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Comparative Simulation of Energy Market Designs

Von der Fakultät für Informatik, Wirtschafts- und Rechtswissenschaften der Carl von
Ossietzky Universität Oldenburg zur Erlangung des Grades und Titels

Doktor der Ingenieurwissenschaften (Dr.-Ing.)

Angenommene Dissertation von

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geboren am 23. Juli 1998 in Augsburg

Tag der Einreichung 22. Juli 2025
Tag der Disputation 10. Dezember 2025

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ABSTRACT

Due to emerging challenges in energy systems, the dynamics and the design of energy markets are subject to change. Simulation models are frequently employed to comprehend the evolving dynamics of future electricity markets. However, existing market models were often developed with specific use cases in mind, which restricts their flexibility and usability. As a result, projects often have to re-implement market simulations because existing ones do not fit their use case.

In this doctoral thesis, it is shown that a flexible market model can cover various energy market designs and produce comparable results for different use case studies. The doctoral thesis investigates the possibility of a generalized approach to simulate and compare different market models, implemented as an agent-based simulation. This approach enables the evaluation of different energy market designs in a comparative manner.

A formalization of the rules and regulations of different energy markets is provided as a foundation, which can then be generalized and used as an abstraction layer. This formalization has been extended and evaluated based on research of existing simulation approaches and energy market designs, as well as feedback from the research community. It includes the definition of contracts between market actors with financial as well as physical power obligations. To ensure interoperability with other tools, an abstraction layer is used to facilitate the use of existing simulation scenario datasets for market simulations. Key performance indicators of simulations can be individually defined and are calculated within the energy market simulation.

Additionally, the described abstraction layer supports continuous market auctions, conditional contracts between participants, and customizable market products. This enables the configuration of a market design as an input to a market simulation and facilitates comparison of different simulation results.

The main artifact of the thesis is the development of an open-source market simulation framework, which fulfills the highlighted requirements of interoperability, modularity and scalability as well as functional flexibility. These requirements emerge from the research question and are necessary for the analysis of different energy market designs. The software design and features are explained through application of the framework to different market designs and use cases.

ZUSAMMENFASSUNG

Aufgrund der sich abzeichnenden Herausforderungen in den Energiesystemen sind die Dynamik und die Gestaltung der Energiemärkte einem Wandel unterworfen. Simulationsmodelle werden häufig eingesetzt, um die sich entwickelnde Dynamik künftiger Strommärkte zu verstehen. Bestehende Marktmodelle wurden jedoch häufig mit Blick auf bestimmte Anwendungsfälle entwickelt, was ihre Flexibilität und Nutzbarkeit einschränkt. Infolgedessen müssen Projekte häufig Marktsimulationen neu implementieren, weil die vorhandenen Modelle nicht für ihren Anwendungsfall geeignet sind. In dieser Dissertation wird ein flexibles Marktsimulationsmodell vorgestellt, welches verschiedene Energiemarktdesigns abdeckt und vergleichbare Ergebnisse für verschiedene Anwendungsfälle liefert. Ziel der Dissertation ist es, einen verallgemeinerten Ansatzes zur Simulation und zum Vergleich verschiedener Marktmodelle zu erstellen. Dieser wird als agentenbasierte Simulation implementiert und ermöglicht die vergleichende Bewertung verschiedener Energiemarktdesigns.

Eine Formalisierung der Regeln und Vorschriften verschiedener Energiemärkte, die dann verallgemeinert und als Abstraktionsschicht verwendet werden kann, wird als grundlegende Markt-Abstraktion erarbeitet. Diese Formalisierung wurde auf der Grundlage von Untersuchungen bestehender Simulationsansätze und Energiemarktdesigns sowie von Rückmeldungen aus der Forschungsgemeinschaft erweitert und evaluiert. Sie umfasst die Definition von Verträgen zwischen Marktakteuren mit finanziellen und physischen Leistungsverpflichtungen. Um die Interoperabilität mit anderen Werkzeugen zu gewährleisten, wird eine Abstraktionsschicht verwendet, um die Verwendung bestehender Simulationsszenariendatensätze für Marktsimulationen zu erleichtern. Wichtige Leistungsindikatoren dieser Simulationen können im Vorfeld individuell definiert werden und innerhalb der Energiemarktsimulation berechnet werden.

Zusätzlich unterstützt die beschriebene Abstraktionsschicht kontinuierliche Marktauktionen, bedingte Verträge zwischen Teilnehmern und anpassbare Marktprodukte. Dies ermöglicht die Konfiguration eines Markt-Designs als Input für eine Marktsimulation und erleichtert den Vergleich verschiedener Simulationsergebnisse.

Das wichtigste Artefakt dieser Arbeit ist die Entwicklung eines quelloffenen Marktsimulations-Frameworks, das die hervorgehobenen Anforderungen an Interoperabilität, Modularität und Skalierbarkeit sowie die funktionale Flexibilität erfüllt. Diese Anforderungen gehen aus der Forschungsfrage hervor und sind für die Analyse verschiedener Energiemarktdesigns erforderlich. Das Softwaredesign und die Funktionen werden durch die Anwendung des Frameworks auf verschiedene Markt-Designs und Anwendungsfälle erläutert.

VORWORT – ACKNOWLEDGEMENT

Dieser wichtige Abschnitt ist all den Menschen gewidmet, welche mich auf meinem Weg dieser Dissertation begleitet haben und mich stets dabei unterstützt haben, sowohl fachlich als auch menschlich. Diese Dissertation ist im Rahmen meiner Tätigkeit an den Instituten **NOWUM-Energy** und **IDT** der Fachhochschule Aachen in Kooperation mit der **Universität Oldenburg** entstanden. Auf dem Weg dorthin durfte ich viele schöne Momente erleben, sowie Mitstreiter und Mitstreiterinnen in der Energiesystemmodellierung kennenlernen.

Während eine Promotion stets eine große Menge Eigeninitiative und Frustrationstoleranz erfordert und die Arbeit selbst einsam vor dem Bildschirm geschrieben wurde, wird das ganze nur möglich durch die wundervolle Unterstützung von wundervollen Menschen, die mich zufrieden auf die vergangenen Jahre der Promotion zurück blicken lassen.

Zunächst möchte ich mich herzlich bei meinem Doktorvater Prof. Dr. Sebastian Lehnhoff für die enorme Unterstützung, Ermutigung und wertvollen Anregungen bedanken. Die stets konstruktive Betreuung und Zielsetzung hat mich in meinen Zielen bekräftigt und mir geholfen auf dem richtigen Pfad zu bleiben. Weiterhin gilt mein herzlicher Dank Prof. Dr. Volker Sander, für die Betreuung der Promotion, das Ermöglichen dieses Weges, sowie die stete Unterstützung. Er hat mir geholfen den Fokus in angespannteren Zeiten auch richtig zu setzen. Besonderer Dank gilt den vielen Wissenschaftlern verschiedener Institutionen, welche ich auf dem Weg kennenlernen durfte. Allen voran Dominik Stollenwerk und Christian Rieke, welche mich in meiner Anfangsphase der Promotion unterstützt haben und mir ermöglicht haben Fahrwasser aufzunehmen - aber auch allen anderen Mitglieder der beiden Institute der Fachhochschule Aachen. Besonders wichtig ist für mich die Kooperation mit der Power-System-Modellierungs-Gruppe, insbesondere Kim Miskiw und Nick Harder, die große Teile des Weges mit mir gegangen sind und durch die ich im steten Austausch viel gelernt habe. Weiterhin möchte ich Christoph Schimeczek danken, der mir als erfahrener Energiemarktmodellierer besonders weitergeholfen hat.

Nicht zuletzt danke ich meiner Familie und meinen Freunden für den Rückhalt, die Unterstützung und das Verständnis, wenn in arbeitsintensiven Phasen wenig Zeit übrig bleibt. Besonders danke ich Michi für die motivierenden und aufbauenden Worte. Ich möchte mich auch bei meinen Eltern Ingrid und Ernst bedanken, die mir immer den Rücken freigehalten und mich unterstützt haben und mir in meinem Leben so viel mitgegeben haben, wodurch diese Erfahrung für mich erst ermöglicht wurde.

CONTENTS

1	Introduction	11
1.1	Motivation	11
1.2	Research Goal	12
1.3	Methodology	16
1.3.1	Design and Development	17
1.3.2	Demonstration and Evaluation	17
1.3.3	Communication	18
1.4	Outline	19
2	Fundamentals	21
2.1	Energy Systems	21
2.1.1	Electricity Demand and Generation	22
2.1.2	Grid Operation and Unit Commitment	23
2.2	Energy Markets	27
2.2.1	Market Evolution and Dynamics	27
2.2.2	Energy Market Roles	29
2.3	Energy Market Design	32
2.3.1	Double Auction Clearing Mechanisms	34
2.3.2	Distribution Transport Capacities	37
2.3.3	Regulatory and Operational Structures	40
2.4	Agent-based Modeling	44
2.4.1	Agent-Based Protocols and Simulation Frameworks	46
2.4.2	Agent Roles	50
2.5	Energy Market Simulations	50
2.5.1	Market Simulation Software	52
2.5.2	Related Energy System Simulation Software	61
2.5.3	Scenario Datasets	62
2.5.4	Summary of Related Work	64
3	Design and Concept	65
3.1	Research Gap Identification	65
3.2	Functional Requirements	67
3.2.1	Agent-based Simulation	67
3.2.2	Power Flow Calculation	67
3.2.3	Market Design Configuration	67
3.2.4	Comparative Simulation	68
3.3	Non-functional Requirements	68
3.3.1	Open-Source Software	68

3.3.2	Modularity	69
3.3.3	Interoperability	69
3.3.4	Scalability	69
3.4	Ontologies and Market Abstractions	70
3.5	Market Model and Agents	72
3.5.1	Market Configuration Categories	72
3.5.2	Bidding Abstraction	74
3.5.3	Agent Interfaces	75
3.6	Modular Software Design	77
3.6.1	Scheduling Events in the Simulation Loop	80
3.6.2	Orchestration and Choreography in Distributed Simulations	82
3.7	Scalable Simulation	87
3.8	Interoperability with existing Energy System Simulation Tools	89
3.9	Prospective Integration of Communication to compatible Simulation Tools	90
4	Market Simulation Artifact	91
4.1	Characteristics of the Simulation Artifact	91
4.2	Configuration Options	92
4.3	Complex Bidding Strategies	97
4.3.1	Power Plant Optimization Module	98
4.3.2	Addition of Avoided Start Cost Calculation	100
4.3.3	Market Model for Linked and Exclusive Orders	103
4.4	Scheduling	105
4.5	Visualization of Outputs	107
5	Evaluation	109
5.1	Functional Requirements	110
5.1.1	Agent-Based Simulation	110
5.1.2	Power Flow	111
5.1.3	Market Design Configuration	112
5.1.4	Comparison of Market Design Changes	112
5.2	Non-functional Requirements	115
5.3	Case Studies	118
5.3.1	Evaluation of German Energy Market Scenario	119
5.3.2	Comparison to Other Simulation Models	124
5.3.3	Two-stage Local Energy Market	127
5.3.4	Fuel Market Coupling Scenario	129
6	Conclusion	131
6.1	Results and Contributions	131
6.1.1	Market Abstraction	132
6.1.2	Market Simulation SPARKLE	133
6.1.3	Evaluation	133
6.1.4	Agent-based Simulation Tool Mango	134

6.1.5	Data Preparation and Accessibility using Open Energy Data Server (OEDS)	134
6.2	Limitations	135
6.2.1	Bidding Strategies	135
6.2.2	Runtime Improvements	135
6.2.3	Expansion Planning	136
6.3	Need for Further Research	137
6.3.1	Creation of a European Simulation Dataset	137
6.3.2	Investigation of Capacity Markets & Dynamic Grid Fees	138
6.3.3	Implementation of Reactive Power Markets & Storage Markets	138
6.3.4	Expansion of Agent Behavior to Reinforcement Learning	138
6.3.5	FIPA Compliant Simulation Communication	139
6.3.6	Integration of Ontologies	139
6.3.7	Adaptation of Intuitive User Interface	140
7	Appendix	141
7.1	Availability of Sourcecode	141
7.2	Used Software and Hardware Tools	141
7.3	MQTT Roundtrip Performance Benchmark	142
7.4	Twostage Simulation Source Code	142
	Glossary	147
	Acronyms	149
	List of Figures	153
	List of Tables	157
	Bibliography	161

1

INTRODUCTION

You never change things by fighting the existing reality. To change something, build a new model that makes the existing model obsolete.

Buckminster Fuller, philosopher, futurist and global thinker [236, p. 138]

1.1 MOTIVATION

As the global energy landscape undergoes rapid transformation, comparative energy market simulation emerges as a critical tool for evaluating and optimizing market designs to meet the challenges of sustainability, efficiency, and security of supply. Past energy crises, as well as the shift in the energy system towards decentralised renewable energy generation, show that conventional energy market models may no longer meet the needs of modern energy markets. The increasing energy demand, the pressure to reduce greenhouse gas emissions and the need to integrate renewable energy sources require a paradigm shift in the way energy is produced, marketed and used. Last but not least, the energy supply crisis caused by the lack of gas supplies to the [European Union \(EU\)](#) via the natural gas pipelines to Russia has led to significant supply bottlenecks, which has also led to repeated criticism of the current design of the electricity market in Europe, especially in Germany. Regulatory stakeholders deliberate on the required adaptations to current energy markets, as outlined in publications [60], alongside ongoing research findings [24]. The latter underscores the importance of simulating how a specific market mechanism would affect proposed changes to its design.

Yet, decisions on changes to the regulatory framework of the energy market are often based on simplified assumptions and theoretical considerations that do not necessarily reflect actual market behavior. In order to be able to analyze various future scenarios with regard to energy market behavior, simulation tools are required that meet the flexibility and scope requirements of a complex energy market simulation. In line with the growing demand for market simulations, there has been a remarkable evolution in energy market design research, facilitated by improved data accessibility,

advances in computational capabilities, and the availability of relevant open source software libraries for comprehensive energy system modeling [89, 186]. It was found after deep investigation that an available open-source simulation tool, which covers the requirements of market design analysis thoroughly and makes a comparison of different market designs possible, is missing for the research community. This topic was found to be of interest as the demand for such simulations has been seen to be high as stated in current research: “there is an emerging need for standardized and realistic test beds for market mechanisms” [229, p. 13].

In recent years, new market concepts as well as support mechanisms for emerging technologies, like **Contract for Differences (CfD)** or **Power Purchase Agreement (PPA)** are uprising [75, 170], which are not yet modeled in most market simulation tools. But also optimizations towards the clearing mechanisms with different pricing schemes as in **Vickrey-Clark-Groves (VCG)** auctions [33, 108], transactive energy markets [13] or local energy markets [229] have to be analyzed in more detail for exploring a future market behavior.

This leads to the necessity to fill the gap of a missing market model, which covers the possibilities to compare such dynamics in a standardized and structured way.

This chapter first introduces the research question and presents the scientific methodology used to tackle this. It closes with an outline of the thesis, which covers the steps toward the resulting simulation framework to simulate energy market designs comparatively.

1.2 RESEARCH GOAL

Coming from the above-outlined motivation, the question of how different energy market models can be analyzed in a comparative simulation becomes the key aspect of evaluation. Simulations offer the opportunity to test different scenarios and analyze their impact on the energy market without using real resources. This makes it possible to develop innovative approaches and evaluate their potential advantages and disadvantages before they are implemented in practice.

This doctoral thesis investigates whether a generalized approach to simulating and comparing different market models is possible, which is implemented as an agent-based simulation. The central research question to be answered is therefore as follows:

Overarching Research Question

How can different energy market designs be evaluated in a simulative comparative manner?

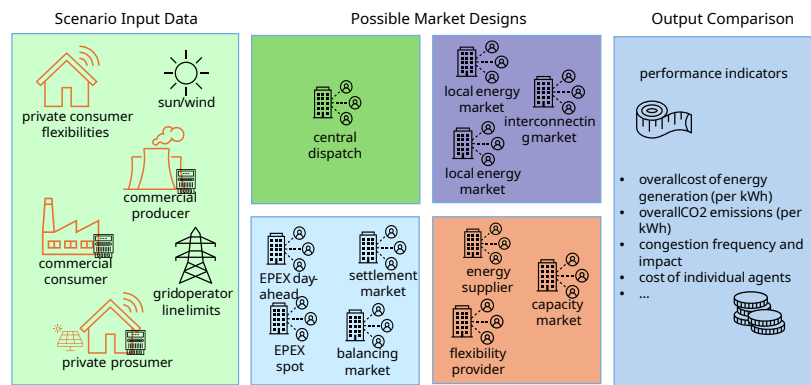


Figure 1.1: Overview of a comparison framework of different market designs. On the left is input data of a comparison scenario, in the middle are different market designs and on the right are performance indicators for the evaluation of a market design.

The focus is on the abstraction of different market models and how these can be simulated with the same framework, which is demonstrated using real-world examples and benchmarks to existing simulation tools. The optimal trading strategy of the market players, the most realistic input scenario and finding the best possible **Key Performance Indicators (KPIs)** are not a core aspect of the project. However, these parts can be further configured and investigated using the framework.

As a prerequisite for answering this question, a formalization of the rules of different energy markets is required, which can then be generalized and used as an abstraction layer. The general input data of a scenario to be analyzed should be easily entered into the model. In addition, generic Key Performance Indicators should be definable and calculated as simulation results.

This leads to a refinement of the overarching research question, which also formulates milestones of the project. The first milestone of the research project is finding an abstraction of energy markets that is sufficient for modeling purposes. It is stated as:

Research Question 1

Which abstract description is able to characterize different market designs to guide their implementation within modular energy market simulation software?

The current energy grid is undergoing change due to the prevailing global climate crisis and the resulting urgent need to switch to sustainable energy generation. The increasing decentralization of power generation poses a challenge to the existing electricity market due to the growth of small **photovoltaic (PV)** systems, wind turbines, battery storage options and the switch to e-mobility. In addition to the necessary expansion of the transmission grid [250] and the decreasing relevance of large energy producers, the question arises as to whether the current market model meets the requirements of the future.

Electricity is currently traded in the European interconnected system through different public marketplaces like the futures market of [European Energy Exchange \(EEX\)](#) and the spot markets, for example, the [European Power Exchange \(EPEX\)](#) or [Nord Pool Spot Energy Exchange \(NORDPOOL\)](#). This is divided into several market levels, such as intraday (spot market) and day-ahead market (merit order/uniform pricing).

The trading on these markets does not yet take into account the capacities of the transmission grids. This means that after the trading period, a so-called redispatch is required, in which the transmission system operators calculate the technical feasibility of the resulting schedule by means of a grid calculation and instruct power plant operators with a capacity of more than 10 MW to correct it if necessary. An extension of the redispatch to all power plants with more than 100 kW was decided by the Grid Expansion Acceleration Act and is implemented from October 2021 [138]. This mechanism, called Redispatch 2.0, is planned centrally throughout Germany by the grid operator cooperation Connect+ [29].

