harder et al. 2025). It provides detailed evaluation of these two state-of-the-art ABMs and back-testing on historical German DAM data. The latter is available as part of the AMIRIS-Examples data package (Nienhaus et al. 2025). Both, model benchmarking and open input data, add to research target 2.2.

A methodological addition to AMIRIS is the fourth supplementary paper (Nitsch and El Ghazi 2023) described in Section A.4. It implements a market coupling agent that allows users of AMIRIS to extend the spatial scope beyond a single market zone. Power transmission to neighbouring market zones can also be interpreted as flexibility to the system, thus contributing to the integration of large shares of intermittent RE generation (Nitsch, Scholz, et al. 2023). This publication and its open source code are attributed to research targets, namely 2.1 and 2.2.

The fifth and last peer-reviewed supplementary paper (Nitsch and Wetzel 2022) in Section A.5 is a preliminary study to the second main paper (Nitsch, Wetzel, et al. 2024). It includes an analysis of the economic potential of power-to-heat-to-power storage systems, which was then extended to a full paper. Similarly to the second main paper, this article contributes to research targets 1.1, 1.2 and 2.1.

Finally, there are two supplementary papers which have not been peer-reviewed. The first in Section B.1 consists of back-testing AMIRIS to the Austrian DAM in 2019 (Nitsch, Schimeczek, and Wehrle 2021). This publication contributes to research target 2.2 by providing an open data configuration for AMIRIS, thus promoting a better understanding of the accuracy of this ESA model. The second paper (Frey, Nitsch, et al. 2024) in Section B.2 presents a unique approach to enrich ESA models, in particular FAME-Io and AMIRIS, with metadata. This benefits model coupling and ensures better comparability between different models, both at human and machine levels. Therefore, the developments achieved in this publication contribute to the open science principles described in research target 2.2.

Figure 3.1 shows all publications related to this thesis and their accompanying research contributions to the ESA domain, particularly ABM of electricity markets. Research contributions include dedicated models and packages, new agent classes in AMIRIS, open data sources, and model workflows. The presentation follows the previously introduced separation into "main papers" (Sections 3.1 to 3.4), "supplementary papers" (Appendix A), and "supplementary non-peer-reviewed papers" (Appendix B). Solid outlines indicate first-author papers, while dashed outlines indicate co-authored papers.

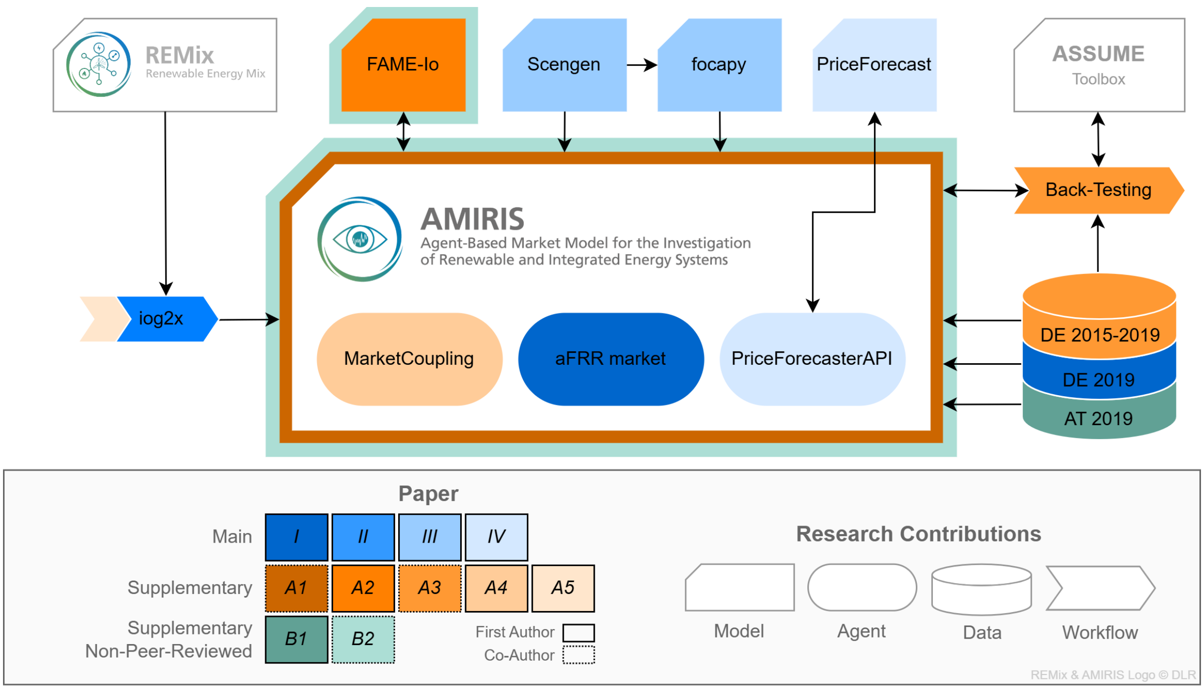

Figure 3.1: Publications and their research contributions.