New measures expand the organizational effort and add further trading layers to the electricity market. Due to the central organization of each trading layer, there is also a single point of failure, the failure of which can have far-reaching consequences.

This raises the question of whether the historically evolved, gradually expanded market model should be replaced by a completely rethought approach in order to utilize local flexibilities [147]. The aims are to reduce the complexity of the market mechanisms, to make them suitable for increasingly decentralized energy generation in the future and to divide the market on the balance sheet through P2P trading [106]. Within the [European Network of Transmission System Operators for Electricity \(ENTSO-E\)](#), there is a view that an adjustment of the market regulations is necessary, but far-reaching adjustments in the direction of the [Locational Marginal Pricing \(LMP\)](#) are not advocated by the EU, while adjustments to more separated market zones are seen as a possible direction [59]. On the other hand, focusing on a redispatch market can also be unstable [102].

To date, the effects of changes to market regulations cannot be considered precisely and in isolation. Simulation tools focus, in general, on the simulation of a specific part of the market process and ignore flexibility. This raises the question of how the comparability of different market mechanisms can be ensured.

To answer this question, a definition of energy market design is needed as well as the characterization of the requirements for a successful abstraction. The functional requirements are found by comparing existing literature as well as original research towards energy market simulations.

Existing Ontologies and energy market simulations are taken into consideration for creating a new market modeling abstraction.

Research Question 2

In what way can different market mechanisms be represented in the simulation?

The second research question takes care of the embedding of the market abstraction into a single simulation framework. In this regard, flexibility is needed towards the implementation of the details of the market design. Such as the used market mechanisms, which can cover different clearing methods, support mechanisms or communication. This includes the flexibility to model a unit commitment with grid constraint on one hand while also being able to model the different bidding types of the wholesale market or [Over-The-Counter \(OTC\)](#) trading.

For an answer to this research question, different energy markets are analyzed to extract well-known and existing market mechanisms, while also taking a look at future market mechanisms in discussion. This is beneficial to also consider future scenarios in the conception and requirements.

Therefore, a selection of market mechanisms is defined prior to the implementation, which is then taken as a reference in the evaluation to showcase the flexibility regarding market implementations of the model.

One of the most important properties of a quantitative comparison are [KPIs](#) used to evaluate the performance of different market designs. Reasonable [KPIs](#) have to be evaluated and applied in a way that makes it easy to adjust overall metrics and draw conclusions from the comparisons. In that order, it is required that the scenarios are still interpretable in a way that the overall complexity of the simulation can still be controlled. This key aspect is handled by the third research question.

Research Question 3

How can indicators of market mechanisms be used to evaluate specific market designs?

From existing market simulations, the used [KPIs](#) are well-known, as well as the metrics that were used in previous market design decisions [67]. Existing research on the extraction of [KPIs](#) as in [3, 4] provides details to look into, yet the actual methodology to calculate and evaluate such indicators in a software framework is missing. The simulation design, therefore, needs to be able to cover the calculation of such metrics in an efficient and extensible way, to offer an accessible evaluation of the simulation results.

1.3 METHODOLOGY

The scientific methodology used in this work employs the Design Science Research Process according to Peffers [182]. Design Science Research is a research paradigm that focuses on the development and validation of prescriptive knowledge.

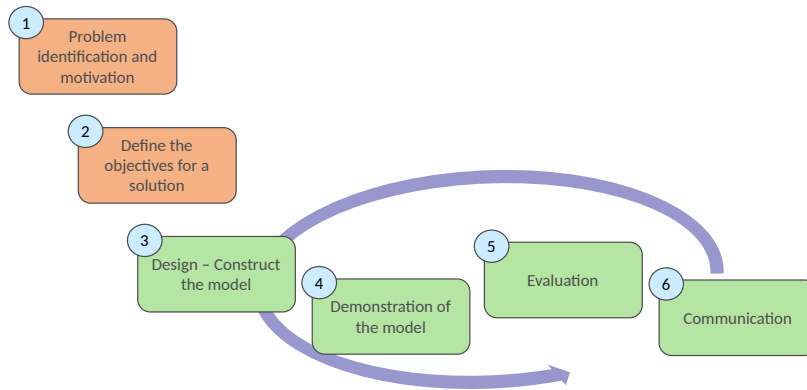


Figure 1.2: Visualization of a design science process after Peffers [182].

A Design Science Research project in general starts with a problem identification, which also includes the identification of the main goals and requirements for a solution [99]. The second step is the definition of objectives for a solution to the outlined problem. Identifying objectives is the bridge from the design problem space to the solution space [7]. The objectives need to be well-defined to make a retrospective assessment of the achievements possible. While this is understandable for functional requirements, it is less deterministic for non-functional requirements or vague objectives like usefulness or intuitiveness [81, 150].

Once defined, however, the objectives enable the creation of a concept that covers the requirements to be met. As the problem indication and motivation include the development of a software tool to model and compare different energy market designs, it focuses on the creation of artifacts that provide value to the given problem statement. Design science research can therefore be seen as a suitable methodology to answer the research questions presented before. An iterative review and evaluation process, as shown in Figure 1.2, is fundamental to this method.

As the stated research question can not be answered with a purely descriptive approach to design science, one of the main artifacts is the simulation tool, which is adjusted to fulfill the requirements in iterative development cycles [100].

In software projects, the communication of results can not only be executed in research journals within every iteration but also create public open-source reference versions in each iteration through a software release cycle of the artifacts with appropriate documentation. This is used to create and document the artifacts during the creation cycles and to draw attention from other researchers as well as software engineers toward the artifact.

1.3.1 Design and Development

The central base element of the market model is the abstraction of the bidding representation, which assumes that every bid needs to contain at least a price and a volume. With these assumptions, a lot of use cases have been represented. However, this assumption did not hold for a scenario where only the ramping and scheduling information is exchanged between the agents and the market, creating a market design that does not receive bids, but information about the agents. Such a simulation might not consider a market at all, as no bidding or price-matching takes place, yet this is a common use case for countries in which an [Integrated System Operator \(ISO\)](#) schedules the dispatch as a central unit. It became clear that bids do not necessarily have to contain a price.

Another assumption was that bids always contain only one price. This idea was falsified by the introduction of block bids. Block bids consist of several individual bids and thus enable the combination of different prices within one bid. This opens up new perspectives on the flexibility and complexity of the bidding structure.

Bids are aggregated into a block using a grouping id. This key figure makes it possible to combine several bids into one block, which is particularly important in complex market scenarios. The flexibility of this grouping proves to be crucial for the realistic modeling of market behavior.

These examples serve as a showcase of the iterative development which helped to understand the requirements better and falsify and improve ideas in the simulation concept.

The design science process conducted by this thesis results in the final prototype [Simulation Platform for Agent-based Research on energy marKet dynamics for Lower Emissions \(SPARKLE\)](#) which provides a basis for further research in the field of energy market simulation. This prototype was developed on the basis of the scientific work carried out and fulfills the previously defined requirements. [SPARKLE](#) offers a platform for flexible and comparative market simulations, which makes it possible to examine different market scenarios and analyze the effects of different bid structures.

1.3.2 Demonstration and Evaluation

In order to provide a coherent response to the research questions, the artifacts offer insights, with each step becoming increasingly complex and being adapted to meet the requirements. The progression of these steps is characterized by the establishment of distinct milestones, the implementation of which is then followed by a process of refinement. The current design of the artifacts is presented at this juncture. The initial step was the Oberseminar 1 (OS1) in June 2022, which showcased the primary related work. Following an evaluation and research of disparate simulation technologies, forces

were combined with the ASSUME project¹ on a working basis to discuss the possible technologies with the external project team. During a research visit in Oldenburg, the initial draft of the market simulation was presented to researchers from OFFIS, the University of Oldenburg, and Constructor University Bremen. This demonstration culminated in a comprehensive exposition of the requirements identified for a market simulation. As a result, the requirements identified for a market simulation were demonstrated using examples in the course of this work. With all required parts aligned, the final artifact SPARKLE is developed and publicly released. Results have been published in reviewed research papers, international conference workshops and through regular presentations in the university.

1.3.3 Communication

During the research, the artifacts of the simulation were discussed with the research community and published. Conceptual market properties and market requirements were summarized in the project report of the BC4P project [20]. First drafts of the conceptualization have been provided to research agent-based modeling in 2023, which covered the main ideas of the simulation tool.

After the first iteration and creation of the tool, a first version has been published open-source as an artifact on GitHub and Zenodo [158]. A case study of the research was then published with a comprehensive look at related work on energy market simulation in [159]. To compare other simulation tools to the proposed simulation, a study was published in EEM2024, assessing differences in dispatch and market behavior between SPARKLE and AMIRIS [160].

An analysis of the sensitivity when simulating different years using consistent data input has been presented at the EEM2025 [maurerInvestigationEndogenousRenewables2025a]. These works form the essential basis for this dissertation. Nevertheless, this thesis offers a more detailed presentation and examination of the concepts and insights found in these papers.

In addition, during the course of this PhD project, various enhancements were contributed to open-source software as a way of giving back to the community and to research in general, for the enormous help that the existence and sharing of results is. A list of relevant projects with a link to the code contribution is given in Table 1.1.

Most of the outlined changes are smaller contributions, yet they are needed and helpful for others using the projects. While it requires knowledge of Version Control Systems (VCSs) and contribution guidelines, it is good practice to contribute to other projects to improve software and investigate or fix issues.

This should also encourage taking time to fix issues when seen or improve small things in used libraries. Even mentioning issues and creating bug reports is often worth the

¹ <https://assume-project.de/>, visited on 19.02.2025

Project	Description of Change
windpowerlib	fix for packaging
linopy	allow suppressing solver output
mango-agents	fixes and improvements to mango simulation framework
entsoe-py	minor fixes
acmart	Biblatex fix for DOI in ACM latex template
tensorflow-docs	update install docs
fame-io	remove deprecation warning
amiris-py	make use of CLI
FlexABLE	add Dockerfile
PyPSA	fix imports
Antares Simulator	dependencies and installation instructions
pomato	fixes for examples
Spyder IDE	various fixes and improvements
Grafanimate	update to latest Grafana versions

Table 1.1: Overview of contributions to related open-source projects throughout the thesis.

effort. Or as Robert Baden-Powell stated, one should "Try and leave this world a little better than you found it" [16].

1.4 OUTLINE

Following the articulation of the research goals and motivation, the methodology for addressing the research questions is outlined, specifically through the application of design science. In the following chapter, the fundamentals of energy system modeling and energy markets are provided in [Chapter 2](#), which is required to investigate the described research questions in more detail. Here, basic concepts of [Agent-based Modeling \(ABM\)](#) are introduced in [Section 2.4](#); the needed background about energy markets is then provided, as well as political instruments to influence the market. In [Section 2.5](#), different approaches to simulate such markets as well as existing simulations are shown as related work.

This preparatory work is taken into account when creating the design and concept in [Chapter 3](#), so that a framework is created that fulfills the requirements and answers the research questions. Therefore, the research gap is introduced in [Section 3.1](#) and then focuses on the establishment of functional requirements in [Section 3.2](#) as well as non-functional requirements in [Section 3.3](#). The concept includes the work on market abstraction and market modeling as well as the impact on the non-functional requirements derived in the previous chapter. Furthermore, the investigation incorporates distributed simulations, which are utilized to encompass a range of use cases,

along with the modularity necessary for their implementation. The details of the final simulation artifact are provided in [Chapter 4](#). Here, a thorough exposition of the characteristics and utilization patterns of the artifact is provided, along with an exposition of the implemented concepts. On one hand, focusing on energy market-related advancements as well as the technical details of interoperability and scalability. The final artifact is evaluated in different use cases according to the Requirements and KPIs in [Chapter 5](#). Finally, the results are summarized in a structured way in the [Chapter 6](#). It also provides a summary of the efforts, the impact on the research questions and further steps and research required.

2 | FUNDAMENTALS

The stone age came to an end, not for a lack of stones, and the oil age will end, but not for a lack of oil.

Ahmed Zaki Yamani, former Saudi Arabian oil minister at OPEC, 1973 [156]

Answering the research questions requires a fundamental background in energy markets and agent-based simulation. First, an introduction to the requirements, evolution and operational insights of energy systems is provided in [Section 2.1](#) and [Section 2.5](#). Current challenges and the need for improvements in decision-making on energy markets are highlighted. [Section 2.3](#) describes different mechanisms of energy markets. This is followed by an overview of the technical details of existing simulation tools for agent-based modeling in [Section 2.4](#). The subsequent section explains the use of agent-based models and their suitability for energy market modeling. Existing energy market models and requirements are discussed in [Section 2.5](#).

2.1 ENERGY SYSTEMS

Our modern society relies on the continuous provision of energy. The complexity of modern energy systems requires coordination and interplay among many stakeholders and actors. From a general perspective, an energy system needs a grid to distribute energy and two or more connection points to the grid where either consumption or generation occurs, while the amount of generation matches the consumption.

This is true for all parts of energy systems, although this thesis focuses mainly on the modeling of electricity generation and supply, as it is a sector with important disruptions due to technology advancements. Most of the concepts of modeling electricity can be similarly applied to other energy systems like gas or hydrogen transmission, though the main focus here remains on electricity without loss of generality.

While the entire electricity supply chain was under single control for many years, it has transitioned to a highly distributed system through the interconnection of grids and the liberalization of energy economics in most countries, especially Germany. This change led to the establishment of typical parties necessary for the maintenance of our energy systems, and new challenges arose. These include the increasing penetration of

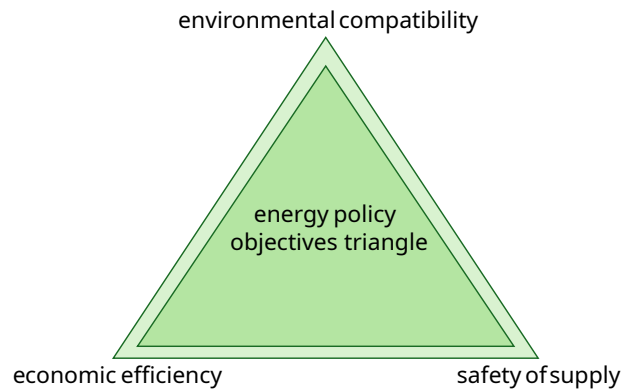


Figure 2.1: Energy policy triangle showing the three targets of environmental compatibility, economic efficiency, and safety of supply [253].

renewable energy sources, the widespread adoption of electric transportation systems, the emergence of smart grid technologies, and the increased importance of cyber-physical control.

The main challenge of energy systems is to produce the same amount of energy at every point in time as is demanded, at the lowest cost (economic), while considering grid constraints and safety (safety of supply) and environmental impact (environmental compatibility). This is also known as the energy policy triangle, shown in [Figure 2.1](#), and its fulfillment is the main driver for adjustments in policies and energy systems.

As an introduction to power systems, the basic properties of generation and demand, as well as energy grids, are described in the following.

2.1.1 Electricity Demand and Generation

Power plants are crucial in energy market models, each with specific operational characteristics. They have defined maximum and minimum power outputs, which determine their range of operation. Additionally, power plants face ramping constraints that limit how quickly they can increase or decrease their output in response to changes in demand. For plants that also provide heat, there are additional constraints related to maintaining efficient heat production.

Different power plants use various technologies, from fossil fuels like coal and natural gas to nuclear and renewables such as wind and solar. Each technology has its own cost structure, influenced by factors like fuel prices, maintenance, and efficiency. This can also include the cost for the connection to the grid, which might also be calculated in the market mechanism.

In energy markets, finding the most cost-effective way to dispatch power involves considering these constraints and costs. Market mechanisms are used to optimize the running power plants to meet electricity demand while minimizing overall system costs. This is known as the unit commitment problem. This process ensures that the

supply and demand are balanced efficiently, leveraging the diverse capabilities and constraints of each power plant.

On the other hand, demand in energy markets is often inflexible, with most end consumers and industries lacking incentives to adjust their usage based on market conditions. This results in a relatively fixed demand, including a baseline level that remains stable regardless of price changes. However, the usage of demand flexibility is grid supportive and acts as one substantial part of future energy systems [39].

As demand can be flexible, it allows users to adjust their consumption in response to price signals. In such cases, flexible demand can set a maximum price it is willing to pay, impacting market prices and efficiency. Additionally, there is often a variable portion of demand that is fulfilled during cheaper production hours, optimizing energy use and supporting grid stability. This so-called flexible demand is becoming more crucial as it allows to shave peaks by 15 to 29 % [221].

Furthermore, the integration of actual load-shifting through storages is an important part of levelizing demand and generation. When evaluating the bidding cost of storages at a market, the profit needs to make up for the efficiency of charging and discharging as well. A well-designed energy market design not only dispatches the energy generation but also provides flexibility on the demand side to transparently communicate the actual preferences and valuations of the good.

2.1.2 Grid Operation and Unit Commitment

Electricity grids are fundamental to modern energy systems, connecting producers, consumers, and other stakeholders to enable the flow of electricity. Beyond interconnection, grids must also manage capacity, ensure reliability, and balance supply with fluctuating demand, especially as renewable energy sources like wind and solar introduce variability. This requires sophisticated mechanisms such as congestion management and demand-side response, as well as hard enforcement of the limits to provide safety of supply.

Within this domain, several constraints need to be taken into account in the energy dispatch. Grids are often considered a typical example of natural monopolies [70], while this view is also challenged in other research [129, 139] investigating a reduction of the monopoly to the transmission and operation of grids¹.

Typically, one differentiates between the transmission grid and the distribution grid, which are operated at different voltage levels and are separated by the role of the operator. This behavior features the aggregation of load on a higher level, while also distributing the localized natural monopoly across multiple smaller actors in a hierarchical manner. Such a centralized view allows for more effective management of the grid as it grows larger and more interconnected, where a coordinated, top-down

¹ Most of the time, grid operators are an oligopoly as more than one [Transmission System Operator \(TSO\)](#) exists, but in one specific area they form a monopoly

approach to system balancing becomes increasingly necessary. Important properties of modeling power grids are given in the following.

Power Constraints

A key element of the network is the power it can handle, which is fundamentally constrained by several interrelated physical characteristics, including thermal limits of conductors, voltage and frequency stability requirements, line impedance, network topology, and dynamic stability considerations as well as grid losses. At present, in most markets, this is inadequately addressed and is respected after the market concludes a clearing result. In Germany, for example, the determination of adjustments to the energy dispatch after the market phase is called redispatch. This is required to avoid congestion on the electricity network at the delivery time [177]. Generally speaking, one can define an operation limit of such a line which includes the above-mentioned constraint so that each line l has a maximum power $p_{l,max}$ that it can transmit in a given time slot t of the set of evaluated times T . This amount should never be exceeded under ideal conditions:

$$\forall t \in T : p_{lt} < p_{l,max} \quad (2.1)$$

This is the general power flow constraint of a grid line, though the actual maximum capacity is not always known as it is dependent on the temperature, wind and irradiation. Efforts have been made to exploit this property by using [Dynamic Thermal Line Rating \(DTLR\)](#) [118], although for simulations this can be neglected as a typical maximum value is generally known.

Having a grid of arbitrary topology, it is required to calculate the power flow of a given dispatch to make sure that the constraints are not exceeded. On the one hand, there is the challenge of deciding which generation units are turned on for the dispatch, which is called the unit commitment problem, while on the other hand, the challenge of deciding the generation volume of the power plant has to be addressed (energy dispatch problem). One should note that this is still only a limited representation of the physical system, which also requires the measurement of the reactive power and stability of the network frequency. These are often neglected for simplification in the following example of grid simulation, where these effects of [Altering Current \(AC\)](#) power are removed by calculating the [Direct Current \(DC\)](#) power flow instead. This leads us to a formalization of the problem as well as its simplifications.

Optimal Power Flow (OPF)

Finding the cost-optimal way including the fuel cost of generators and any other operational costs to do this dispatch is known as the unit commitment energy dispatch problem. In its general form, it is a non-convex non-linear problem, which can be

approximated to the following convex **Direct Current – Optimal Power Flow (DC-OPF)** optimization problem for every time step $t \in T$ by minimizing the objective cost Equation 2.2 [43, 223]:

$$\forall t \in T : \text{minimize } \sum_{i=1}^n C_i(P_i(t)) \quad (2.2)$$

Under the overall power balance constraint:

$$\forall t \in T : \sum_{(i,j) \in \mathcal{B} \times \mathcal{B}, i \neq j} F_{ijt} + P_i^D - P_{it} = 0 \quad (2.3)$$

where the line flow from i to j is:

$$F_{ijt} = B_{ijt}(\theta_i - \theta_j) \quad (2.4)$$

Respecting the generator usage limit:

$$P_i^{\min}(t) \leq P_i(t) \leq P_i^{\max}(t) \quad (2.5)$$

Voltage angle limit:

$$\theta_i^{\min}(t) \leq \theta_i(t) \leq \theta_i^{\max}(t) \quad (2.6)$$

Where:

- $C_i(P_i(t))$ is the cost function of generator i as a function of its power output at step t $P_i(t)$,
- n is the total number of generators,
- $P_i(t)$ is the output power of generator i ,
- $P_i^{\min}(t)$ and P_i^{\max} are the minimum and maximum output power of generator i ,
- $P_i^D(t)$ is the demand at bus i ,
- \mathcal{B} is the set of buses of the grid,
- $B_{ij}(t)$ is the complex power flow through line ij ,
- B_{ij}^{\max} is the susceptance of the line ij ,
- $\theta_i(t)$ is the voltage angle at bus i ,
- θ_i^{\min} and θ_i^{\max} are the minimum and maximum busvoltage angle at node i .

Various optimization techniques such as gradient-based methods, evolutionary algorithms, and interior point methods are used to solve the optimization or some approximation of it [256]. Yet, there are also approaches using Machine Learning techniques to solve the problem of training an algorithm on calculating the grid states from a given power flow [95, 251]. Such applications are useful if the same grid has to be solved multiple times while small deviations in the result from the optimal calculation can be tolerated. The typical simplification of the convex linear OPF can be achieved by replacing the voltage angles constraint with the sole capacity of the line [192]. For other applications, it might not suffice to solve the simplified DC-OPF problem but needs to solve the AC problem, which is generally non-linear and not convex, making an exact calculation complex. However, in most typical market simulation scenarios, the simplified power flow calculation is sufficient.

Failure Safety

While in an ideal world, the grid constraints are never exceeded and power lines or generating power plants never fail, reality has to be prepared for such situations. If the power line to some agents of the grid fails, such agents can not provide electricity anymore, which needs to be made up by other power generation plants. The TSO is obliged to ensure balance and prevent cascading failures through grid resilience and redundancy. This is why N-1 grid contingency is required, which means that the network should be able to cope with the failure of a single line without cascading effects of further failures. [62]. In more crucial cases, it can even be required to also have safety if two lines are failing (N-2 contingency). While other parts of the grids, which have less of an impact – especially in low-voltage grids – do not even have the safety of N-1 contingency.

Grid contingency analysis is similar to the application of power flow calculation with additional power flow constraints. In more detail, for the **Line Outage Distribution Factor (LODF)**, additional constraints for each potential outage of a branch c for all other branches b in the sub-network are added to ensure that they do not become overloaded beyond their capacity l_{max} [107, p. 130]. Here $f_{b,t}$ and $f_{c,t}$ are the flows before the outage, $LODF_{bc}$ are the load factor for the adjusted load and $f_{b,t}^{(c)}$ is the load after the outage of branch k :

$$|f_{b,t}^{(c)}| = |f_{b,t} + LODF_{bc}f_{c,t}| \leq l_{max} \quad \forall b \quad (2.7)$$

When these problems are not calculated by a central dispatcher or ISO, but in a distributed manner, additional challenges arise, as is the case for energy markets. This requires additional communication and obligations, which are given in the next section covering fundamental concepts of energy markets. Such energy markets can, in theory,

create cost-optimal results of dispatch without central scheduling while also providing safety, if considered in the market design.

2.2 ENERGY MARKETS

While there is generally a clear idea of an energy market, the exact scope of what is included or excluded is often not discussed. When discussing different energy market designs, it is important to note that this is more than just about a single market. It also includes the regulatory framework and incentives, as well as the obligations of participation and contraction [6]. Furthermore, information flow and communication, as well as trust, can be seen as part of the energy market design as well. A definition of an energy market design is given below, based on the investigation of influences of bidding behavior.

What is an energy market design?

Energy market design is defined as the sum of incentives, participants, rules, and contractual obligations that structure and regulate a set of energy markets. This includes requirements for market entry and participation, as well as incentives related to trading, energy delivery, and communication [159].

As the energy system and surroundings change, the requirements of the energy market design change too. This can especially be seen in the change towards the liberalized energy market, but also through the recent changes and extensions to the market design.

2.2.1 Market Evolution and Dynamics

For the coordination of energy dispatch and transactions of energy distribution, energy systems went from a centralized revenue structure with bilateral support structures towards a liberalized distributed market. While this can not be said for all regions, a general movement towards markets that are trading in shorter terms can be seen throughout the last centuries [32]. This went from the beginning of having the complete supply chain in one hand to the distributed systems existing today. Even then, along the supply chain, bilateral contracts took place between companies with less regulation. Still, the initial phase of the energy market was characterized by a centralized structure supporting local monopolies. Large-scale power plants generated energy, which was then distributed to consumers through a single energy distributor (left side in Figure 2.2). In this scenario, entities held control over both the grid and production facilities.

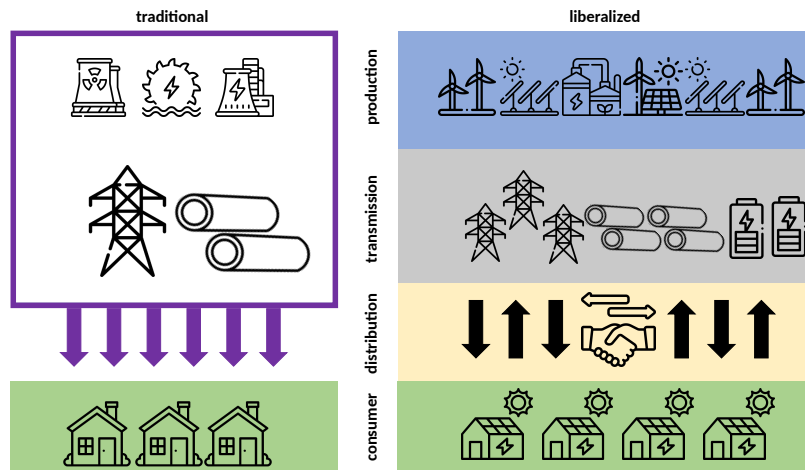


Figure 2.2: Market liberalization allowed to break up monopolies. In the regulated market small generation is traded flexibly. Therefore, decentralization enables integration of new players and opportunities [54].

To address the centralization of power in the local monopolies, the European energy market underwent a paradigm shift toward liberalization, driven mainly through regulatory changes. In Germany, the amended Energy Act of 1998 transposed the EU Directive on the internal market in electricity into national legislation, abolishing regional monopolies. In 2003, the second energy package was adopted, under which industrial and residential customers have a wider choice of energy suppliers, increasing competition [189]. In 2009, the third energy package was adopted, introducing further rules on unbundling, independent regulators, and enhanced consumer rights. This includes the establishment of the Agency for the Cooperation of Energy Regulators (ACER), the ENTSO-E and European Network of Transmission System Operators for Gas (ENTSO-G) [69]. The fourth energy package was adopted in 2019 and focused on congestion management and citizen energy communities [45]. The fifth energy package is adopted in 2024 and includes standardization of long-term contracts as well as a wider adoption of the EU Emission Trading System (ETS). This ongoing process involves a departure from centralized control to a more open and decentralized structure, removing barriers of market entry. [69]

In a liberalized market, distinct roles are assigned, and regulatory measures ensure that a single entity can control only one role. Although this necessitates rigorous oversight, it mitigates the market power held by individual entities. The roles of grid operator and energy producer are separated in a liberalized market, enabling consumers to purchase energy from any connected producer, fostering competition (right side in Figure 2.2). However, the complexity of the market introduces high entry barriers for new participants, particularly hindering smaller producers.

The liberalized market structure also led to the emergence of energy suppliers, aggregating consumers to purchase energy on the wholesale market. While this reduces the

number of participants, it disconnects end-users from directly trading produced energy on the wholesale market. Consequently, end-users are decoupled from incentives arising from short and midterm price fluctuations. Such price signals could serve as a mechanism for direct demand-side management, aligning with transactive energy concepts [124].

The dynamic interplay between historical centralization and the ongoing liberalization process underscores the complex evolution of energy markets, reflecting efforts to balance market efficiency, competition, and consumer engagement.

The liberalized power market might fail to meet climate targets regarding the avoidance of CO₂ emissions if changes to the market design do not materialize [135]. Kraan suggests that modernizing energy systems requires a flexibility market and much higher CO₂ prices to incentivize the renewable energy targets.

2.2.2 Energy Market Roles

Despite the long-standing existence of energy market concepts, there is no standardized way of how energy markets work and which participants exist within a market design. Of course, the energy market exists to bring demand and generation together to buy and sell from each other. So we typically have at least three different actors in such an interaction, or four if some kind of transport through a grid is involved. Yet, generally speaking, no full definition of actors exists, as involved actors vary from the desired accuracy and complexity of a simulation. For example in [96], more than 35 participants and actors involved in energy trading for **Electric Vehicles (EVs)** are defined.

A definition of market actors, including recommendations on an improved market design focusing on flexibilities is found in the **Universal Smart Energy Framework (USEF)** framework [233]. Related models which were used for capacity remuneration mechanisms are listed in [37], highlighting the limited comparability between results and scenarios.

Multiple market simulations consider a day-ahead market as sufficient to explain most market dynamics, however, other aspects of the market design, like the availability of a balancing market, also affect the bidding behavior [190]. Furthermore, the market design is one of the components that requires adaptation to future scenarios, highlighting the focus on simulating details of energy market roles [171].

For future scenarios, various projects inspect the usage of **Local Energy Markets (LEMs)**, which also react to flexibility in smaller scales [229].

The adoption of new rules and constant adjustments to the European energy markets is discussed by the **EU Parliament** [110]. Similarly, focus on carbon policies, ancillary services and congestion management can require additional market actors [48].

It is important to note that a generalizing approach based on the existing literature may not accurately capture the nuances of complexity and fundamental actors. For instance, one could examine whether the incorporation of trust and metering operators

contributes meaningfully to a market design and its simulation.

The main actors of an energy market are displayed in the following, with the understanding that they are not intended to be exhaustive.

- Grid operator
- Consumer/Producer/Prosumer
- Market operator
- Specific roles (through market design)
 - Metering point operator
 - Aggregator (electricity supplier)
 - Balancing provider
 - Others

Grid Operator

Grid operators are responsible for the management and operation of the electrical grid infrastructure. Their primary role is to ensure the reliable and efficient transmission of electricity from power generators to consumers.

It is typically separated into two types, which is the local distribution grid operated by a [Distribution System Operator \(DSO\)](#) and for further distances, the transmission grid operated by [TSO](#).

The operation of a power grid is traditionally considered a natural monopoly, due to its capital-intensive nature, durable assets, and the high costs associated with building and maintaining the infrastructure [85]. It has been challenged in recent times [129, 139] due to the breaking up of other monopolies in the energy sector, though it still is considered a monopoly. It is therefore highly restricted and not competitive but has incentives through regulations. These include a fixed surplus rate and laws to incentivize spending money.

Operation fields of the grid operator include expansion planning, congestion management, grid security and resilience as well as the provision of reactive power. Simulations of future scenarios typically as well focus on the expansion planning.

Consumer/Producer/Prosumer

Typical participants of the electricity grid either consume energy, produce energy or do both, depending on a more or less controllable scheduling. Producers are an important role in the energy market which produces the energy sold on the market. One typically differentiates between [Variable Renewable Energy \(VRE\)](#) and controllable thermal power plants.

Examples of prosumers can either be storage operators or demanding participants, who have a surplus of (renewable) generation that is fed into the grid. Conceptually, this role evolves organically through the integration of new technologies. While flexible

consumption was less common, incentives for flexible demand are now passed on to the consumers as options to react to dynamic pricing exist.

Switching to prosumer usage makes it possible to behave grid-supportive in both directions, enabling new business models and incentives for balancing power, reducing the need for dedicated reserve power plants which are dispatched to avert power loss events. Such roles are separated in the USEF design into separate Balancing Service Providers.

Traditionally, small consumers are invisible in the energy market as they are cumulated by an aggregator – often known as an electricity provider. This hides the actual flexibilities of the consumers from the market, leading to missing transparency [31].

Aggregator

Aggregators are responsible for bundling consumers, prosumers or small power generators (so-called **Virtual power plant (VPP)**). They are typically responsible for the provision of electricity to the market as well as the billing of aggregated entities. In many systems, the respective role can be seen as the electricity supplier or flexibility service provider. Sometimes actual price signals are passed on by individuals, while more often an average price is used over a larger period of time, such as a year, which does not take into account the use of flexibility of end users in the aggregation.

Through the law of large numbers, the aggregator can minimize the trading risk by reducing the variance of the energy demand it is aggregating. Furthermore, the existing market entry barriers can be avoided through aggregation, as the cost of licenses to participate in a market is split across the aggregated entities.

Market Operator

The market operator is the central instance that informs participants about the opening and closing of markets. It applies a given market mechanism so that the resulting market clearing creates generation and demand obligations for the participants.

There can be multiple market operators opening and closing, one for each bidding option. A single clearing often includes products for different time schedules, like the day-ahead market for different hours – but also overlapping products are possible. Besides of the actual clearing, the admission to the market, additional obligations and entry barriers are also duties of the market.

The plain market results form a unit commitment for energy dispatch, yet energy markets can also bundle other services, like balancing markets, auctioning of subventions/support policies or flexibilities.

An essential part of their role is also the provision of transaction guarantees, as the liability for an offer is not dependent on the liquidity of the other market participants, therefore taking over the risk of transactions. This aspect is often neglected as the property of trust in a transaction plays a rather minor risk for most wholesale participants, but is more crucial for local energy markets [11].

Balancing Provider

As the physical demand and generation can deviate from the market result, balancing providers provide optional energy by monitoring physical signals like the network frequency and voltage.

The provisioning of balancing energy can be auctioned through a balancing market as it is the case for many energy systems. In Germany for example, pre-qualification measures have to be taken care of before participating in the provision of balancing energy [80]. In the USEF framework this is liberated through balance responsible parties, which qualify for balancing and provide other market participants with the ancillary service [233].

Here, one can make a distinction between actual balancing power provided and the on-call duty of these generation and demand plants to serve power.

Others

Additional roles can be defined in the market framework. This might not be necessary for the operation of a power system, but allows to adjust incentives, reduce congestions or simply increase realism. In many cases, the grid operator handles the operation of the unit commitment directly by centrally calculating the dispatch as is the case for various ISOs. Typical additional parties include the metering provider or the management of the balancing accounting. Depending on the resolution of the simulation one can also include charging station operators and flexibility service providers as participants on an energy market.

2.3 ENERGY MARKET DESIGN

Historically, energy dispatch was aligned vertically, with decisions made by a central authority or an ISO. However, modern energy systems have transitioned to a market-based approach where energy dispatch and scheduling are determined through market mechanisms. Energy markets provide a platform where producers and consumers can interact to determine the price and quantity of exchanged energy. The market-based approach aims to deliver energy at the lowest possible cost by fostering competition between producers and consumers, which in turn drives efficiency. This strives for the theoretical concept of perfect competition in which all sellers would sell energy for the **Natural Price** [187]. The idea of this is to create the correct incentives for investment and operation decisions, without coordinating the dispatch with a ISO which would act as a monopolist.

Having perfect competition in contrast would also require an infinite amount of buyers and sellers, homogenous sold goods, no transaction costs and perfect information [18,

187]. As all participants are profit-maximizing, their best option would then be to bid their marginal cost [222].

While this is generally considered impossible to achieve in the real world, electricity trading was often at least perceived as a homogeneous traded good. However, this is not truly the case as the value varies between time, location, time to market and ecological factors as shown in [103]. Additionally, some participants have high market power due to a high share of trading capacity and power generation on energy markets (for example the *Électricité de France (EDF)* in France [209]). This is tackled generally in the power sector through regulations of market power [97].

Plain theoretical models do not always explain behavior, due to imperfect assumptions of omniscient bidding behavior. Therefore, it is useful to simulate the real market characteristics in an agent-based market model. Energy market models generally simplify complex real-world dynamics by assuming perfect competition, neglecting externalities, or using aggregate supply and demand curves. These simplifications can be necessary for computational feasibility and analytical tractability, but limit the ability to capture certain market realities. Still, each market can only be seen as a simplified model of reality, covering only partial aspects.

Markets can generally be divided into continuous markets, which receive a continuous stream of demand and supply bids, and markets with a clearing interval, which aggregate all demand and supply bids until the clearing takes place. In both cases, a clearing function is used to match the supply bids with a respective demand bid that exceeds the price.

There are markets in which a fixed demand is set, noting that a fixed amount of supply is accepted. Energy systems prior to liberalization often did not use market-based mechanisms at all, as the whole energy supply chain is in the hands of a single operator. The challenge in energy market simulations is to model effects that are beyond the scope of the market model itself to reflect on the consequences of the underlying simplification in the energy market.

Looking at concepts from game theory and mechanism design, a set of requirements for a cost-optimal clearing mechanism for two-sided/double auctions is given in the following as the foundation of a market mechanism lies in the following properties.