4 Discussion and conclusions

This chapter puts my findings in context with recent literature in Section 4.1. The limitations of the applied modelling approaches and their potential impact on the results are discussed in Section 4.2. Section 4.3 concludes the thesis by summarising the contributions to the individual research targets while Section 4.4 outlines potential future research avenues.

4.1 Contextualisation to existing literature

This section positions my research findings within the broader academic literature, demonstrating how my work contributes to existing knowledge while acknowledging areas of convergence and divergence with current research.

The literature consistently demonstrates that refinancing flexibility option (FO) through arbitrage on day-ahead markets (DAMs) is challenging under current market conditions. Specifically, research indicates that arbitrage across European DAMs is insufficient for economic viability, requiring either substantial cost reductions or multi-market participation (Hu, Armada, and Jesús Sánchez 2022). Coordinated bidding across balancing reserves, intraday markets, and DAMs, on the other hand, substantially increases profitability (Miskiw, Kraft, and Fleten 2025). Another study found that optimal market participation depends on specific technical specifications, with pumped hydro storage benefiting most in multi-markets, battery storage in intraday markets, and hydro reservoirs in DAM (Löhndorf and Wozabal 2023). While single-market operation can achieve profitability, overall revenue is maximised through multi-market arbitrage (Agrela, Rezende, and Soares 2022), with some studies reporting up to five-fold increases in net present value for multi-market battery storage applications (Sorourifar, Zavala, and Dowling 2020). Research emphasises that trading in sequential electricity markets requires sophisticated strategies that account for associated risks (Kraft et al. 2023), validating the emphasis on FO strategies applied in this thesis.

The literature regarding optimal FO configurations matches the evolution of findings across this thesis. Paper I supports the common finding that low energy-to-power (E2P) ratios are most profitable for battery storage systems (Schmidt and Staffell 2023). However, Paper IV reveals that medium-term E2P ratios become more profitable when the collective impacts of multiple FOs are considered endogenously, suggesting that isolated analysis may underestimate the value of longer-duration storage. This shift in results can be explained by substantially higher renewable energy (RE) capacity shares assumed in Germany's 2030 scenario of Paper IV compared to Paper I. Germany's current power plant capacity already surpasses the RE levels modeled in Paper I, creating fundamentally different price dynamics and revenue opportunities between the two studies. Furthermore, the hourly DAM clearing interval prevents short-duration storage from fully exploiting intra-hour price spreads, potentially favoring mid-range E2P systems. Incorporating additional short-term markets could alter these results and represents an important direction for future research.

The literature confirms the critical importance of electricity price forecasting quality, with studies demonstrating that input data selection and hyperparameter choices significantly impact forecast accuracy (Keles et al. 2016). These findings are directly supported by the comprehensive evaluation presented in Paper III. Research on other agent-based models (ABMs) like PowerACE (Weiskopf et al. 2024) confirms that forecast quality substantially affects energy systems analysis (ESA) simulation results (Fraunholz et al. 2021). Other studies document revenue increases directly attributable to improved forecast quality (Amor, Möbius, and Müsgens 2024). Pre-trained models, which can be used without scenario-specific training (Ekambaram et al. 2024), could help overcome some of the forecasting challenges identified in this research. These promising methodological developments might improve the capabilities demonstrated in Paper III.

The literature acknowledges the diversity of electricity market modelling approaches, each with distinct strengths and limitations (Ringkjøb, Haugan, and Solbrekke 2018). This thesis leverages one of the key strengths of ABM (Klein, Frey, and Reeg 2019) by endogenously linking different modelling domains. This capability is demonstrated through the integration of machine learning (ML)-based forecasts in Paper IV.

Existing research also emphasises the critical importance of accurately modelling electricity markets and price variability, particularly when evaluating FOs engaged in arbitrage (Ward, R. Green, and Staffell 2019). However, the literature acknowledges the fundamental challenge that far-future scenario validation is impossible, as the energy transition requires immediate action (Ringkjøb, Haugan, and Solbrekke 2018). Wholesale market design changes may significantly alter revenue potential for market actors (Silva-Rodriguez et al. 2022). Furthermore, increasing RE production may amplify electricity price volatility in Germany through 2030 (Liebensteiner, Ocker, and Abuzayed 2025), creating both opportunities and challenges for FO deployment. Model comparison approaches, such as in Paper A3 or for other electricity market models (Ruhnau, Bucksteeg, et al. 2022), emphasise the importance of rigorous backtesting and adherence to open science standards. Consistent with established considerations in ESA (Pfenninger, Hawkes, and Keirstead 2014), the results should be interpreted not as predictions but as scenario analyses providing insights into general sensitivities and trends, as acknowledged in the following limitations section.

4.2 Limitations

The following limitations must be acknowledged when interpreting the results of this thesis and their broader applicability.

As with many ESA, this research focuses on rapidly evolving energy systems where fundamental assumptions may be challenged by unforeseen developments. Several key uncertainties could significantly impact the findings. The pace of RE deployment, particularly photovoltaic installations, continues to exceed projections, potentially altering the market dynamics and price patterns that form the basis for FO revenue calculations (Creutzig et al. 2017). Unexpected cost reductions in existing technologies could reshape the competitive landscape. Similarly, external shocks as the 2022 energy crisis can fundamentally alter energy market dynamics in ways that historical data, but also most scenarios cannot anticipate (Ruhnau, Stiewe, et al. 2023). Such disruptions can create both opportunities and challenges for FO deployment that are not captured in the modeled scenarios. Further, the presented scenarios mostly focus on the near-future, such as 2030. The dynamics of net-zero energy systems (Azevedo et al. 2021), which are targeted for 2040 and beyond, may be very different and require further detailed study, such as endogenous modelling of power plant investment (Willeke, Kochems, and Nienhaus 2025).