1. individual rationality (IR) – participating in the auction should never be a losing move itself [240].
2. incentive-compatible (IC)/truthful – ensuring that every bidder receives the best long-term result when bidding the true value (strategyproof) [42].
3. economically efficient (EE) – ensuring that the allocation of items maximizes the total value to all participants, achieving a socially optimal outcome. This is done by selecting the outcome that maximizes the sum of the reported valuations [240].
4. balanced budget (BB) – means that all monetary transfers happen between the participants of the auctions, without the auctioneer giving or taking liquidity

from the market. The reduced form – weak balanced budget – defines that the auctioneer may take liquidity, but never add to the market [15], which is more likely to occur in reality.

5. fairness – the mechanism is designed to be fair in the sense that the outcome is determined solely by the participants' valuations, without any bias towards any particular participant.

Yet, it is impossible to create a market clearing mechanism that covers all of the properties as noted in Myerson-Satterthwaite theorem [168]. This is generally applicable to the two-sided energy markets considered in this paper. As well as to supply chain auctions, where bidders have to bid on multiple markets at the same time [44] (e.g., a gas power plant buying gas supply to produce electricity). In such auctions, transportation costs should also be taken into account, which usually is not the case for simplification reasons. Often, fairness can be ensured by considering all bids as anonymous bidders which reduces the possibility of cheating and abuse of market power. Generally, the game-theoretic approaches do not consider computational efforts and transportation challenges and therefore might as well not be scalable [188].

Even as various ideal assumptions for the distribution of knowledge and market power are taken, such results from mechanism design are an important foundation for energy market clearings and the distinction of which clearing mechanisms are available. The subsequent investigation examines a range of suitable mechanisms.

2.3.1 Double Auction Clearing Mechanisms

Energy markets typically involve resource allocation in double auctions, which are a special set of multiunit auctions, in which multiple units of the same (homogenous) items are traded from sellers to buyers. Less deregulated markets only consider a single price auction with an inflexible demand, which is known (or estimated) beforehand. Yet, these also tend to move to liberalized markets to increase market incentives for flexible demand. Regarding the simulation, this setting can also be modeled as a double auction with only one buyer. Therefore, to compare different future scenarios of auction mechanisms, the inspection of requirements for two-sided auctions is essential. From the side of clearing mechanisms in energy markets, various options arise, while two major ones dominate the existing energy markets. These two, as well as other mechanisms, are provided in the following.

PAY-AS-BID is a market mechanism that clears individual bids, where the selling (generation) price is lower than the buying (demand) price. Such bids are then cleared so that the selling price is accepted and paid by the matching demand.

In this case, **truthful bidding** does not win, as it does not include the anticipated market price and would therefore not be profitable. Opposed to that, **strategic bidding**

is required, which includes such expectations of values and embedded risks. In simulations, it is therefore hard to use, as the bids appear lower than they would be in reality, as an unknown margin is added to all selling bids. From the demand side, it makes sense to bid truthfully, as bids below a given threshold are not matched. Beyond this, bidders can outprofit others by buying and selling at the same time (which is sometimes prohibited) or abusing market power.

While the pay-as-bid market mechanism is neither truthful, efficient, nor fair, it is a common mechanism used in energy as well as stock markets. This is due to its simplicity and usefulness in markets that do not have fixed auctions but are running trading in real-time.

PAY-AS-CLEAR is an alternative mechanism that clears the market based on the highest accepted bid, where all successful sellers receive the same clearing price, which is typically the price of the last accepted bid. It is also known as "uniform pricing" or "merit order clearing".

In a pay-as-clear mechanism, bidders are incentivized to submit truthful bids that reflect their actual willingness to sell (so their [Natural Price](#)). Since all accepted bidders receive the same clearing price, there is less incentive for strategic bidding; participants can bid their true costs without fear of losing out on potential profit margins. This leads to a more efficient allocation of resources, as the market clears at a price that reflects the true balance of supply and demand.

Pay-as-clear enhances incentive compatibility (IC) and efficiency (EE), but it can also introduce its complexities. Market participants generally reach optimal behavior by bidding truthfully as bidding a lower price would create scenarios in which a seller has to sell below the marginal cost. Bidding above the marginal costs would create situations in which the seller does not produce revenue despite the clearing price being above the marginal price of the unit [101]. However, the mechanism favors the demand perspective as only the generation price has to be paid without influence of the last demand bid's price.

On the other hand, all successful bidders benefit from higher clearing prices, which creates high overall costs in situations of low available supply, making it seem unfair as total dispatch cost increases dramatically [101]. This can lead to situations where market power is concentrated among a small number of suppliers, potentially undermining fairness if not properly regulated.

While pay-as-clear mechanisms offer advantages in terms of transparency and efficiency, their effectiveness depends on the broader regulatory framework and market structure in which they operate. Furthermore, it has to be noted that the exact adoption of the mechanism is important. For example, application of sealed second-price pay-as-clear auctions can incentivize bidding zero for all bids but the first to reduce the paid price for the first item [57, 188].

VICKREY CLARK GROVES AUCTIONS use the submission of sealed bids and allocate goods based on the highest combined bids. Notably, the price paid by each winning bidder is not their submitted bid, but rather the externality they impose on other bidders. This encourages participants to bid their true value, as the final price is independent of their own bid.

In a one-sided market where only one set is paid, the bidders of a Vickrey auction have to pay the second price [238]. Extending this concept to general markets, a VCG mechanism describes a generalization of this by having a value function v_i of the i th bidder in V to assign a real value to an item X .

$$v_i : X \rightarrow \mathbb{R}^+ \quad (2.8)$$

where the mechanism f gives the maximized utility for biddings $v_i \in V$ bidding on the good a in the set of all goods A so that

$$f(V) \in \arg \max_{a \in A} \sum_{i=1}^{n=|V|} v_i(a) \quad (2.9)$$

Such a mechanism f is called a VCG mechanism, maximizes the utility and is incentive-compatible [174, p. 218].

One can generalize this concept to multi-item double auctions. The clue of this is, that VCG auctions are then not relying on a balanced budget as the auctioneer takes from or adds liquidity to the market. However, implementing VCG mechanisms in real-world energy markets can be challenging [199]. Increasing the complexity of mechanisms reduces the general understanding on a high level. Therefore, market simulations can help to overcome the complexity by providing a way to interact and analyze the results. VCG mechanisms are also popular in novel concepts of peer-to-peer trading of energy markets [9, 33, 108].

Comparing the VCG mechanism with the current pay-as-clear work, one notices that the pay-as-clear market mechanism is beneficial for the demand side, which has to pay lower prices as the last demand bids price is not considered. This reflects the actual situation of demand, in which the majority is not flexible and therefore demand bids are often near the maximum price, through the strong requirement of safety of supply. Yet the increasing elasticity in demand through the establishment of flexible demand might change this in the future, requiring different market mechanisms based on VCG.

While all of the discussed mechanisms are often used in energy markets, they do not include limitations of transport capabilities.

2.3.2 Distribution Transport Capacities

Most energy markets execute trading without reflection of the actual transport capacities. The trading result within a zone can therefore exceed grid limits in some parts of the electricity grid. This simplification makes it possible to create comparable prices within a market zone and simplify trading, as the distribution cost is split across the participants, independent of the trading results. This also creates a market mechanism that is easy to understand, as the inclusion of network properties quickly becomes quite complex for larger networks. Such a market, therefore, does not consider the grid at all and executes the trading as if an unlimited amount of interconnections is available – or as it is often called – as if the whole market area is on top of a [copperplate](#) which transfers energy[243]. Typically, this is addressed by creating a correction of the resulting market dispatch, by calculating the physical feasibility, including the grid limits. This correction is called *redispatch*. Another possible mechanism is to create a second auction after the first, in which agents have to bid in the direction to reduce the congestion.

While it is generally also possible, to reduce the size of market zones and split countries into separate market zones to reduce the effect of this simplification (which would create smaller copperplates) a different approach is to include the grid limitations in the market mechanism by solving a power flow model as shown in [Section 2.1.2](#), creating a nodal view on the grid in the market step to tackle this problem directly in the trading. The grid operator role, therefore, must be integrated in the market dispatch, which requires additional communication. The discussion of whether nodal vs. zonal market mechanisms are best used in energy markets is still not finally solved and is further discussed [130].

Discrete Market Interval

One major challenge for the grid is the discrepancy between the time intervals of the market, which acts with discrete time intervals and the physical power flow, which is a continuous measurement. Expressed differently, the market is handling energy (Wh) while the physical grid handles power (W). Operating the grid and ensuring that the sum of the generation equals the total consumption at any time is crucial to the stability of the whole energy system.

For every discrete time-slot t in the set of time slots $T_{discrete}$ and for every i th market participant of the market participants V the sum of all traded energy a must be net-zero:

$$\forall t \in T_{discrete} : \sum_{i=1}^{n=|V|} a_{it} = A_t = 0 \quad (2.10)$$

Thereby a is positive for sold energy (production) and negative for bought energy (consumption) at the market. This must also be true for the physical energy flow e . In

this case, the energy flow is continuous without fixed intervals. In every fixed delta t we are therefore integrating over the continuous energy of a node e_{is} :

$$\forall t \in T_{discrete} : \int_{t_0}^t \sum_{i=1}^{n=|V|} e_{is} ds = E_t = 0 \quad (2.11)$$

Finally, the traded amount A_t must match the physical energy flow E_t for every discrete time-slot t in $T_{discrete}$:

$$\forall t \in T_{discrete} : A_t = E_t \quad (2.12)$$

This formulates the unit commitment problem, which requires the physical flow to match the demand at every moment on the grid.

While it is generally required that the above equations hold for every point in time, energy markets only reflect discrete intervals. Typical time slots are 15 minutes as on the [Day-Ahead-Market \(DAM\)](#), 1 hour and longer, as typical on the Futures markets and 4-hour time slices are typical on the balancing markets. Yet there also are ongoing discussions about decreasing the temporal granularity to 5 minutes [32].

As a consequence, consumption peaks and drops that happen during a time slot are not represented accurately as the average over a whole time slot is used for the market settlement.

Balancing Energy

To still meet the requirements of a balanced grid, the intertemporal deviations during a trading time slot are managed through balancing energy, which is typically auctioned through a dedicated balancing energy market or through regulatory requirements.

It also has to be ensured that sufficient balancing energy is always available to compensate for major grid fluctuations, without damaging the network or causing outages. The volume of this can be managed centrally or with a dedicated auction at a balancing market, while the actual allocation typically happens through a tender.

As shown in [Figure 2.3](#), one differentiates between three different types of balancing capacity. The first is the Primary reserve capacity, also called [Frequency Containment Reserve \(FCR\)](#), which has a [full activation time \(FAT\)](#) of 30 seconds in which they need to provide energy for up to 30 minutes [80]. Additional (slower) balancing capacity is triggered after 20 seconds and needs to be fully activated after 5 minutes, the secondary reserve or [automatic Frequency Restoration Reserve \(aFRR\)](#). Finally, the tertiary reserve capacity (or [manual Frequency Restoration Reserve \(mFRR\)](#)) can be activated, which has a [FAT](#) of 15 minutes. If the sum of balancing energy provided during that time is not enough to balance out the grid, additional measures are taken through replacement reserves or the wholesale intraday market. Providing balancing energy is therefore required to maintain a stable grid frequency in electricity grids.

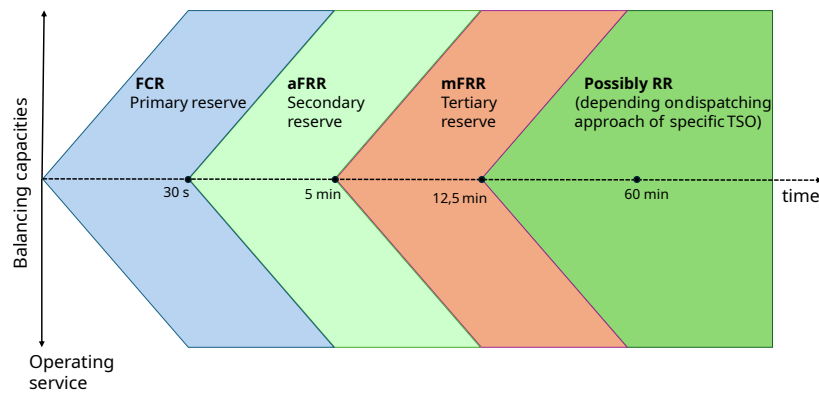


Figure 2.3: Overview of balancing energy types in European energy market inspired by Next Kraftwerke [172].

In Europe's interconnected grid, balancing energy is provided per nation on a separate market layer, while the amount of balancing energy is calculated by the grid operators. The national results are coordinated through the **PICASSO** platform for aFRR, the **MARI** platform for mFRR and the **TERRE** platform for slow control energy with an activation time greater than 12.5 minutes [61].

Demand and Generation Forecasting

To ensure a stable energy system each participant forecasts the amount of demanded or generated energy to buy/sell at the market. As the energy forecast has its uncertainty, the traded energy of a unit i for a time interval t does not always match the respective energy flow:

$$a_i t = e_i t + \Delta e_i t \quad (2.13)$$

The sum of all deviations $\Delta e_i t$ must be balanced out by balancing providers to secure the grid stability. The process of finding the best schedule for the next time slot during a day-ahead clearing is getting less stable with the increase of renewable energy generation, as those depend a lot more on the current weather situation [116]. While the instability of generation is quite new, consumption has never been completely stable as consumer behavior is not accurately predictable.

This effect evens out through the law of large numbers the more consumers are aggregated by an electricity provider. But in **Peer-To-Peer (P2P)** market designs, the uncertainty for a single household can be excessively large, ending in high costs for prosumers with a bad forecast, as they have to pay fees for $\Delta e_i t$ for every time-slot [49, 255].

To reduce the risk for a single prosumer, aggregating small prosumer groups that trade together at the market are one possible solution, which is also known as VPP. Another approach would be to use batteries as energy cache to reduce Δe_{it} .

Small market participants cannot manually enter or generate their forecast on a daily basis, without having a bad user experience for most people who aren't interested in the energy prices. Therefore, forecasting has to be done automatically with a forecasting system, which constantly predicts the best strategy for a_{it} based on historical data and the available generation capabilities.

The evolution of energy markets has been a transformative journey, shaping the coordination of supply and demand with price information. Over its 140-year history, power grids and associated markets have transitioned through distinct phases, each influencing the relationship between producers and consumers.

2.3.3 Regulatory and Operational Structures

While it is important to declare the participants of the market design, it is also of utter importance to look at the real-world market background. Typically, the market mechanisms are executed as an optimization problem, taking zonal or nodal constraints into account. One can split the calculation of market results in a hierarchical market into subproblems using Benders decomposition as done in [76]. This is especially helpful if created problems are too large to be solved directly. Solving the European Single Day-Ahead Coupling (SDAC) market, which is synchronized across multiple market zones, requires to be solved in about 10 minutes to keep enough time for publishing the results [41]. This is done using the Euphemia algorithm [169], which solves 96 15-minute time slots at once and includes the topologies and constraints to calculate a flow-based result of the European cross-zonal market [58].

IMPLEMENTATION PROCESS OF NEW MARKET MECHANISMS IN EUROPE

In Europe, the ACER monitors the market behavior and proposes changes to improve EU electricity markets and market design, enacted through the Regulation on Wholesale Energy Market Integrity and Transparency (REMIT) [68]. This includes the overarching overview of all existing markets in the current European energy market design shown in Figure 2.4. ACER investigates issues and researches impact by engaging with national regulatory authorities and market participants, as well as the ENTSO-E. The results of this phase are publicly announced with organized feedback from public consultation, workshops and hearings. If required, a recommendation to the European Commission is formulated, which then runs through the legislative process and is then transposed into national law as part of the European harmonization process [2]. This process can take several years and requires continuous monitoring of market situations afterward as well for impact analysis.

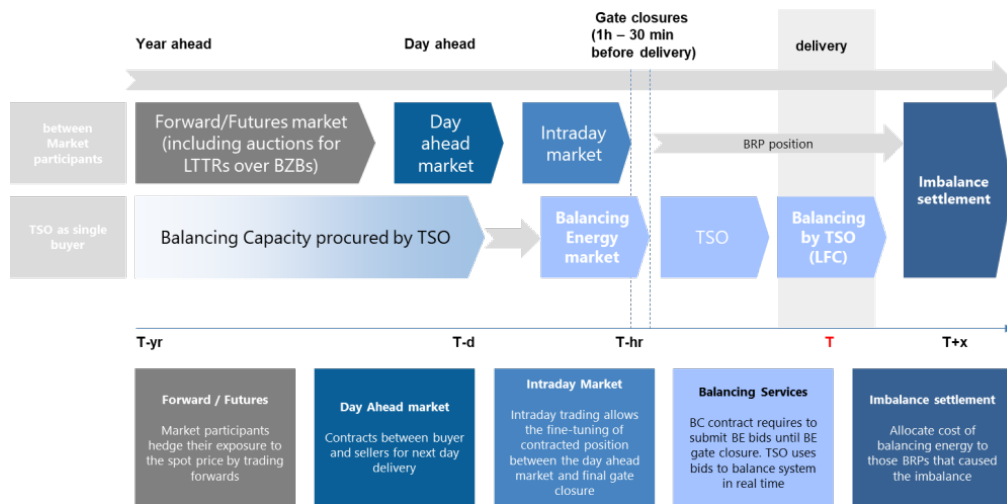


Figure 2.4: Focus of ACER market rules containing different generalized timeframes of trading [1].

FLOW-BASED MARKET COUPLING

As each country has transfer capabilities, limited through the grid's transfer capacity, the **Net Transfer Capacities (NTC)** between two zones can be simulated through a fixed method. However, the maximum transfer capacity between two zones also depends on the transmission to other nodes [235]. Given the example, that a node A includes a transmission line to B, while also including a line to C, the maximum transmission limits differ from the plain NTC values in a flow-based domain exemplarily shown in Figure 2.5. This shows that the export from A to B (y-axis) can exceed the net capacity under given circumstances, depending on the export of B to C (x-axis), allowing a generally larger area in the flow-based scenario than with respect to the NTC alone. An open-source tool which models and respects such **Flow-Based Market Coupling (FBMC)** is publicly available in POMATO [244].

NODAL PRICING

While **FBMC** includes the actual transmission line capacities between zones, the usage of nodal pricing further increases the resolution to individual nodes and lines of the actual physical power grid. One way to implement this method is to include the line capacities in the market clearing and calculate the marginal cost at every node of the grid. In this case, the market has to calculate the **Locational Marginal Pricing (LMP)** before clearing and therefore needs to know about the grid perspective. This also assumes that all trades and ramping flexibilities of each market participant are known to the market operator. Recent investigations of modeling **FBMC** under uncertainties show that it outperforms dispatch simulations of only using **NTC**, while usage of nodal pricing would decrease the total dispatch cost further [245].