My work does not explicitly account for the impacts of climate change on energy system operation. Climate change affects both RE generation profiles and electricity load patterns, such as by novel RE generation time series or through shifting heating and cooling demand. Additionally, climate-related infrastructure disruptions could fundamentally alter the value proposition for flexibility services, potentially making decentralised FOs attractive and essential for system resilience. These evolving climate impacts represent an important limitation in long-term FO economic assessments.

My findings do not fully capture the flexibility potential from sector coupling applications across households, industry, heating, and transport sectors. There is a significant uncertainty to which extent these cross-sectoral FOs can be mobilised in order to provide flexibility on a system-level (Gaafar et al. 2024). This aspect could certainly reshape the competitive dynamics modeled in this research and ultimately impact the profitability of individual FOs. Although the methodological approaches developed can be applied to multiple market zones, this work focuses primarily on the German energy system. The energy transition progresses at different rates in neighbouring market zones, which can create novel cross-border effects that are not captured in the analysis. Market coupling mechanisms provide some representation of these interactions, but the detailed modelling of heterogeneous transition pathways across interconnected European markets remains beyond the scope of this research.

The analysis presents a limited picture of FO revenue potential due to its primary focus on DAM simulation. Except for Paper I, which incorporated a representation of an automatic Frequency Restoration Reserves (aFRR) market, the research does not employ a multi-market approach that would capture a wider spectrum of revenue opportunities available to FOs. Existing literature suggests that overall revenue increases when multi-market arbitrage across markets is pursued (Agrela, Rezende, and Soares 2022). However, consistent with the cannibalisation findings presented in Paper IV, these additional revenue streams would likely face similar profitability limits as FO market penetration increases and competition intensifies (Deman et al. 2025). It is also worth noting that the electricity market modeling in AMIRIS does not fully capture the possibilities of strategic bidding, such as portfolio effects or complex bids. With increasing shares of FOs, this could become an important aspect for future studies (Signer et al. 2025).

Ongoing discussions about electricity market design adaptations could also substantially impact FO economics. Besides the ongoing harmonisation from hourly to 15-minute DAM clearing intervals (European Parliament and Council of the European Union 2019), discussions are about market zone splitting (Mörtenkötter et al. 2025) or transition to nodal pricing (Knörr, Bichler, and Dobos 2025), new RE remuneration schemes (Schlecht, C. Maurer, and Hirth 2024), dynamic grid tariffs (Stute and Klobasa 2024), or complete reworks of market design, such as capacity markets (Ölmez, Ari, and Tuzkaya 2024). Each of these modifications could fundamentally affect the revenue situation for FOs. Modellers should also be aware of the biases inherent in any of the presented ESA model, which is especially important when using the ML-based electricity price forecasts.

4.3 Conclusions

The goal of this thesis was to contribute to a better understanding of FOs in energy systems with high shares of RE. Through systematic application of ABM to investigate electricity markets, this research provides significant contributions to the identified research targets while advancing both methodological capabilities and practical insights for the energy transition.

Research target 1.1 Identify operational strategies for FOs that perform reliably in future electricity market scenarios with increasingly high RE shares The analysis of operational strategies reveals that FO performance in RE-dominated systems depends critically on both individual strategy selection and the broader system context with significant implications for system-wide deployment. Paper II establishes an understanding of operational strategy impacts by comparing profit maximisation versus system cost minimisation approaches for a single large-scale FO accounting for its own price impacts. As anticipated, profit maximisation generally outperforms system cost minimisation in terms of economic revenue potential when the storage system is the sole large-scale FO in the system. However, the research also reveals a dependency on the storage system's role within the energy system. The analysis demonstrates that the storage system achieves higher revenue per installed MW when alternative ways of providing flexibility, such as grid extension, are unavailable. This finding can be interpreted as an early indication of cannibalisation effects, where the presence of competing flexibility sources reduces individual FO profitability. The strategic implications suggest that FO operational strategies must account not only for their own technical capabilities but also for the availability and deployment of alternative system flexibility resources.

Paper IV advances the understanding of operational strategies by analysing their performance under competitive conditions with multiple FOs. The research demonstrates that storage strategy selection has substantial impacts on both overall revenue generation and operational characteristics such as charging cycles. Quantitatively, risk-averse strategies achieve approximately 20% lower profits compared to risk-taking strategies. The competitive analysis focuses primarily on risk-taking strategies to investigate cannibalisation effects. A fundamental challenge emerges when FOs collectively influence market prices yet possess only limited awareness of their own price impacts when optimising their individual strategy. This poses a problem, particularly for short-duration storage systems (low E2P ratios) that can lead to significant cumulative market effects. These short-duration systems would benefit substantially from more sophisticated operational strategies that explicitly account for their collective price impacts during dispatch decisions.

The findings reveal that reliable FO operational strategies for high RE scenarios must incorporate several key elements, and that a trade-off must be struck between maximising revenues and minimising risk. This includes enhanced price impact awareness that account for their own market influence, and approaches that respond to changing competitive conditions as FO market penetration increases. Furthermore, the research suggests that operation of FOs cannot be considered independently of technical specifications and market structure. The interaction between strategy selection, technical parameters (particularly E2P ratios), and competitive environment creates challenges that traditional approaches accounting for only single or few FOs cannot adequately address. The evolution from individual optimisation (Paper II) to competitive analysis (Paper IV) demonstrates that operational strategies that appear optimal in an isolated analysis may prove suboptimal when deployed at scale.

Research target 1.2 Evaluate how technical specifications (e.g., capacity & power) of FOs influence refinancing potential under varying cost assumptions The progression across papers demonstrates that optimal technical configurations depend critically on market context and competition levels. Paper I establishes foundational insights for a single FO system operating in a multi-market setting. The analysis reveals that small E2P ratios perform optimally for DAM arbitrage with aFRR market participation, as these configurations best exploit short-term price volatility across both markets. The research quantifies that round-trip-efficiency (RTE) improvements of 1% translate to approximately 2.5% additional revenue, highlighting the high impact of technical performance on economic outcomes. However, this analysis focuses solely on revenue generation without comprehensive cost assessment, limiting insights into actual refinancing potential.

Paper II shifts focus to system-scale storage technologies, specifically Carnot batteries, revealing that storage costs represent the most critical factor for revenue generation. The analysis identifies that energy specific investment costs should be below 35 EUR/kWh for economic viability. This marks an ambitious target that highlights the challenge of making large-scale high-temperature storage economically competitive. RTE improvements emerge as a valid secondary optimisation target, consistent with Paper I findings. Importantly, the revenue situation proves sensitive to scenario assumptions, particularly regarding competing flexibility, such as grid expansion, which directly affects the Carnot battery's market position and revenue potential.

Paper IV provides the most comprehensive insights by analysing technical specifications within a competitive market scenario that also account for endogenous price impacts. This study reveals different results to those found in earlier studies. In contrast to Paper I's conclusion favoring low E2P ratios, the competitive analysis demonstrates that higher E2P ratios tend to be more profitable. This reversal occurs because longer-duration storage can participate actively across more hours of operation, providing greater market flexibility. The competition analysis reveals that the number of profitable arbitrage hours remains similar across different scenario configurations, but higher E2P ratios enable storage systems to capture value across extended periods. However, the research identifies a profitability plateau as long-term storage systems are surpassed by medium-term configurations. This suggests that E2P ratios have to be aligned with the existing electricity price dynamics in order to effectively provide operational flexibility. Consistent with findings in Paper II, storage cost reductions generally provide greater profitability improvements than converter cost reductions, emphasising that energy storage capacity costs are a critical parameter to FO economic viability. The competitive analysis further reveals that either long system lifetimes of at least 10 years or significant cost reductions are necessary for profitability when FOs compete with other market participants.

Collectively, these findings demonstrate that optimal FO technical specifications are not static parameters but depend critically on market structure, competition levels, and system-wide deployment scenarios. The evolution from favoring short-duration storage systems in individual analysis to medium-duration systems in competitive environments illustrates the importance of considering market context in technology development and investment decisions. The consistent emphasis on storage cost reduction across multiple studies provides clear guidance for research and development priorities in FO technologies.

Research target 1.3 Quantify the impact of increasing market penetration of competing FOs on their profitability in DAM

The evolution towards understanding competition effects represents a central achievement of this thesis. Paper I analysed variants of a single small-scale price-taking storage system, providing valuable insights into revenue potential while explicitly acknowledging the limitation of not accounting for competition among FOs. Paper II advanced this research by examining a single grid-scale storage system that accounts for its own price impacts, yet still did not capture interactions among multiple FOs, thus this critical gap remained. Recognising this limitation, Paper III advanced time series forecasting capabilities for ABM in energy transition scenarios. This work established the technical foundation necessary to investigate competition among FOs by enabling accurate price forecasts in RE-dominated markets with fundamentally different dynamics than historical years. The methodological innovations in this regard are then continued in Paper IV, where extensions to AMIRIS, particularly the design and implementation of AMIRIS-PriceForecast, enable simulation of competing FOs. This is achieved by endogenously modelling price feedbacks from multiple FOs which affect their revenue potential. This capability allows, for the first time, the analysis of both homogeneous and heterogeneous

FOs technologies competing in future energy transition scenarios.

The results reveal significant cannibalisation effects that have strong implications for FO deployment strategies. Once a certain market penetration threshold is reached, dependent on the specific power and capacity specifications of the FO technologies, both collective and individual revenues decline significantly. This finding directly challenges current trends and interest for large-scale FO deployments which often neglect their collective feedback on DAM prices. My results thus contribute critical insights for policy and investment decisions. Most significantly, my analysis suggests that connection requests for grid-scale storage of more than 200 GW submitted to German transmission system operators (Enkhardt 2025) are very likely far beyond what can be refinanced from DAM arbitrage alone. This conclusion has immediate practical relevance for energy system planning and highlights the importance of considering competition effects in FO deployment strategies.