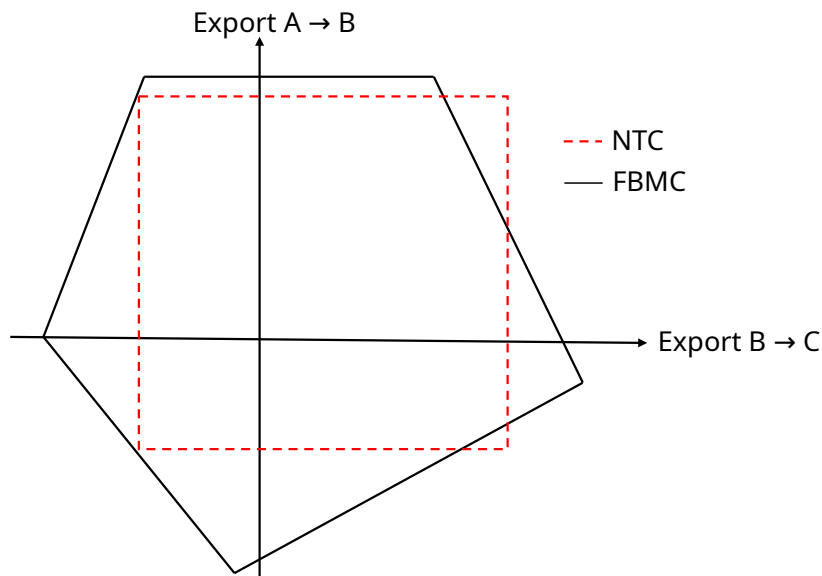


Figure 2.5: Flow-Based Market Coupling constraints in comparison to NTC flow domain from Zone A to B and C. Constraints of FBMC model the interplay of transferring capacity between the zones. Inspired by [235]

OVER-THE-COUNTER TRADING

Not every bid and contract is traded at a centralized market. Instead, OTC trading is typically settled through bilateral communication between market participants. Therefore, no obvious communication records of trades are aggregated at a central auction house. This can be compared to P2P trading, where wholesale market participants can trade off-market and records of trades only exist between the participating actors. In reality, there also exist auction houses for OTC trading which provide predefined contracts of the bilateral trades. This also includes some kind of risk assessment and matching of market actors interested in such trades.

In a simulation, it is difficult to model bilateral communication if no first communication between the actors was established. This can be fixed through the idea of a continuous market, at which contracts can only be accepted by specific market actors. In this case, the peer-to-peer OTC trading uses pay-as-bid clearing and includes queries to the markets list of unresolved orders. If a matching order is sent to the auction house and matches the correct trading participant, it is cleared immediately.

REDISPATCH MARKET

In typical redispatch, after clearing the day-ahead products, the market result is communicated towards the TSOs which is obligated to provide a grid calculation and pay for adjustments of the dispatch in areas, where the estimated dispatch is not feasible due to grid constraints. The adjustments calculated from this dispatch are distributed through a redispatch system. Fundamentally, this behaves similarly to a market, where adjustments to their bidding are distributed across the participants who

take part in the initial market clearing. Such mechanisms reduce grid congestion, while the process also comes at costs. As redispatch actions require paying the accepted price to the initial bidder without retrieving energy, while also requiring paying a power plant closer to the demand to ramp up for compensation.

CENTRALIZED ENERGY SYSTEM OPERATION While the usage of market mechanisms seems substantial from a view used to energy markets, many countries have not yet implemented market based mechanisms for energy dispatch and expansion planning. For example, in India, there is an ISO handling all energy generation centrally. In this setting, a wholesale market exists, which is not competitive [220]. The day-ahead market has been recently adopted in Brazil while there was just a week-ahead market until 2021 [167, 184].

SUPPORT POLICIES A **Feed in tariff (FIT)** provides a minimum tariff price for a given asset. If the market price is above that tariff price, the asset is compensated with the actual market price. If the market price is below the tariff's price, the tariff's price is still paid. This support policy is typically in charge by a governmental actor to set incentives for the construction of renewable power plants. Such a **FIT** is typically only granted to specific assets of a given size and technology.

Power Purchase Agreements (PPAs) on the other hand enables a fixed remuneration for the provided energy of an asset. Such contracts are typically used for long-term marketing of variable assets and are typically traded outside of marketplaces (**OTC**). The assets are therefore removed from the wholesale market, as the buying party of the PPA receives the physical right to use or resell the generated amount. The contract price of the PPA is the settlement price to which every single unit is sold, while the amount is typically unconstrained and solely coupled to the maximum power of the asset.

Contract for Differences (CfD) is a financial support instrument in which the deviation between a base price and a benchmark price is paid in both directions between the two contractors. A typical example benchmark price is the **Intraday 3-hour pre delivery average benchmark (ID3)** or the Day-Ahead market results. The payment is enforced in regular intervals, typically monthly, while the contract duration can last multiple years. This way, high-paying market situations have to be paid back to the contractor, while a base price is established. Unlike **PPAs**, which provide generation independent of the market price, a **CfD** first requires that a power plant is considered in the market dispatch by bidding sufficiently low prices. **CfDs** therefore react to the market situation and behave market-oriented in contrast to a plain contracted feed-in [12]. This, of course, comes with an increased volatility in the contracts volume.

As suggested by Greece to the **EU** in 2022 in response to increasing energy prices, one could extend the usage of **CfD** to non-renewables [84]. However, such an approach would undermine needed price signals for demand and fossil generation, as the typical

Contract	Type	Needs price index
CfD	financial	yes
Market Premium	financial	yes
Fixed market premium	financial	no
Swing Contract	energy	yes/no
PPA	energy	yes/no
FIT	energy	yes

Table 2.1: Overview of different energy market support policies. While all calculate the payout from the actual dispatch of the unit, not all require the additional market price. Such support policies are either contracted outside the market as **OTC** or auctioned by a support entity, e.g. the government.

dispatch scheduling of conventional power plants is based on price signals as described before in [Section 2.3](#). Leaving out these measures through a **CfD** would create an incentive to increase production without respecting market signals to optimize dispatch cost.

FIT, **CfD**, **PPA** and market premiums typically rule for two reasons: either as a support or subvention or to reduce risk from price volatility. The differences are not only in the time the payment takes place but also in the contracted volume. For example, a **PPA** typically contracts the whole bidding amount, regardless of the market prices. While a **FIT** can be tied to additional constraints to only pay out if the market price is positive at all. These differences are also outlined in [Table 2.1](#).

2.4 AGENT-BASED MODELING

Having created an overview of the economic background and energy market design, the focus of the following section is put on the modeling of individual market participants through agent-based modeling.

ABM is a computational approach widely used in various scientific fields to simulate the interactions of autonomous agents within a defined environment. These agents can represent individuals, entities, or even complex systems. In this context, an agent is an entity that acts according to a set of defined rules, and its behavior is modeled through software simulations [117, 128]. This methodology allows for the modeling of individual characteristics, behaviors, and decision-making processes of distinct actors [149].

Energy system modeling projects are typically categorized into two broad approaches:

1. Top-down models (market equilibrium, central flow calculations, omniscient view)
2. Bottom-up models (optimization, agent-based simulation)

Top-down models provide an aggregate view of energy systems but oversimplify real-world energy systems by assuming central control and uniform behavior based on a calculated market equilibrium. This limits their ability to model systems with diverse, decentralized participants. In contrast, bottom-up models like agent-based simulations are more suited for simulating energy systems with many participants, each acting with unique strategies [148]. These models represent individual agents (e.g., utilities or consumers) and allow for complex interactions, such as price formation and market dynamics while accounting for uncertainties and adaptive decision-making [164]. Agent-based models provide a detailed representation of electricity markets with heterogeneous participants, making them suitable for studying evolving conditions and the effects of policies or innovations.

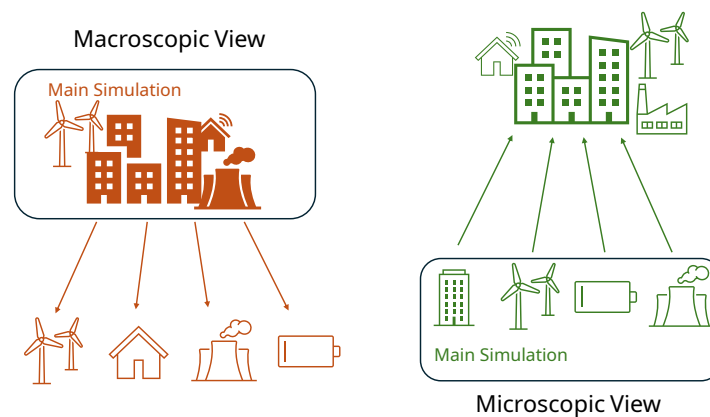


Figure 2.6: Top-down simulations (left) focus on macroscopic results which are upsampled for individuals, while bottom-up simulations (right) model individuals themselves and draw general conclusions for the whole system. Agent-based simulations generally tend to the bottom-up approach.

A schematic view of this is shown in [Figure 2.6](#), presenting how bottom-up simulations draw conclusions about the macroscopic system by simulating all actors individually, while top-down simulations begin with a macroscopic view of actors and data. [ABM](#) emphasizes bottom-up simulation, where collective behavior emerges from the interactions and behaviors of individual agents.

In this case, the model typically involves a spatial environment where agents navigate and interact with each other and their surroundings. This can be contrasted to equation-based models and statistical models, which operate on data attributes and their distribution [149]. Without additional data, statistical models struggle to model scenarios with different baseline assumptions, where there is no historical data to build on.

One of the key strengths of agent-based simulation models is the ability to deviate from normative equilibrium conditions or strategies. This makes them superior to statistical and fundamental models for analyzing liberalized electricity markets as actors can apply different logic to the bidding behavior [216]. This also makes it feasible

to initialize each agent which corresponds to a market participant with a different bidding strategy. **ABM** allows researchers to study complex systems, analyze emergent phenomena, and explore the effects of individual-level interactions on complex overall system behavior with heterogeneous behavior of the individual agents. Large problems can therefore be divided into smaller less dependent problems, suitable for scalable computation. The flexibility of **ABM** enables the representation of diverse agent behaviors, making it a valuable method for understanding real-world complexities and dynamics. On the other hand, **ABM** often incorporates many complexities by hiding behavior in subdivisions, which can make testing and debugging cumbersome, if no behavioral assumptions can be made.

The following compares different existing agent frameworks by evaluating their suitability for agent-based market simulations.

2.4.1 Agent-Based Protocols and Simulation Frameworks

In the communication of agent-based systems, different software frameworks exist. Lingua Franca is a polyglot language describing behavior through actions and discrete event-based reactions, inspired by and extending the work of Ptolemy and Kepler [119, 146, 191] used in the Ptolemy project from UC Berkeley.

It features a methodology to run distributed simulations through a separate runtime Infrastructure [145] and utilizes the definition of reactors, which define common patterns of interactions and causality between agents.

As an agent in this regard is defined through state and behavior, one can further narrow down the behavior to actions and reactions and define state through static components and variable components. Each agent can therefore be pictured as a container interacting with other agents or environments as seen in Figure 2.7.

More in the area of co-simulation, there is the MOSAIK framework, which allows defining inputs and outputs of simulation parts, making it possible to create adapters between different technologies, by manually defining the expected inputs and outputs of a simulation [178]. A more generic method is the utilization of existing standards for agent communication. Derived from the prior Protocols **ARTIMIS COmmunication Language (ARCOL)** and **Knowledge Query and Manipulation Language (KQML)** the **Foundation for Intelligent Physical Agents (FIPA) Agent-Communication Language (ACL)** standard established [71]. This standard defines performatives and how communication happens. As it does not define the used transport layer as well as the used ontology of the agents, it is up to the implementation to create and adapt useful ontologies for agent communication [134]. Therefore, adoption of the standard has stalled in recent years, as **RESTful** interfaces became more popular for the definition of intercommunication between computer systems. Still, there are two major open-source agent-based libraries striving for **FIPA ACL** compatibility. The ACL can be seen as

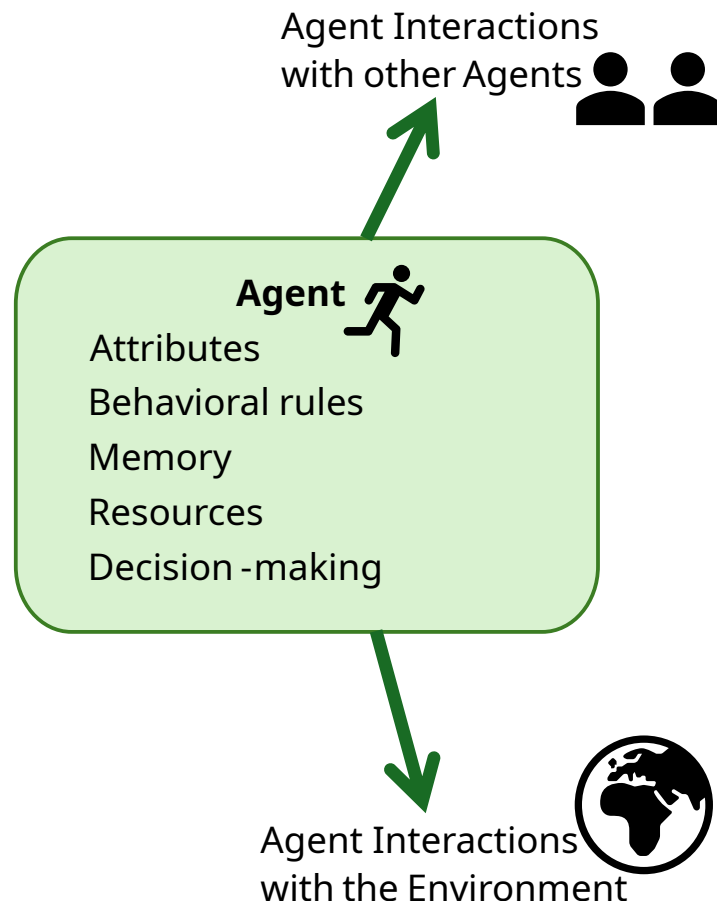


Figure 2.7: Interaction of an agent with its environment. Agents contain state and behavior and can interact with the simulation environment or other agents. Inspired by [148]

a foundation for striving for open standards in agent behavior and also comes with examples of ontologies to be used².

In the following, different agent-based frameworks are evaluated for their use in market simulation. Ideally, the findings from FIPA ACL and Lingua Franca are tackled in the modeling of agent-based systems of the future.

JADE is a Java framework implementing the FIPA ACL. **Java Agent Development Framework (JADE)** does not feature the idea of reactions in message handling. Instead, one can define behavior as subroutines that are continuously executed and can wait until a specific message is received. JADE implements different Transport Layers for ACL, so-called Message Transport Protocols and can be run distributed with formerly Simple Object Access Protocol (SOAP) and XML based Hypertext Transfer Protocol (HTTP) or Remote Method Invocation (RMI) [22]. As in most distributed simulation

² <https://www.fipa.org/specs/fipa00091/SI00091E.html>, visited on 11.12.2024

tools, an orchestration layer is not present, requiring the creation of scripts to start a **Command Line Interface (CLI)** on different hosts or manual intervention.

MANGO-AGENTS is a recent Python framework, which focuses on an event-based simulation and configures agents to either act at a given place in time or react to messages from other agents [179, 212].

The concept of **modular python agent framework (mango)** is very related to how **FIPA ACL** is used. Actions and reactions also resemble parts of the **Lingua Franca** approach, while concurrent actions are possible through event scheduling with **AsyncIO**. In a simulation, a set of agents are aggregated in one container, which can communicate with agents in other containers. Mango supports **HTTP Websockets (WS)** connections as well as **Message Queue Telemetry Transport (MQTT)** for such distributed simulations. Actions configure circumstances under which an agent wants to do a background task or send messages to other agents, while reactions define the actions that are executed when a message is received. This makes it possible to configure a typical market agent through a limited number of agent methods as shown in **Figure 2.8**.

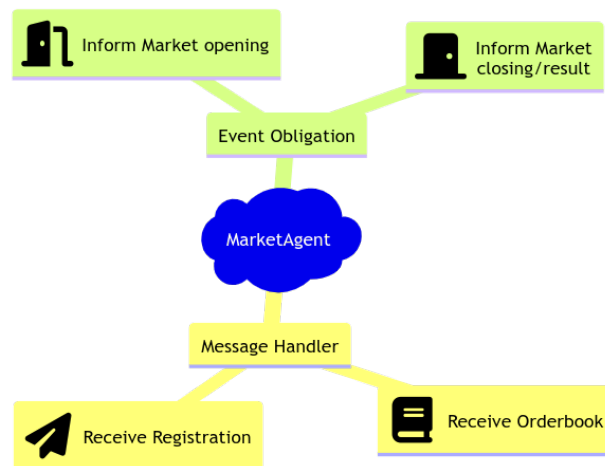


Figure 2.8: Visualization of obligations (top) and message handlers (bottom) of a sample market agent modeled with mango agents.

FAME is a Java framework written by the **Deutsches Zentrum für Luft- und Raumfahrt (DLR)**, which can be used to model agent-based behavior [211]. A distributed simulation utilizing **Message Passing Interface (MPI)** for process intercommunication is available as a plugin. Although unrelated to the development of mango-agents and **JADE**, it shares many common concepts, for example, the inbox of incoming messages, which are scheduled to agents running in the simulation process. Yet one has to configure exact times or repetitions in which agents have to operate prior to

the simulation run. The simulation input and output are configured through a binary protocol, which is made convenient through the wrapper library [FAME-I/O](#) [176].

REPAST / REPAST4PY is an agent-based simulation framework, which is specialized in grid-based simulations, which can be drawn on some coordinate system, allowing interactions with objects in reach. It heavily utilizes [MPI](#) and is suited for [High Performance Computing \(HPC\)](#), efficiently partitioning a larger problem into subproblems by distributing the grid as smaller parts of the grid across compute cores. For market simulations, this is not suitable, as nearly all agents are interacting with a single market agent which has to be accessible to all cores. A simulated market typically halts the simulation, as every market waits for all agents to submit the bids, creating a variety of checkpoints throughout the simulation time. A method to reduce interference with parallel execution are ghost agents for agents which are near the coordinates of the next computation core. This creates a reference of the copied ghost agent to the other computing [Central Processing Unit \(CPU\)](#). Due to the requirement of a coordinate system to run such a simulation, this is not well suited for energy market simulations.

MESA is an open-source Python simulation tool, striving to allow simple simulations similar to what the commercial NetLogo offers [163]. It generally includes [Graphical User Interface \(GUI\)](#) components and simulates agents using a single act method. In contrast to event-based simulations, each agent has an act method, reacting to the current state of the simulation when the agent is awakened by the simulation. It does not provide a method to run distributed simulations, but has visualizations based on Jupyter Notebooks integrated.

Framework	Language	FIPA-ACL compliant	event-based	distributed simulation	transport layers
JADE	Java	●	◐	●	HTTP, SOAP, RMI
Mango-Agents	Python	●	●	●	HTTP WS, MQTT
FAME	Java	○	◐	●	MPI
Repast / Repast4Py	C++/Python	○	●	●	MPI
MESA	Python	○	○	○	○

Table 2.2: Overview of the features of different agent-based simulation tools. Mango suffices the simulation requirements.