Research target 2.1 Expand ABM to simultaneously capture both individual FO economics and their collective impact on system dynamics
This thesis achieves a fundamental advancement in ABM capabilities by systematically developing the methodological foundations necessary to model both individual FO economics and their collective system-level impacts. The progression across papers demonstrates a clear evolution from isolated individual analysis to comprehensive multi-agent competition modelling. Paper I introduced a aFRR market representation as an external optimisation model which uses AMIRIS simulation results. Agents bid with their opportunity costs across multiple markets, thereby facilitating multi-market revenue simulation. However, this initial implementation has some critical limitations, such as missing feedback from the external aFRR model to the DAM, and the focus on a single small-scale storage device.

Paper II addressed the feedback limitation through integrated FO implementation that captures system-scale storage impacts on market dynamics. By enabling FOs to account for their own price impacts, the agent aims to maximise profits or minimise total system cost. This establishes a closed feedback loop that simultaneously analyses individual economics and system-level storage impacts which is a crucial advance towards realistic FO modelling. The automated model coupling linking energy systems optimisation model (ESOM) and ABM further enhances this contribution, addressing the complementary limitations where AMIRIS cannot define cost-optimal power plant parks while REMix cannot fully capture market dynamics. However, the challenge of modelling multiple competing FOs remained unresolved (see Section 2.2.1.2). Paper III provides the methodological breakthrough that enables endogenous competition simulation. FOs require sophisticated price forecasts for schedule optimisation, but traditional approaches fail when multiple FOs act on identical signals. The packages focapy and AMIRIS-Scengen present powerful tools for this analysis. By quantifying errors of ML-based electricity price forecasts specifically in future energy system scenarios, this work proves that ML can provide enhanced and accurate electricity price forecasts. This implementation therefore represents a fundamental methodological cornerstone that finally prepares AMIRIS to model competing FOs.

Paper IV applies all these methodological advances by implementing ML-based price forecasting for FO agents within AMIRIS. This integration achieves the primary objective of analysing FO competition modelling while capturing their impact on DAM. This enables realistic analysis of future energy transition scenarios with increasing FO market penetration. Further emphasis was placed in the general software publications of AMIRIS (see Paper A1) and FAME-Io (see Paper A2). Through this systematic progression, the thesis successfully transforms AMIRIS from a model capable of analysing only isolated individual FOs to a comprehensive platform that simultaneously captures individual economics and collective system dynamics. This advancement enables, for the first time, realistic ABM assessment of FO deployment accounting for both technical performance and market competition effects.

Research target 2.2 Develop modular open-source software packages to enhance reproducibility and facilitate comparative assessment of FOs

This thesis makes substantial open science contributions to the ESA modelling community through consistent development of modular software packages, enhancement of existing tools, and provision of data. The progression across the presented papers demonstrates increasing sophistication in software development practices and community engagement. In Paper I, a pre-FAME instance of AMIRIS was used. Although, this version is not directly compatible with the current versions of the model, it contributed important foundational elements, such as backtesting data for the German DAM in 2019, which is now part of the open AMIRIS-Examples (Nienhaus et al. 2025). Similarly, supplementary Paper B1 extended this data contribution with Austrian DAM backtesting data for 2019, enhancing the empirical validation resources available. Paper II marked a significant advancement in open-source contribution quality as it applies a fully open AMIRIS model instance. Additionally, the iog2x workflow provides a generic coupling mechanism that can convert any model producing GDX result files, such as REMix, to be accessible to AMIRIS. This tool extends beyond the specific use case in the paper to enable broader model coupling applications (Sarfarazi, Sasanpour, and Cao 2023; Torralba-Díaz et al. 2024; Kochems et al. 2024).

Paper III holds two major software contributions through two comprehensive packages. AMIRIS-Scengen provides a flexible scenario generator for AMIRIS that serves multiple purposes. It allows multi-scenario analysis and also generates training data sets for ML applications. focapy delivers a complete software package for training and inference in ML time series prediction. It fills a critical gap in the ESA domain, as it is targeted for users applying and working with time series in ESA models. Paper IV features comprehensive AMIRIS model extensions. The AMIRIS-PriceForecast extension makes time series forecasts available during AMIRIS model runtime, therefore fundamentally improving the model's forecasting capabilities. It is implemented with a flexible FastAPI-based interface that enables use both within and outside the AMIRIS ecosystem. The high performance of these tools enables the demanding simulation of competition among multiple FOs, opening new research possibilities for the community.