Summarizing the results from the analysis of agent-based simulation tools, [FIPA ACL](#) is the most promising agent-based communication protocol. Even though the standardization is quite dated, more recent standardized protocols for [ABM](#) are not

available. An overview of different [ABM](#) simulation tools is given in [Table 2.2](#). As a result, Mango-Agents offered convincing flexibility and modeling paradigms and is therefore used as the foundational agent-based framework for the simulation of energy markets. It should be noted that although Mango and JADE support FIPA ACL, they do not currently implement a common transport layer and are not directly compatible, leaving true cross-platform compatibility as a topic for the future.

2.4.2 Agent Roles

Tightly coupled with agent-based modeling is the usage of agent roles. While there is no formal definition of a role, it can be seen as a pattern to connect related obligations and interactions with other agents into a formalized structure. One can imagine an agent trading with a market, while also communicating the flexibility potential of its generation to a reserve market. This would be two different roles of the same agent. Using such concepts makes it possible to configure individual behavior through a modular system where functionalities can be turned on and off depending on the needed market design. The roles can be reused and provide great flexibility in their usage. The role-based approach in mango-agents aligns well with the structure of energy systems, where different market participants assume various roles to fulfill their functions. By leveraging this pattern, researchers can develop more robust and realistic models that better capture the complexities and [Energy Market Roles](#) of real-world energy markets.

Fortunately, mango-agents supports this concept out of the box and makes it possible to activate or deactivate specific behavior at runtime [151].

2.5 ENERGY MARKET SIMULATIONS

While research on [Agent-based Modeling \(ABM\)](#) of energy markets has been around since the 1990s, the field of research is not yet very standardized.

As described in the previous section, various maintained agent-based simulation frameworks are open-source available. Similar, actual simulation tools, which do not only provide the rough framework but also the implementation of specific scenarios and agent behavior exist [92, 123, 196, 216, 219]. When simulating the energy market, a basic distinction must be made between fundamental models, which calculate the central equilibrium top-down, and agent-based bottom-up simulations. The latter enables a better approximation, as future trends and changes can also be taken into account [147]. Many market models only deal with the modeling of individual parts of existing market processes, use fixed time series for demand and generation or only deal with financial aspects of the electricity market. Concepts for [Locational Marginal](#)

Pricing (LMP) and Local Energy Market (LEM)³ that have already been applied in practice have also not been evaluated comparatively.

For this purpose, it is first necessary to classify the common objectives of energy market regulations. By liberalizing the natural monopoly of energy generation, a restriction of the monopoly to grid operation was achieved. The set of rules that describes the processes between electricity generation and supply is known as the market framework. It can consist of several market levels or be managed without a free market, as is the case with central dispatch.

The market framework has the primary objective of safe operation, avoiding outages and providing reliable energy. Secondary objectives include reducing operating costs, maximizing public welfare, favoring renewable energy due to its low CO₂ emissions and ensuring free access to the energy market. The fulfillment of these goals can be measured by metrics like:

- Total cost energy production (per kWh)
- Total CO₂ emissions (in g/kWh)
- Frequency of overloads (various metrics)
- Costs/profit of the individual participants
- Comparison with grid expansion

The operation of the electricity grid is seen as a natural monopoly, as a parallel infrastructure cannot be implemented economically. However, different grid operators can cooperate with each other and be integrated into the same market framework.

The following data describing the framework environment is invariant for the simulation:

- Weather time series
- Existence of the grid operators
- Structure of the existing grid and connected producers/consumers/prosumers
- Flexibility behavior
- Feed-in capacities

An energy market design therefore describes the rules governing financial flows, energy flows and utilization information (e.g. flexibility requests), other market participants and their functions. The market framework must achieve the aforementioned objectives and can utilize the flexibility of consumers and offer various trading products. Eurelectric interprets flexibility in this context as "the modification of generation injection and/or consumption patterns in reaction to an external signal (price signal or activation) in order to provide a service within the energy system" [65]. This assumes a few requirements when integrating flexibility into a market simulation. First of all, it is necessary to be able to model the information, energy and cash flows of a market

³ <https://www.ffe.de/veroeffentlichungen/altdorfer-flexmarkt-und-comax-zusammenspiel-von-verteil-uebertragungsnetz-fuer-ein-effizientes-netzengpassmanagement/>, visited on 11.12.2024

framework in a meaningful way. Using various metrics, comparability can then be simulated and the advantages and disadvantages of a new type of framework can be considered.

The following is a description of existing efforts in the field of energy market simulations.

2.5.1 Market Simulation Software

In the area of market simulation, there are only a few projects to date that deal with the simulation and comparison of market mechanisms in the same tool. A large number of projects deal with the investment planning and profitability analysis of individual power plants. No available macroeconomic modeling of current exchange processes, including consideration of existing grid capacities, was found in the research carried out. Often, only the global market equilibrium is calculated without taking into account the characteristics of the current market. So-called “smart bids” and custom products like peak products or block orders are often not taken into account, meaning that the optimal equilibrium cannot be traded on the market because it is not offered.

An idealistic market simulation should fulfill the following criteria

1. Integration of various market processes and their trading products
2. open-source and transparent development to enable further research [89]
3. agent-based simulation (bottom-up) [252]
4. Scalability of the simulation by dividing it into different processes [17]
5. Consideration of the current load flow in the price calculation [237]
6. Possibility to compare different market models (decentralized vs centralized vs status quo vs market equilibrium) [160]
7. Enables the use of different market-clearing algorithms

Many existing market simulations are limited to the simulation of products and consumption based on historical data.

Some models support the simulation of market processes. These are listed in table 2.3. Whereas DA stands for day-ahead, ID for intraday, RE for balancing energy market and DV for direct marketing.

As can be seen there, the functionalities of the simulation software vary greatly. The source code of the simulation is not available for some projects and little can be said about the scope of the market simulation at the time. Projects that are limited to calculating a market equilibrium by solving an LP (often modeled with GAMS) are unsuitable for evaluating different market mechanisms but can be used as a benchmark for proximity to the macroeconomic optimum.

The research on existing simulation software for energy markets was largely carried out by keyword searches and tracking references in free software portals and journal

model	year	market design	source code available	agent-based	distributed system	grid calculation	comparative market
Gridsingularity Exchange [87]	2016-now	LEM	●	●	●	○	○
lemlab [260]	2021-2024	LEM	●	●	◐	○	○
SIMONA [104]	2021-now	○	●	●	○	●	○
ASAM [82]	2021-2023	DA, ID, RE	●	●	○	◐	○
AMIRIS [131]	2016-now	DA, ID, DV	●	●	●	○	○
USEF [233]	2016-2017	USEF	●	●	○	◐	○
FNCS [19]	2008-2017	Double-Auction	●	●	◐	◐	○
AMES/PSST [137]	2008-2023	SCUC/SCED	●	●	◐	◐	○
PowerMatcher [132]	2014-2017	○	◐	●	●	○	○
Maon [120]	2012-2021	DA	○	○	○	●	○
PowerACE [125]	2014-now	DA	○	●	○	◐	○
ÖkoFlex [142]	2014-2017	DA	○	●	○	◐	○
MASCEM [205]	2012-now	DA, ID, RE, DV	○	●	◐	◐	○

Table 2.3: Overview of existing energy market simulation tools - comparison of different market designs is not covered in existing tools.

publications as well as the aggregation of knowledge from conferences and discussions. Other sources include GitHub⁴, summaries for energy simulations such as from the Open Energy Platform (OEP)⁵, the OpenMOD initiative⁶ and similar collections⁷, as well as research in scientific papers, mailing lists and the OpenMOD forum⁸. Search engine keywords included "double auction simulation", "energy market simulation", "electricity co-simulation", "agent-based energy market simulation", "double auction market co-simulation", "market simulation".

In the following, the relevant energy market frameworks are described.

GRIDSINGULARITY EXCHANGE was founded with the incentive to decentralize the current market. In addition to focusing on blockchain-based approaches, the project also considers modeling of LEM. Key features of the tool include a simulation of a stepwise intraday auction, as well as the ability to include relative fees of a market matcher. The open-source software Gridsingularity Exchange offers options to simulate energy market scenarios with different grid topologies, which are configured as a

⁴ https://github.com/FZJ-IEK3-VSA/awesome_time_series_energy_system_modelling, visited on 09.07.2024

⁵ <https://openenergyplatform.org/factsheets/models/>, visited on 09.07.2024

⁶ https://wiki.openmod-initiative.org/wiki/Open_Models, visited on 09.07.2024

⁷ <https://github.com/prototypes/open-sustainable-technology> and <https://github.com/OpenEnergyPlatform/awesome-sustainable-technology>, both visited on 09.07.2024

⁸ <https://forum.openmod.org/>, visited on 11.12.2024

hierarchical tree. It offers capable simulation integration of a hierarchical market with percentage network charges with each level passed, i.e. for each hop as shown in Figure 2.9.

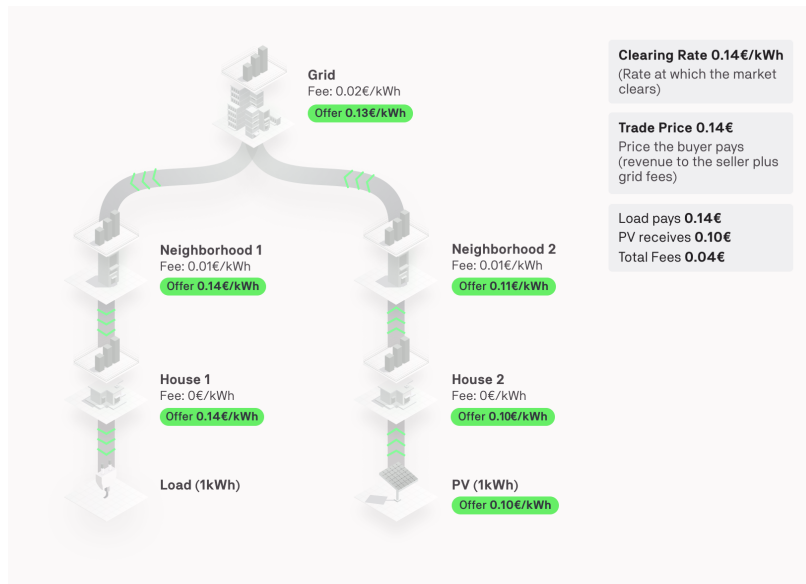


Figure 2.9: Visualization of possible energy market configuration in the Gridsingularity Exchange [88].

While the market configuration is tied to different configurations of a spot market, balancing market or settlement market, all of these use a pay-as-bid market clearing mechanism and can not be configured extensively. The pay-as-bid clearing is done by taking turns for each agent while each turn of the market increases the bids by a given relative amount with a configurable steepness of the agent incentives. While this is an interesting approach, it does not reflect actual market dynamics as this type of clearing allows for a given third-party agent to learn bidding from the linear bids of the other agents. In the simulation, one auction consists of 60 individual sub-biddings, taking place in 15-second intervals, to make up for continuous pay-as-bid simulation [90]. Gridsingularity Exchange (GSY-e) can run both simulations and as a real-time market with external agents, making it suitable for distributed simulations. Yet, it does not include power flow calculation or feature a way to compare different market simulations.

Blockchain in energy systems

It has to be noted, that the usage of blockchain technology is aimed at solving scenarios in which there is no single trusted entity available [254], which is generally not the case for energy grids in which all physical participants and connected parties have to be known ahead to grid operators. Furthermore, while transactions are very well secured on a given blockchain, the **oracle problem** – linking the real-world generation to digital assets – in a tamperproof way, and various scalability and adaptation issues are often problematic for the adoption of blockchain-based systems [197, 241].

LEMLAB is a toolbox for evaluating local energy markets, focusing on a bottom-up approach using agent-based modeling [260]. **Local-Energy-Market Lab (lemlab)** is being used at the Technical University of Munich for a research project with a field test of a local market⁹ and has a successor simulation tool, **HAMLET**. While a grid calculation has not yet been taken into account, it allows to have single local energy markets to trade market liquidity. The tool focuses on the addition of individual households and their flexibilities and views the wholesale market as a constant external price. Lemlab has been used to analyze the impact of Flexibility from **EVs** in local energy markets [257]. While the original **lemlab** project included an interface to replicate transactions on a blockchain, this is not part of the successor due to performance reasons [259]. Instead, **HAMLET** includes more features related to the market configuration and parameterization of **PV**, wind turbines and heat pumps using common Python libraries. Reports from LemLab also show that the usage of blockchain technology is very limited through the insufficient transaction rate [258]. While blockchain advocates claim that this can be solved by Layer-2 blockchain technology [23], the drawbacks in comparison to traditional approaches, like the **oracle problem**, remain. Concluding, lemlab provides individual insights into its specific use case but does also miss the flexibility to simulate different market abstractions and grid calculation.

SIMONA is an agent-based simulation environment, which offers a simulation toolbox for carrying out and implementing large-scale agent-based electricity grid simulations with a focus on distribution grids. **SIMONA**'s tooling focuses on grid planning and flexibility analysis and includes a discrete event simulation of the grid state. While this would be feasible without agent-based communication, it allows for changes to the input time series and updated agent load and generation through a distributed simulation [126]. This also allows for modeling environmental changes as well as flexibilities through **EVs** and **Combined heat and power plant (CHPP)**. From a technical perspective, **SIMONA** allows to import data from their own **PowerSystemDataModel** format as well as from **SimBench** and the proprietary **PowerFactory**.

⁹ <https://web.archive.org/web/20220519044523/https://reghee.de/feldtest-daten/>, visited at 21.05.2022

As it focuses on the grid dynamics of a power system, it does not take market mechanisms into account. It is a popular and maintained open-source agent-based simulation tool that is usable for co-simulation and integration in existing simulations through the supported import formats.

ASAM is an agent-based model for modeling energy markets created as part of a PhD thesis. **Ancillary Services Acquisition Model (ASAM)** models the existing day-ahead and intraday market and then calculates a redispatch based on a grid calculation with **Python for Power System Analysis (PyPSA)**, which is not part of the source code [82]. The simulation suits the research questions, but does not make the general adoption of generalized examples inconvenient, as there does not exist documentation or examples. The simulation runs in a single thread and is implemented in an object-oriented way using **Multi Agent-based simulation in Python (MESA)**. From a simulation perspective, the calculation of each next time step is triggered in the main process for each class iteratively, creating an execution dependency of the agents that has to be respected from the calling simulation. Changing the execution order or adding additional agents does therefore require adjustments to the whole simulation framework, making it tied to the inspected design. The architecture of the simulation is shown in Figure 2.10.

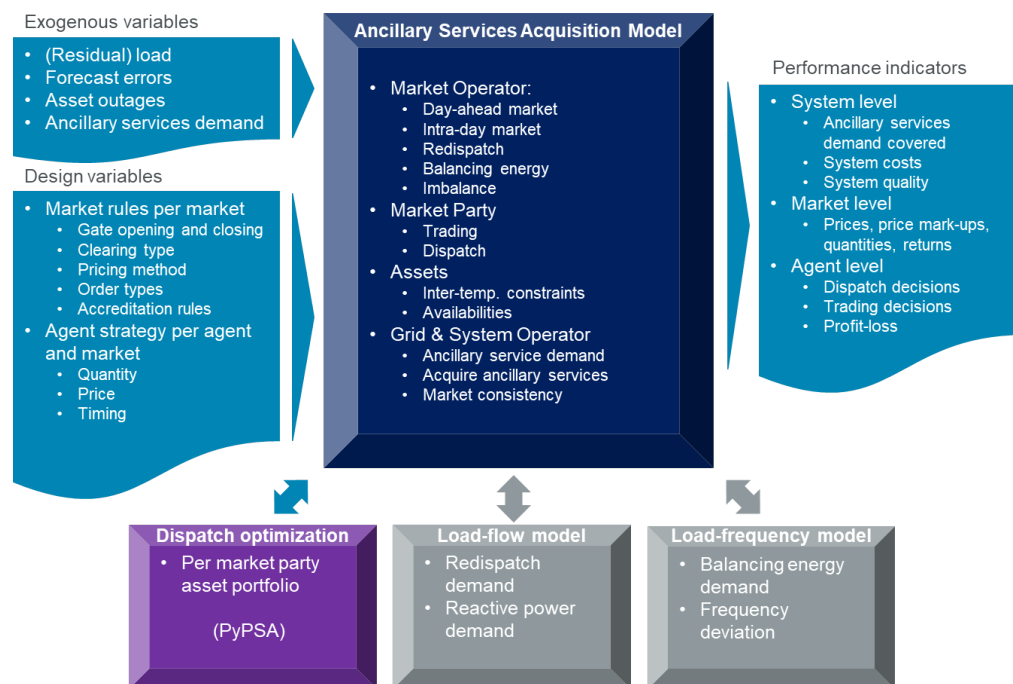


Figure 2.10: Architecture of the ASAM simulation framework from [82].

AMIRIS was developed to research various support mechanisms for renewable electricity generators [51, 210]. The focus of **Agentenbasiertes Modell zur Integration**

Regenerativer in den Strommarkt (AMIRIS) was placed in particular on the simulation of the direct marketing of Renewable energy Law (EEG) plants [55]. AMIRIS' main focus lies on the German energy market, while simulations for other regions like Austria are simulated as well [175]. It was also used in a comparison to the fundamental E2M2 model, which shows the effect of uncertainties and missing information modeled in agent-based simulation [227]. AMIRIS has been available as open source since February 23, 2022 and is in active development. Control energy and grid restrictions are not taken into account, and market mechanisms other than the day-ahead market have not yet been considered. Though AMIRIS includes various support mechanisms like Feed-In-Tariff, PPAs and market premiums [73]. Distributed computing can be done through an OpenMPI interface, which does have benefits for large enough simulations. It is based on the open-source **Framework for distributed Agent-based Modeling of Energy systems (FAME)**, which is also being developed by DLR. Various similarities exist between the usage of FAME and mango, which are presented later on in the implementation chapter.

USEF was developed to utilize the existing flexibility of the energy grid in market mechanisms. The **USEF** defines different roles such as prosumers, aggregators, balance responsible parties (BRPs), and DSOs, emphasizing the central role of Aggregators in bundling small flexibility assets. USEF's Flex Trading Protocol specifically focuses on the exchange of flexibility between aggregators and DSOs to resolve grid constraints [232]. By providing a common language and market design, USEF aims to lower costs for the innovation and development of smart energy products and services. Multiple real test beds are using the USEF framework to locally trade flexibility [86]. The framework definition mainly includes a novel market model for flexibility trading, though there also is an agent-based simulation framework as a reference implementation¹⁰. The focus of USEF is on expanding the European market mechanism by enabling flexibility to be aggregated and sold to the grid operator [233]. An overview of the participants and interactions of USEF are shown in **Figure 2.11**. As the reference implementation does serve a sole purpose, there are no other market mechanisms implemented.

FNCS is a compilation of different simulation programs that communicate with each other via the message broker ZeroMQ. The **Framework for Network Co-Simulation (FNCS)** includes a network simulator, grid simulator and market components. The discrete network simulator ns-3 handles the communication in the simulation, making it possible to simulate outages and communication limitations as well. The wholesale market is mapped with Matpower, while the transmission network is calculated by GridPACK. GridLab-D enables the simulation of smart grids and local markets. This vast requirement of different tools makes the simulation not suitable for beginners. The

¹⁰ <https://github.com/USEF-Foundation/ri.usef.energy>, visited on 19.02.2025

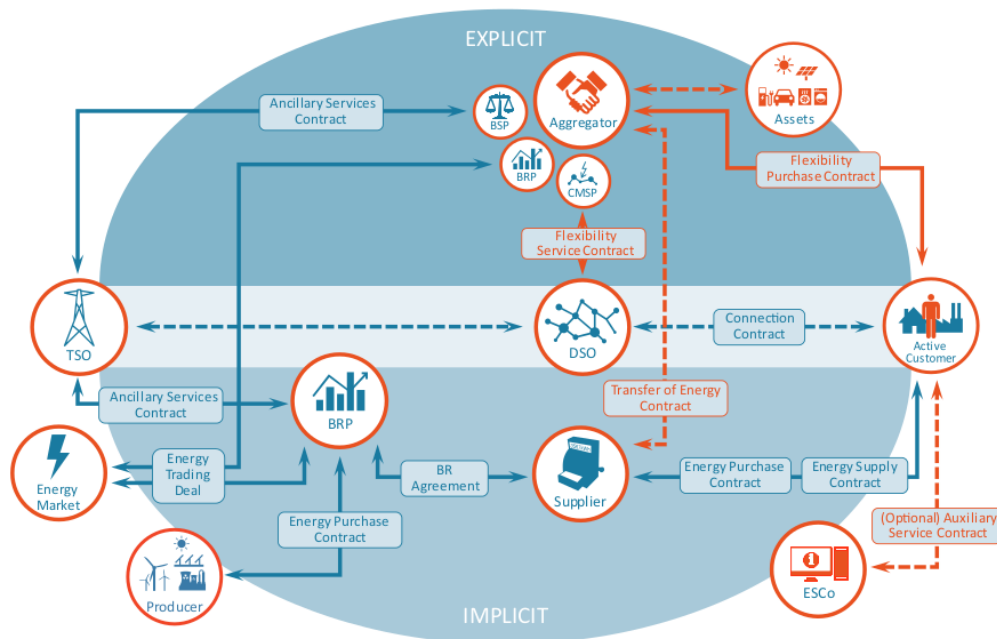


Figure 2.11: Architecture of the USEF market framework from [233].

market mechanisms available are a double-blind auction or a simulation with fixed demand or fixed supply (based on fixed quantity or fixed price). Changes to the market design are not inherently possible and require changes to the interfaces as well. While different components are integrated in the C++ simulation, the resulting software stack has a high complexity and has not been actively developed since 2017.

AMES/PSST is used to simulate market areas in the United States of America and is available on GitHub as *PowerSystem Simulation Toolbox (PSST)*¹¹. The *Agent-Based Modeling of Electricity Systems (AMES)* framework enables the simulation of day-ahead security-constrained unit commitment (SCUC), security-constrained economic dispatch (SCED) and real-time SCED. An optimal load flow in the overall system is calculated centrally. Version 5 of the AMES framework uses *FNCS* to simulate the US market. The test system of *Electric Reliability Council of Texas (ERCOT)* is simulated, showing a focus on a similar use case, which can not be easily extended to, for example, the European energy market.

POWERMATCHER is a Java software for simulating smart grid agents, which was subsequently published as open source but has not been maintained since 2017¹². The tool was developed by the Dutch Organization for Applied Scientific Research (TNO) to evaluate the integration of renewables and flexible market participants. It enables

¹¹ <https://github.com/ames-market/psst>, visited on 11.12.2024

¹² <https://github.com/flexiblepower/powermatcher>, visited on 04.04.2025

target-oriented management of electricity systems and is based on an agent-based setting. While PowerMatcher uses auctions to calculate a result, the auctions can be seen more as explorations of all the demand/supply relations. The market can then calculate the optimal dispatch like an ISO. A key component is the integration of concentrators which aggregate multiple device agents. The market auctioneer, therefore, aggregates all information and optimizes across all relations and constraints [132]. While this comes to a scalable solution and provides great advancements in coordination mechanisms for information aggregation, it does not include markets in the traditional sense and also does not include different market designs. Besides the matching of demand and supply, hence the origin of the name, PowerMatcher also respects the constraints of the distribution grid to avoid congestion.

MAON was created as a commercial spin-off of the IAEW of RWTH Aachen University and deals with the simulation of the European interconnected grid and its market mechanisms. It supports the use case of a zonal market optimization where all units bid their marginal price which is known beforehand. In contrast to the first assumption, no agent-based simulation is used and market behavior can not be adapted or changed throughout the simulation. The simulation results apply to day-ahead results without strategic bidding, based on the modeling assumptions. The inclusion of grid capacities is respected as additional constraints to the optimization problem and can calculate NTC as well as FBMC [181]. For this, a large Linear Problem (LP) is constructed and solved. Maon offers a commercial simulation of generation and market prices as a web service [120] and is not open to research.

POWERACE is an agent-based simulation model for the analysis of liberalized electricity markets [164]. The forward market and day-ahead market, as well as the simulation of energy demand and energy generation, can be simulated [125]. The project description states that the results are compared with the ELTRAMOD fundamental model. The model initially focused on the German market but was extended to support other European market areas. It has been used to study CO₂ emissions of EV in [248], as well as capacity remuneration mechanisms such as capacity markets [36, 79]. It is still in development and adjusted to recent research questions of market zone splitting. While parts of the source code were made available in 2024, there is no working example published with it.

In 2024, partial source code was made available on the university GitLab¹³. Due to the lack of availability of core parts, it is not possible to assess the implementation of other market mechanisms or run simulations.

ÖKOFLEX deals with the use of consumer flexibility as an economic component [142]. This resulted in a fundamental model focusing on the simulation of flexibility added

¹³ <https://gitlab.kit.edu/kit/iip/opensource/powerace>, visited on 09.01.2025

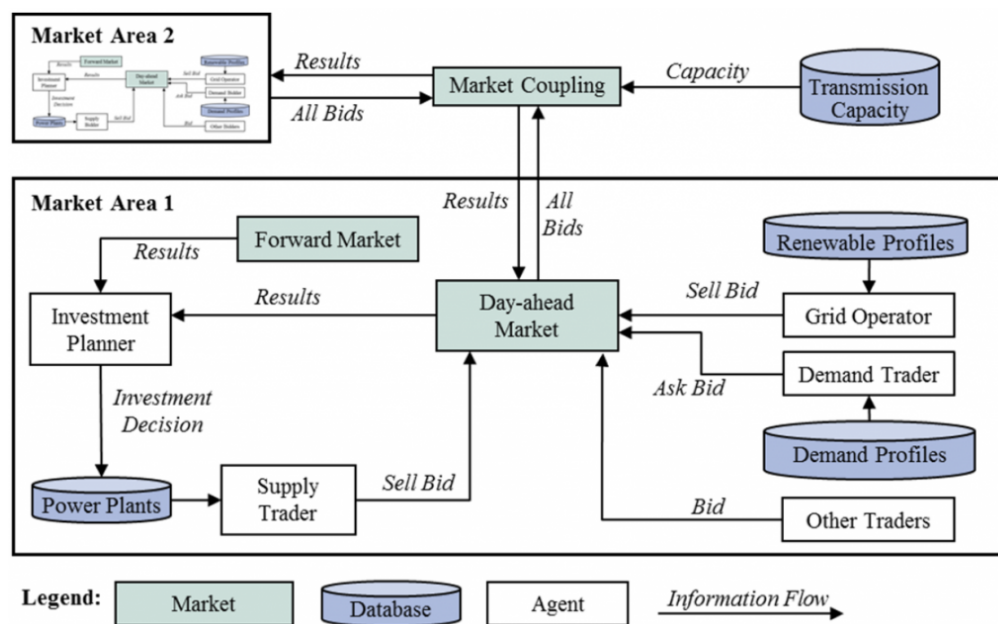


Figure 2.12: Description of the PowerACE model from [125].

through VRE. An integration of other market players is possible, while the simulation of different market models is not investigated [141]. Development has halted on this project after the end of funding and existing results were not published open-source.

MASCEM is a market simulation tool that can be used to simulate market processes. A core contribution of **Multi-Agent Simulator of Competitive Electricity Market (MASCEM)** is the implementation of market processes through a market ontology, which describes the participants and their role [78]. A network calculation and balancing market exists with the tool MASGriP, which is developed by the same faculty and can be attached to the market simulation. Unfortunately, the tool is not available but can be accessed via a **Representational State Transfer (REST) application programming interface (API)**, limiting its reusability and adaptability. Various additions to the core model were made to analyze balancing markets of the **Iberian Electricity Market (MIBEL)**. [200], the Nordic energy market **NORDPOOL** [207] and complex bidding [202]. The rules of the market (and of course the logic of the agents) are not included in the ontology, which describes how and which communication happens in the simulation¹⁴. The interaction of **AMIRIS**, **MASCEM** with additional **GAMS**-based models is investigated in the <https://traderes.eu> research project. Pointing out that there is a demand for interoperability between research tools on energy markets.

¹⁴ <http://www.gecad.isep.ipp.pt/mdpi/energies/845690/files/onto/local-market.ttl>, visited on 11.12.2024

OTHER MARKET SIMULATION TOOLS

Other widely used proprietary software are MARKAL/TIMES and NEMS, some of which also enable market simulation, but are also not available for other researchers. NEMS enables the calculation of market equilibria by solving several LPs [74]. TIMES, the successor to MARKAL, also enables market simulation through global calculation of the market equilibrium by modeling with [General Algebraic Modeling System \(GAMS\)](#) [109]. There is also a proprietary MATLAB model GAPEX, consisting of MASCEM, ALBidS and MASGrip [203], which can simulate the day-ahead, intra-day and balancing energy market. The market model MICOES from Fraunhofer is a fundamental GAMS model developed to compare market models and simulate balancing power markets [133], due to the unavailability of the framework, the functionality can not be confirmed and is rather unknown. Other models like the open-source OnSSET¹⁵ allow the investigation of electrification cost of a country, based on open geospatial data using a [Geographic Information System \(GIS\)](#).

2.5.2 Related Energy System Simulation Software

High-quality software libraries for simulating energy systems that focus on specialized use cases common in [Energy System Modeling \(ESM\)](#) are publicly available. These software libraries are particularly useful in scenarios such as grid optimization within a market simulation or the calculation of demand or renewable energy time series from weather data. Additionally, they can be utilized as standalone optimizations within the logic of individual agents, contingent on the systems managed by said agents.

1. Pyomo [40] – general library to define linear problems and solve these with various available solvers
2. PyPSA [35] – power flow calculation in Python
3. PandaPower [226] – power flow calculation in Python with a similar range of functions as PyPSA but different programming paradigms
4. oemof [234] - simulation framework for energy systems, which provides libraries pvlib, windpowerlib, deflex and demandlib to calculate renewables and demand profiles
5. open_eGo [8] – toolkit to create synthetic distribution and transmission grids from OpenStreetMap data

Many other projects dealing with the simulation of energy systems focus on setting up an optimization problem (often in GAMS¹⁶, Modelica¹⁷ or with Pyomo¹⁸), which is then solved centrally for a specific scenario and a specific time range [77, 140, 166,

¹⁵ <https://github.com/OnSSET/onsset>, visited on 09.01.2025

¹⁶ <https://www.gams.com/>, visited on 9.12.2021

¹⁷ <https://www.openmodelica.org/>, visited on 9.12.2021

¹⁸ <https://www.pyomo.org>, visited on 9.12.2024

224]. Popular frameworks of that kind are OSeMOSYS [180], urbs [231], Renpass [195], Calliope [185] and FINE [246].

Some of these also include grid capabilities, while the majority disregards grid considerations and the provision of balancing energy for simplicity. The range of functions between these *ESM* frameworks overlaps and varies in implementation details as well as the use of different configuration files and interaction patterns for users and programming paradigms. For example, while the model is generally object-oriented in PyPSA and can be modified at runtime, Calliope requires the usage of a configuration YAML file. This also displays the definitions of the time series, but can not be used without externalities from files.

Oemof models can be extended through functions and hooks into the optimization level and allow deeper modification of the optimization. In contrast, a central EnergySystemModel can be used with FINE, to which individual buses, generators/sources and demand/sink can then be added in an object-oriented manner. The main aims of these include optimal dispatch calculation and economic operating costs as well as investment planning but do not provide the option of bottom-up market simulations. Still, as example datasets of energy systems are often already available, interoperability between established tools and newly created tools provides a better basis for adoption in future market modeling.

Software libraries such as PowerPlantMatcher can also improve data quality and automatically remove duplicates when merging different sets of structural power plants datasets [83]. Furthermore, osmTGmod+ and dingo enable the generation of synthetic transmission grids and distribution grids, respectively [8].

Atlite provides a tool to calculate regional renewable potential for solar and wind generation based on the weather data from [European Centre for Medium-Range Weather Forecasts \(ECMWF\)](#) for a given location or geographic cutout [105].

2.5.3 Scenario Datasets

The conclusions drawn from simulations can only be as good as the input data provided. Often, non-negligible efforts have to be taken into account to calibrate input data and price assumptions, when trying to benchmark a historic scenario. In many cases, access to historic validation data is not granted, while generally, multiple datasets have to be merged and pre-processed to be used in market simulations [160].

While there are calibrated datasets for market simulations of historic years available [34, 198], the parsing can be quite demanding due to different data formats and especially different interpretations of timestamps, usage of indices and the like. Using explicit schematic data that references relationships between structural data and temporal data, as given by AMIRIS, is therefore helpful to lower the barriers of using existing datasets [173]. Of course, such datasets are becoming outdated quite soon, often requiring manual work to aggregate data for newer years. An approach to improve access to often

used public datasets is given with the Open Energy Data Server which unifies access by continuously downloading the data from different sources and providing updated records in a single database [157]. This tool has been developed and improved as data input throughout this thesis and can be used as input data for market simulations. The core workflow shown in Figure 2.13 includes scripts that download the most recent data from the original datasources. Plenty of sources like SMARD, ENTSO-E, ENTSO-G, ECMWF, market master data records (MaStR) are available in the distribution. The data is then stored in a unified format in a PostgreSQL database, allowing interaction from multiple interfaces. Interactions can be a REST-API using PostgREST, direct database access or visualization web interfaces like Grafana.

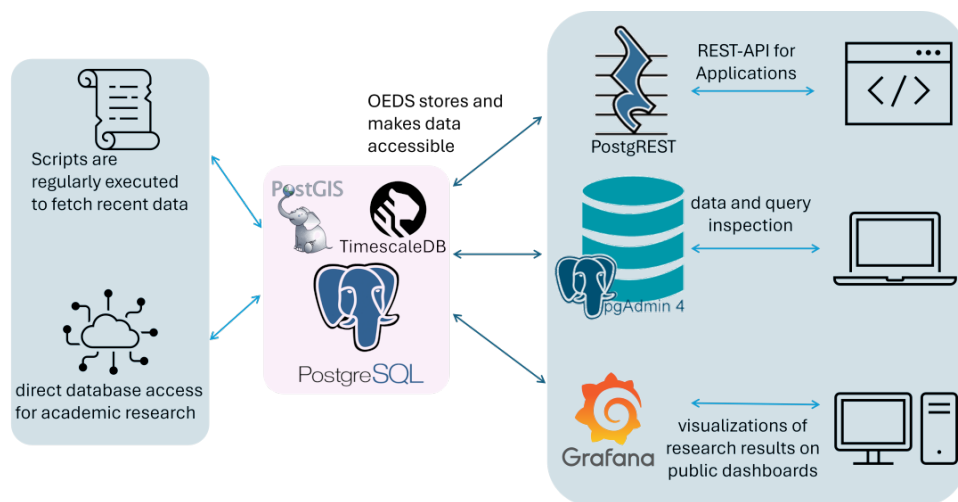


Figure 2.13: Visualization of the interplay of components from the Open Energy Data Server [157].

In the domain of *ESM* research, significant advancements have been observed in recent years, particularly concerning the accessibility of data. The availability of historical datasets and information on installed systems has increased significantly in recent years as more public institutions provide open data access without usage restrictions. A trend to publish datasets under a permissive license under the *FAIR* principles makes using and reusing possible [98, 247]. In particular, the provision of a complete download of the market master data register in October 2021¹⁹, as well as the provision of electricity generation data through the transparency portal of *ENTSO-E*²⁰ since 2015 and statistical scenario data available from *DeStatis* [53] represent a small selection of positive efforts in the area of open data. Furthermore, the research consortium *NFDI4Energy* is indicative of the significance of management of research data.

¹⁹ <https://www.marktstammdatenregister.de/MaStR/Datendownload>, visited on 9.12.2024

²⁰ <https://transparency.entsoe.eu>, visited on 9.12.2024

2.5.4 Summary of Related Work

The result of this analysis is that a simulation tool with a dynamic market framework does not yet exist and is also not known in the specialist literature. It is not yet possible to compare different market systems from one framework. This area therefore signifies a complete novelty. A modern simulation library should not be developed from scratch, as many tools for energy systems are already available in open source.

The addition of a comparison of different market models to the simulation tools also represents a further enrichment for energy system simulation research. Existing tools enable purchases on an exchange but do not represent the various trading products, e.g., the [EPEX](https://www.epexspot.com/en/tradingproducts)²¹. For example, linked blocks or exclusive blocks are not shown in the offers. An investment in further research into the development of freely accessible market simulation is therefore an important and innovative contribution to energy informatics.

²¹ <https://www.epexspot.com/en/tradingproducts>, visited on 11.12.2024

3

DESIGN AND CONCEPT

Abstraction is the elimination of the irrelevant and the amplification of the essential.

Robert C. Martin in "Agile Principles, Patterns, and Practices in C#" [154]

This chapter aims to describe a simulation design and concept to cover the research questions provided in [Section 1.2](#). The research question is divided into three parts, which are different in their requirements. First, the overall research gap is identified in [Section 3.1](#), covering the need for an open-access simulation tool and how a path towards it is possible, as well as showing which existing models exist and what is missing with those.

When evaluating market design changes, it is crucial to simulate the effects and outcomes of those. But also the accessibility is of concern, as other parties should be able to retrospectively confirm and understand the results and the data used for the simulation.

Interviews with researchers in the field of energy market simulations [112, 115], grid operators [113, 114], and advisors [111], made clear that there is demand for improvement in this field. From this, both functional and non-functional requirements were derived, which are also reflected in the research questions and presented in [Section 3.2](#) and [Section 3.3](#). The interviews were also used to iteratively develop and expand the concept, and to compare concepts with the views of other stakeholders in the field.