Beyond the main papers, the supplementary contributions demonstrate sustained commitment to research software and community building. Given that modelling FOs is a critical challenge for many ABM (Schimeczek, Khanra, and Signer 2025), these contributions address pressing community needs. The model comparison with ASSUME provides valuable benchmarking insights (see Paper A3), while the market coupling algorithm enables endogenous simulation of multiple market zones in AMIRIS (see Paper A4). I also followed community engagement efforts (Nitsch, Schimeczek, Nienhaus, et al. 2025), including multiple conference presentations[1], enhanced and peer-reviewed model documentation (see Paper A1), and establishment of a weekly open forum[2]. These initiatives have fostered a growing external community and attracted external code contributions, demonstrating the practical value and adoption of the developed tools. Furthermore, the FAME framework provides a powerful and flexible software suite for ABM in the ESA domain. My specific work in Paper A2 on FAME-Io follows high software development standards and findable, accessible, interoperable, reusable (FAIR) principles, with recent enhancements in Paper B2 including metadata capabilities that improve interoperability and scientific reproducibility. Collectively, these software contributions represent a comprehensive selection of tools that not only enable the specific research presented in this thesis but also provide the community with robust, well-documented, and interoperable software packages that will facilitate future research.

[1] `https://zenodo.org/communities/amiris/`

[2] `https://gitlab.com/dlr-ve/esy/amiris/amiris/-/wikis/Community/Support`

4.4 Outlook

The research presented in this thesis opens up several avenues for future investigation, both in terms of content and methodological focus. Future work should examine the impact of FOs at different grid levels, in particular the interaction between transmission system operators and distribution system operators. The contribution of FOs, e.g. large-scale battery storage systems, to reducing redispatch costs could also be another promising research direction. This would include the optimal allocation of battery resources in the electricity grid and their systemic impact, such as system costs and grid stability. Investigating the regulatory aspects that either enable or constrain the participation of batteries in system services could also be an important research direction. While energy-only markets have traditionally dominated European electricity systems, the increasing penetration of RE has intensified discussions on the need for explicit capacity remuneration mechanisms (Strbac et al. 2021). Changes in market design, in particular the introduction of a capacity market, demand a thorough investigation of their impact on FOs, especially on their investment and operation and how these changes are implemented across different market zones (Bucksteeg, Spiecker, and Weber 2019). The interactions between such mechanisms and the provision of flexibility require further in-depth analysis. Finally, expanding the range of scenarios would allow for the exploration of more diverse energy transition pathways, including different rates of electrification across sectors and different technology mixes.

From a methodological perspective, several extensions would strengthen the research presented. The introduction of an intraday market would allow the investigation of additional revenue streams for FOs allowing for a more complete assessment of profitability. Advancing the competition modelling between FOs would further benefit the understanding of avalanche effects and how they can be mitigated. Extending the available forecasting methods to better represent uncertainty and increase the realism of agent decisions would improve model validity. This could include stochastic optimisation techniques that better capture the probabilistic nature of uncertainty in electricity price forecasts. Finally, extending both the spatial and temporal scope could contribute to a broader understanding of new situations due to climate change and assess the contribution of FOs to system stability.

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A Supplementary peer-reviewed publications

A.1 AMIRIS: Agent-based Market model for the Investigation of Renewable and Integrated energy Systems

Authors: Christoph Schimeczek, Kristina Nienhaus, Ulrich Frey, Evelyn Sperber, Seyedfarzad Sarfarazi, Felix Nitsch, Johannes Kochems, A. Achraf El Ghazi
Corresponding Author: Christoph Schimeczek
Journal: Journal of Open Source Software
Volume: 8 (84)
DOI: 10.21105/joss.05041
Status: Published 17 April 2023

Abstract: AMIRIS is an agent-based model (ABM) to simulate electricity markets. The focus of this bottom-up model is on the business-oriented decisions of actors in the energy system. These actors are represented as prototypical agents in the model, each with own complex decision-making strategies. The bidding decisions are based on the assessment of electricity market prices and generation forecasts, and diverse actors deciding on different time scales may be modelled. In particular, the agents' behaviour does not only reflect marginal prices, but can also consider effects of support instruments like market premia, uncertainties and limited information, or market power. This allows assessing which policy or market design is best suited to an economic and effective energy system. The simulations generate results on the dispatch of power plants and flexibility options, technology-specific market values, development of system costs or CO_2 emissions. One important output of the model are simulated market prices. AMIRIS is developed in Java using the FAME-Coreframework (Schimeczek et al., 2023) and is available on GitLab. One important design goal was to make assumptions and calculations as transparent as possible in order to improve reproducibility. AMIRIS was successfully tested on different computer systems, ranging from desktop PCs to high performance clusters.

Author Contributions: Christoph Schimeczek is the lead author of this paper. The AMIRIS model is a software programme developed at DLR more than a decade ago. At the time of writing, there are 13 people who contributed to the model, 8 of whom are still working on it today. Christoph Schimeczek is the current owner of the software, and he wrote the original draft with Kristina Nienhaus. All authors, including myself, have edited and revised the manuscript.

A.2 FAME-Io: Configuration tools for complex agent-based simulations

Authors: Felix Nitsch, Christoph Schimeczek, Ulrich Frey, Benjamin Fuchs
Corresponding Author: Felix Nitsch
Journal: Journal of Open Source Software
Volume: 8 (84)
DOI: 10.21105/joss.04958
Status: Published 17 April 2023

Abstract: We present FAME-Io, a Python package designed to help users and creators of agent-based simulation models (ABM) better manage the preparation and processing of their input and output data sets. The package was built with the needs of researchers in mind. FAME-Io was specifically developed to interface with the open framework FAME and is published under the open Apache-2.0 licence. The software offers various logging capabilities, shell-integrated help and documentation, as well as extensive pre-run integrity checks and helpful warning messages. It also allows individual data components to be easily extracted and used in secondary workflows. The code itself is operating system independent and follows best practices in software development. Test coverage, at the time of writing, is 92 % and the project uses continuous integration and offers frequent releases.
Author Contributions: I am the lead author of this paper. The software FAME-Io was mainly designed and implemented by myself and Christoph Schimeczek. Ulrich Frey and Benjamin Fuchs, both senior scientists at DLR, helped with modelling sprints and advising on certain design patterns. I led the conceptualisation of the paper and wrote the first draft. All four authors reviewed and edited the original draft. The external review, which included paper and software improvements, was mainly done by myself and Christoph Schimeczek.

A.3 Know Your Tools - A Comparison of Two Open Agent-Based Energy Market Models

Authors: Florian Maurer, Felix Nitsch, Johannes Kochems, Christoph Schimeczek, Volker Sander, Sebastian Lehnhoff
Corresponding Author: Florian Maurer
Journal: IEEE Xplore - Proceedings of the 20th International Conference on the European Energy Market (EEM) 2024 in Istanbul, Turkiye
Volume: n.a.
DOI: 10.1109/EEM60825.2024.10609021
Status: Published 8 August 2024

Abstract: Due to the transition to renewable energies, electricity markets need to be made fit for purpose. To enable the comparison of different energy market designs, modelling tools covering market actors and their heterogeneous behaviour are needed. Agent-based models are ideally suited for this task. Such models can be used to simulate and analyse changes to market design or market mechanisms and their impact on market dynamics. In this paper, we conduct an evaluation and comparison of two actively developed open-source energy market simulation models. The two models, namely AMIRIS and ASSUME, are both designed to simulate future energy markets using an agent-based approach. The assessment encompasses modelling features and techniques, model performance, as well as a comparison of model results, which can serve as a blueprint for future comparative studies of simulation models. The main comparison dataset includes data of Germany in 2019 and simulates the Day-Ahead market and participating actors as individual agents. Both models are comparable close to the benchmark dataset with a MAE between 5.6 and 6.4 EUR/MWh while also modelling the actual dispatch realistically.
Author Contributions: Florian Maurer, a PhD student at the University of Applied Sciences in Aachen, is lead author of this paper. Florian Maurer, myself, Johannes Kochems and Christoph Schimeczek designed the model comparison between ASSUME and AMIRIS. While Florian Maurer implemented the actual model comparison, myself and Christoph Schimeczek worked on the data collection and preparation. I implemented the software for automated backtesting of AMIRIS using historical data. Florian Maurer wrote the original draft of the paper, while all co-authors discussed and revised the manuscript.

A.4 Energy Systems Analysis Considering Cross-Border Electricity Trading: Coupling Day-Ahead Markets in an Agent-Based Electricity Market Model

Authors: Felix Nitsch, A. Achraf El Ghazi
Corresponding Author: Felix Nitsch
Book: Operations Research Proceedings 2023
Conference: Annual International Conference of the German Operations Research Society (GOR), Germany, August 29 – September 1, 2023
DOI: 10.5281/zenodo.10561382 [accepted preprint]
Status: In print

Abstract: This work introduces a new day-ahead market coupling mechanism as part of AMIRIS, an agent-based market model for renewable and integrated energy systems. The mechanism enables researchers to analyse cross-border electricity trading and its effects on electricity markets. Bids and asks from local traders are processed by a central "MarketCoupling" agent. This agent minimises the total system cost of providing electricity by dispatching cross-border demands based on available transmission capacity. The proposed algorithm achieves cost-effective market coupling by prioritising transfer between markets with the highest price differences. The implementation is demonstrated in a case study of four interconnected markets. The results indicate a re-allocation of demand from the more expensive markets to the cheaper ones, leading to a minimisation of total system costs. Computation times are roughly doubled compared to runs without market coupling, but still remain below 9 minutes per run for a comprehensive European scenario for a full year when executed on a standard laptop computer. Besides large-scale cross-border coupling, the algorithm could also be used for much smaller market zones (i.e. "nodal pricing"). It is available as part of the open-source model AMIRIS.
Author Contributions: I am the lead author of this paper. I was responsible for the initial concept of the market coupling, which included defining the requirements and coordinating with the AMIRIS product owner Christoph Schimeczek. The implementation, testing and documentation was done together with A. Achraf El Ghazi, a senior scientist at DLR. The first draft of the paper was written by me. A. Achraf El Ghazi reviewed and edited the initial draft.

A.5 Profitability of Power-to-Heat-to-Power Storages in Scenarios With High Shares of Renewable Energy

Authors: Felix Nitsch, Manuel Wetzel
Corresponding Author: Felix Nitsch
Journal: Energy Proceedings - Proceedings of the 14th International Conference on Applied Energy 2022 in Bochum, Germany
Volume: 28
DOI: 10.46855/energy-proceedings-10258
Status: Published 2022

Abstract: Intermittent electricity generation from variable renewable energies will lead to an increased demand for flexibility options in the future. Power-to-heat-to-power storage technologies present high potentials for large-scale application. However, investments in such technologies are still hampered by technical and economic challenges. To address the latter, the possible revenues in electricity markets need to be analysed. For this, we simulate the German electricity market in ambitious defossilisation scenarios. We use different operational strategies for the storage (minimising system costs versus maximising storage profits) that show a wide range of storage profitability. The operator benefits from its attributed market power (i.e. assuming perfect foresight in a rolling horizon window) to generate positive net profits. Further research may focus on market situations with increased market competition.
Author Contributions: I am the lead author of this paper. The main research work of this paper was shared between Manuel Wetzel and me. Manuel Wetzel designed, extended and applied the part on the energy system optimisation model REMix, while I designed, extended and led the work on the agent-based electricity market model AMIRIS. I also ensured the coupling of the two models through a dedicated workflow. The original draft was written by me and edited by Manuel Wetzel.
Note: The peer-reviewed publication in the Journal of Energy Storage, see Section 3.2, is a comprehensive and extensive continuation of this work.

B Supplementary non-peer-reviewed publications

B.1 Back-testing the agent-based model AMIRIS for the Austrian day-ahead electricity market

Authors: Felix Nitsch, Christoph Schimeczek, Sebastian Wehrle
Corresponding Author: Felix Nitsch
Journal: Zenodo
Volume: n.a.
DOI: 10.5281/zenodo.5726737
Status: Published 9 December 2021

Abstract: The energy transition requires significant changes to current energy systems. Especially electricity markets are in the spotlight of policy-makers, investors, and researchers. This is due to the emergence of new market participants and innovative technologies disrupting the dominance of conventional power supply. Thus, we present the open agent-based electricity market model AMIRIS, which allows investigating current and future electricity systems. In this work, we apply AMIRIS to simulate the Austrian day-ahead electricity market prices. We use but freely available data in hourly resolution for the year 2019 and perform a back-test of the model with historical prices. The results show a high level of agreement of simulated results and historical data with regard to statistical characteristics (e.g. average price and price duration curve). However, AMIRIS tends to overestimate lower prices and underestimate higher prices. Also, AMIRIS does currently not include strategical bidding components and looking at the price time series, differences between the simulated and historical values are apparent. We conclude that the flexibility and the convenient parameterisation of AMIRIS make it a powerful tool to assess today's and tomorrow's research questions in the field of energy economics. However, for deeper insights on the electricity market, further research is required to integrate bidding strategies of, e.g. energy storage system operators.

Author Contributions: I am the lead author of this paper. The research design, data collection and preparation was carried out by myself and Christoph Schimeczek. Sebastian Wehrle, a researcher at BOKU University Vienna, provided detailed insights and data for the Austrian hydropower modelling. I carried out the analysis and comparison of AMIRIS modelling results with historical data. I prepared the original draft of the article, while Christoph Schimeczek and Sebastian Wehrle reviewed and edited the manuscript.

B.2 FAIRification of Energy System Models: The Example of AMIRIS

Authors: Ulrich Frey, Felix Nitsch, A. Achraf El Ghazi, Christoph Schimeczek
Corresponding Author: Ulrich Frey
Journal: Zenodo
Volume: n.a.
DOI: 10.5281/zenodo.10797150
Status: Published 12 March 2024

Abstract: Two criticisms are often associated with energy system models. First, many models are so complex that they are not reproducible outside the developer's group. Just the parameterisation of the model requires days and special knowledge. Second, many models cannot be validated by external users, since core data is missing or is internal. The solution may be a combination of transparency through FAIR data and the transition from closed model building to open-source. This presentation demonstrates the process of switching from closed to open source for the agent-based model AMIRIS, the FAIRification of its data by linking it to the Open Energy Ontology and the enrichment with metadata, and community building as well as the publication in open journals like JOSS.
Author Contributions: Ulrich Frey is the lead author of this paper. The design of the metadata representation in the AMIRIS model and FAME framework was carried out by Ulrich Frey, myself and Christoph Schimeczek. The implementation of the metadata annotation in AMIRIS was carried out by all four authors with supervision by Christoph Schimeczek. The original draft was written by Ulrich Frey and reviewed and edited by all co-authors.
Note: This work was published as part of the proceedings of the 1st NFDI4Energy Conference in Hanover.

C Curriculum vitae

Education

Ruhr University Bochum	*Bochum, Germany*
Doctoral Student at the Faculty of Mechanical Engineering	05/2020 – 09/2025
University of Natural Resources and Life Sciences	*Vienna, Austria*
Dipl.-Ing. in Environment and Bio-Resources Management	10/2015 – 08/2018
University of Natural Resources and Life Sciences	*Vienna, Austria*
B.Sc. in Environment and Bio-Resources Management	10/2011 – 09/2015

Work experience

AIT Austrian Institute of Technology	*Vienna, Austria*
Visiting Researcher at the Competence Unit Integrated Energy Systems (IES)	05/2025 – 07/2025
German Aerospace Center (DLR)	*Stuttgart, Germany*
Researcher at the Institute of Networked Energy Systems	09/2018 – 09/2025
Deggendorf Institute of Technology	*Deggendorf, Germany*
Research Assistant at the Applied Computer Science & Bionics Technology Campus	11/2017 – 08/2018