From there, the design of the simulation artifact is derived, which is created with the requirements in mind. This covers existing ontologies and market descriptions in [Section 3.4](#), the creation of a novel market abstraction in [Section 3.5](#), modern software design patterns in [Section 3.6](#) as well as interfaces to create interoperability to other simulation tools in [Section 3.8](#) and [Section 3.9](#).

3.1 RESEARCH GAP IDENTIFICATION

As noted in the section [Agent-based Modeling](#), a standardized simulation framework for simulation of different energy market designs has not yet been established. Yet, the

approach to energy market simulations is not new, even when limiting related research to open source agent-based models.

It is not only the simulation itself but also a generalized approach to the modeling of energy market designs and what is included in such.

This is tackled in the first research section, which covers the creation of a market abstraction grounded on the latest research. While energy market configurations are already available in existing simulations, these lack flexibility towards more generalized market designs, which might consist of multiple markets.

Therefore, a new market simulation tool is designed in a way that suits the needs of agent development and covers the features outlined in the next section. The proposed model, as well as its main features, are the core contribution to the research field of energy market design and simulation, but are not limited to it. An updated table of existing models is shown in [Table 3.1](#).

model	year	market design	source code available	agent-based	distributed system	grid calculation	comparative market
Gridsingularity Exchange [87]	2016-now	LEM	●	●	●	○	○
lemlab [260]	2021-2024	LEM	●	●	◐	○	○
SIMONA [104]	2021-now	○	●	●	○	●	○
ASAM [82]	2021-2023	DA, ID, RE	●	●	○	◐	○
AMIRIS [131]	2016-now	DA, ID, DV	●	●	●	○	○
USEF [233]	2016-2017	USEF	●	●	○	◐	○
FNCS [19]	2008-2017	Double-Auction	●	●	◐	◐	○
AMES/PSST [137]	2008-2023	SCUC/SCED	●	●	◐	◐	○
PowerMatcher [132]	2014-2017	○	◐	●	●	○	○
Maon [120]	2012-2021	DA	○	○	○	●	○
PowerACE [125]	2014-now	DA	○	●	○	◐	○
ÖkoFlex [142]	2014-2017	DA	○	●	○	◐	○
MASCEM [205]	2012-now	DA, ID, RE, DV	○	●	◐	◐	○
Proposed Model	2023-now	various	●	●	●	●	●

Table 3.1: Adjusted table from [Table 2.3](#) which also contains the proposed model covering the required features.

In the following, the functional requirements to answer the research questions are discussed.

3.2 FUNCTIONAL REQUIREMENTS

As shown in [Table 2.3](#), many market simulation tools have various functionalities in common. Still, the requirements for future energy market simulations differ, leading to different market adjustments that are required and were analyzed in literature [[72](#), [171](#), [225](#)].

3.2.1 Agent-based Simulation

Agent-based simulations refer to the modeling of each participant in the simulation as an individual agent that can behave differently. The concept as well as different alternatives have been discussed in [Section 2.4](#), which shows well that agent-based modeling is a good fit for simulations that can resemble large complex systems such as energy markets. Different models have different requirements, though generically, a lot of flexibility is needed. This flexibility can be handled by agent-based simulations as the behavior can be configured differently for every participant in the market simulation. While also allowing to simulate of complex models, with a high load of different data configurations. Yet agent-based simulations can also be used for small understandable scenarios and embed statistical strategies and evaluations as well as seen in the comparison of two agent-based simulations in [[160](#)]. As they allow deeper insights into the behavior of individual agents, [ABM](#) is set as a requirement for future market simulations.

3.2.2 Power Flow Calculation

In energy systems, it is important to respect power flow constraints to manage the risk of power outages as described in [Section 2.1.2](#). However, current market mechanisms often do not consider the constraints as discussed in [Section 2.3.3](#). To enable the integration of power flow calculation in energy market simulations, this has to be considered in the simulation framework. One key requirement of a future energy market simulation is the integration of a power flow component.

Power flow calculation is needed to model line utilization as well as the benefits of locally generated energy on the congestion of the power grid.

3.2.3 Market Design Configuration

As shown in the related work and existing simulations, most tools are built for a specific market design, requiring new development when making adjustments to the market. Therefore, it is needed to be able to configure a market design in a way that is as precise as possible, while also keeping as many as possible options and different

kinds of markets. This makes it possible to simulate a variety of energy market designs, which is needed for answering the research question. Ways to model different market designs are to be drawn from ontologies and existing simulation models, to cover a broad overview and compatibility to existing use cases of simulations.

3.2.4 Comparative Simulation

Finally, derived from the research question of comparative market simulation, the focus on comparability is seen as a separate functional feature. As different markets create different outcomes, comparability and insights of changes to the market design or other aspects of the simulation should be thought into the design of newly created simulation tools. This includes visualizations of comparability as well as the inclusion of *KPIs* to evaluate the results of the simulation, depending on the aspects in question.

3.3 NON-FUNCTIONAL REQUIREMENTS

In addition to functional requirements, a comprehensive list of non-functional requirements must be fulfilled to ensure the widespread adoption and effective use of the developed market simulation. These requirements address critical aspects such as usability, performance, and integration capabilities that are essential for usage in ongoing development and scientific research.

3.3.1 Open-Source Software

Open-source software is vital for scientific simulations as it ensures reproducibility, allowing other researchers to verify results – a fundamental principle of the scientific method. Transparency is significantly enhanced since the source code can be peer-reviewed, fostering trust within the research community. Furthermore, open-source development encourages collaboration and innovation, enabling researchers from diverse backgrounds to contribute improvements and share insights. This accessibility not only democratizes the use of advanced simulation tools but also accelerates the pace of research by making resources available to a broader range of scientists and institutions. The success of an open-source project is contingent upon its publication under a permissive license, the presence of documentation, and the implementation of functional tests. An initiative that assesses a project's usage of licensed work to ensure its inclusion is referred to as REUSE. The REUSE ecosystem encompasses automated checking of the specification, thereby ensuring that all distributed works include information for other researchers regarding the reusing conditions [66]. Therefore, not only the data but also the software simulation adheres to the FAIR principles [98].

3.3.2 Modularity

Modularity is essential for improving maintainability and adaptability within a simulation tool. A modular architecture allows for easier updates and the addition of new features without disrupting the entire system, which is particularly important in scientific research where requirements frequently evolve. This flexibility promotes efficiency by enabling the reuse of components across different projects, thereby reducing redundancy. In terms of a market simulation, modularity enables the integration of new agent behavior, new mechanisms and adaptation to changes, so that future scenarios can be modeled as well. Additionally, clear modular structures facilitate understanding and collaboration among developers and researchers, making it simpler to onboard new contributors and share knowledge about the system.

3.3.3 Interoperability

Interoperability is a critical requirement as it enables seamless data exchange with various tools and formats commonly used in research. This capability allows the software to integrate smoothly into existing workflows, enhancing its overall utility and effectiveness. By supporting multiple standards and protocols, an energy market simulation remains relevant even as the scientific landscape evolves. One example is the standardized [FIPA ACL](#), which defines agent intercommunication in such a way that [ACL](#) compatible implementations in other languages are compatible. Furthermore, the integration of tools and the provision of an interface to allow programmatically embedding software into a larger ecosystem, such as [MOSAIK](#), facilitates the utilization of a simulation tool with existing simulations. The adoption of adapters and strategies enables interoperability with distinct implementations while preserving modularity and configurability.

This flexibility fosters collaboration among researchers utilizing different platforms and tools, promoting a more integrated approach to energy market simulations.

3.3.4 Scalability

Scalability is crucial due to the high computational demands associated with scientific research. Scalable software can efficiently handle complex simulations involving large datasets or numerous agents, significantly reducing the time required to obtain results. The ability to leverage advancements in computing power – such as distributed computing or cloud resources – without necessitating major rewrites ensures long-term relevance for simulations. This flexibility allows researchers to utilize the software effectively for both small-scale tests and large-scale simulations while maintaining consistency in results across different scenarios.

3.4 ONTOLOGIES AND MARKET ABSTRACTIONS

Modeling energy markets requires a broad understanding of their fundamental principles. Given the significant variation in market characteristics, it is crucial to develop an abstraction language that defines baseline structures and possible configurations.

One approach to this challenge is evaluating existing markets and systematically cross-referencing their features using a morphological box, as demonstrated by Rebeca Ramirez Acosta [3]. The morphological box method helps to identify common characteristics and key design elements. More broadly, it serves as a powerful tool for exploring diverse energy market designs and assessing potential future configurations. However, due to the wide range of energy market structures, defining a single configuration language that encapsulates all possibilities remains complex. Existing research provides related methodologies, including market ontologies, which facilitate categorization and establish a domain-specific language for energy markets.

Ontologies offer multiple advantages, such as serving as machine-readable glossaries that incorporate cross-references and relational structures. This allows for enhanced interoperability and interactive visualization of research domains. For instance, the [Open Energy Ontology \(OEO\)](#) [30] defines general energy-related concepts, such as power plants and fuel sources, but lacks representations of market participants and their interactions. However, ontology languages like [Web Ontology Language \(OWL\)](#) are machine-readable, enabling direct representation of market mechanisms and participant interactions. This capability, in theory, supports model coupling and the establishment of a standardized interface for defining market designs. A visualization of the OEO can be seen in [Figure 3.1](#)¹.

The simulation tool MASCEM utilizes the ontology [Energy Market Ontology \(EMO\)](#) to define the agent's behavior. This is an approach that is taken by MASCEM, which focuses on the representation of a market and also defines individual agents [203]. An agent-based approach is taken to represent the individual behavior and different strategies of individual agents. Although the [Resource Description Framework \(RDF\)](#) files are available as [OWL](#), the framework is not available for custom simulations, making it impossible to debug and extend this framework to other extents.

Originally designed to simulate competitive multi-agent markets, it was showcased throughout the years with simulations of the Iberian market [208], NORDPOOL market [207] and recently thrives for interoperability between three different black-box models from the same organization [201]. As it is nearly impossible to create such ontologies without implicit assumptions and internals, it is necessary to freely distribute the internals.

A closer examination of [EMO](#) reveals that its design is not well-suited for multi-market configurations requiring freely definable market clearing mechanisms. For example, a

¹ A more comprehensive viewer for the ontology is available at <https://service.tib.eu/webvowl/#iri=https://openenergyplatform.org/ontology/oeo/releases/oeo-full.owl>, visited on 11.12.2024

Open Energy Ontology Viewer

Open Energy Ontology / OEO viewer

The OEO Viewer is a research prototype tool to visually browse the Open Energy Ontology. External tools like TIB's terminology service are more sophisticated for browsing and searching ontologies;

Search classes:

Name: process attribute ID: OEO_00030019
 Definition: A process attribute is a dependent occurrent that existentially depends on a process.

SHRINK EXPAND PARENT FOCUS FIT

Figure 3.1: Visualization of Open Energy Ontology OWL definition from [30]. Interacting with the definitions and interconnections of an ontology are possible through web-based viewers.

market in EMO can have up to one Day-Ahead market and up to one Intraday market – strictly defining markets by name and not by functionality [78]. In contrast, other energy-related ontologies – such as SAREF and BRIG – primarily focus on energy measurement data and can be integrated using FIWARE as a context broker [25]. However, these ontologies lack a dedicated description of energy markets.

While ontologies offer valuable high-level overviews, their practical implementation often requires considerable effort. Consequently, a more loosely coupled configuration design – one that maintains interoperability through widely adopted data exchange formats like YAML – proves to be a more accessible and adaptable solution for configurations. In that regard, efforts have been made to also convert OWL ontologies into the better human-readable YAML format, making way for an easier conversion between different definition languages [218]. This is taken into consideration in the design of the market abstraction, which is used in the market simulation artifact.

3.5 MARKET MODEL AND AGENTS

In this section, the conception of the market model is covered, which is implemented in the provided artifact of this thesis. While many studies include discussions about energy market design, the definition of such a market is often omitted. Still, existing definitions are found for example in [206, 229]. In the case of the [Energy Market Ontology \(EMO\)](#), this definition is use case driven and does not suit a more general investigation of energy market designs and different markets.

Including the different related work to create a definition of energy markets led to the new formalization of the definition below.

What is an energy market design?

Energy market design is defined as the sum of incentives, participants, rules, and contractual obligations that structure and regulate a set of energy markets. This includes requirements for market entry and participation, as well as incentives related to trading, energy delivery, and communication [159].

This includes all options to trade and additional mechanisms that influence the investment or bidding behavior of all agents.

More specifically, an abstraction that covers the resulting changeable parameters from the above definition needs to be found. Although it is exceedingly difficult to establish the completeness of a definition, there is empirical evidence that the abstraction in question covers the requirements of existing and assumed markets, thereby rendering it an effectively useful abstraction. This is one core contribution, which makes it possible for other simulation frameworks to build upon. It has to be noted, that the given abstraction does not make assumptions about the agent behavior or define which inputs can be defined in the model to create outputs (which is possible to provide as input as shown later), it focuses on the configuration parameters of the market and includes bidding constraints, temporal constraints, locational constraints and market entry barriers. The final abstraction is shown in [Table 3.2](#) and is discussed in the following subsections.

3.5.1 Market Configuration Categories

The first aspect of market configuration involves defining market products, which delineates trading intervals. A market product's description, drawn from [EPEX](#) trading options, includes delivery duration, the number of deliveries per market cycle, and the offset from market opening time [63]. For instance, a typical day-ahead market features a single hourly trading product spanning the next 24 hours, with bidding commencing a day in advance (e.g., [(HOURLY, 24, next day)]). The duration and frequency of market openings determine which time slots are tradable. This category

category	market config item	description
market product	product type	energy or capacity or heat
	market products	list of available trading products
	volume unit	string for visualization
	price unit	string for visualization
opening & duration	opening hours	recurrence rule of openings
	opening duration	time delta
price formation	market mechanism	name of method used for clearing
	additional fields	list of additional fields to base bid
	query available offers	boolean
bid constraints	maximum bid	max allowed bidding price
	minimum bid	min allowed bidding price
	maximum volume	largest valid volume for a single bid
	volume tick size	step increments of volume
	price tick size	step increments of price
specialized config	maximum gradient	max allowed change between bids
	eligible obligations lambda	function checking if agent is eligible

Table 3.2: Description of the parameters used to configure a single trading option/market extended from [3, 204]. The configuration of multiple market products allows for extensive configuration of trading options. Taken from [159].

closely aligns with the price formation category, which outlines the clearing method. By allowing a freely defined market mechanism for clearing and specifying additional fields for market mechanism function reliance, this abstraction facilitates modeling various markets. Examples include clearings based on grid signals (e.g., nodal markets), complex bidding options (block order, all-or-nothing, exclusive orders), OTC trading, and subsidies/policies. Attention to clearing frequency within the method is crucial, and employing the technical standard for defining recurring events, as described in RFC 5545 [52], enables precise and highly configurable recurrent schedules.

```

1 eligible_obligations_lambda = lambda agent: agent["technology"]
   in ["demand", "wind", "solar", "biomass"] and agent["
   max_power"] <= 100 # kWh

```

Listing 3.1: Definition of eligible obligations lambda method for German feed-in tariff.

The eligible obligations lambda function is used to model market entry barriers. This control method can be passed as a function reference (typically also known as a callback function), as part of the market configuration. Formally, the type signature of the function is $f(\text{unit}) \rightarrow \text{bool}$, while unit is the map of properties of an agent. This allows to restrict access to the market for some agents, based on properties like minimum power, maximum power or technology, as shown in Listing 3.1. While the

initial intention is to have an unnamed short function (so-called lambda function in Python), it is also possible to create more complex explicit functions, which operate on the dictionary with information about the agent.

3.5.2 Bidding Abstraction

Bidding behavior in energy trading necessitates a defined delivery timeframe and volume according to the market configuration. For instance, a bid may offer 100 MW of power for delivery from 2023-06-30 00:00 to 2023-06-30 01:00, resulting in 100 MWh of contracted energy, shown in Table 3.3. Positive volumes denote generation, while negative volumes represent demand. This generally requires the usage of signed floating-point calculation, as fractions of energy can be traded as well. To tackle this, the market configuration allows setting `price_tick` and `volume_tick`.

start-delivery	2023-06-30 00:00
end-delivery	2023-06-30 01:00
volume	100
price	32
sender id	118

Table 3.3: Exemplary bid showing mandatory fields used in all markets. The volume is positive for generation while it is negative for demand bids. The sender id contains a unique id of the bidding agent.

That way a conversion of bids to ticks is made. Given a `volume_tick` of 0.1MW, allowing to only bid volume multiples of 0.1, one can divide the sent volume by the tick size to have the market representation without fractions. Our volume then represents ticks of the given tick size instead of the actual volume, leaving agents and markets with integer calculation, which gives correct results, independent of the hardware platform and accuracy of floating point.

$$\text{round}(\text{bid_volume} / \text{price_tick}) = \text{volume_tick} \quad (3.1)$$

After the calculation of the market result, the `volume_tick` is converted back to the actual representation in the bidding agents as it is used in the output. This is required so that the market works for financially sensitive bids as well.

Extending this bidding abstraction enables the modeling of other market behaviors similarly. An exemplary bid with mandatory fields is provided in Table 3.4 for clarity. Additional fields can accommodate complex bidding, such as block orders, allowing for conditional negative bidding and accurate representation of power plant behavior as shown in [206]. The configuration can be expanded with identifiers like "base id"

and "link id" to link multiple blocks, crucial for modeling power plant bidding behavior and ramping constraints, akin to the European energy market representation [63, 217].

start-delivery	2025-06-30 00:00	2025-06-30 00:00	2025-06-30 01:00
end-delivery	2025-06-30 01:00	2025-06-30 01:00	2025-06-30 02:00
volume	100	50	100
price	32	16	16
sender id	118	118	118
base id	0	1	2
link id	-1	0	0

Table 3.4: Link bid requiring the first bid, with base id 0 to be accepted by the market to be able to activate the other two bids as well.

3.5.3 Agent Interfaces

An agent acting on the market generally just needs to react to market openings and market closings. It handles multiple units and therefore aggregates their bids. As there are many common checks in the bidding agents, the bidding agent is a common ground interface to submit bids of all units attached to it.

Generally, two ways of submitting bids are respected here.

1. individual bids per unit
2. aggregated portfolio optimized bidding

The first bidding type is the more common bidding type, which is similar to the bidding done in other simulations. The second option creates an aggregated orderbook of all attached units, allowing portfolio optimization as done by typical aggregators [233].

Given a portfolio of five power plants where each has:

- minimum power: 300
- maximum power: 800

Without portfolio optimization, one would, for example, bid the following for each of the power plants: 300 power for the higher price and 500 with the marginal price. But with portfolio optimization, it is only required to consider the minimum power of the smallest power plant with flexibility for higher power amounts. This is possible as one only needs to consider the smallest ramping and is (mostly) flexible to increase power from there. Using portfolio optimization can therefore reduce the offered price in contrast to single-unit bidding.

Of course, this gets more complex once ramping constraints are added, but also allows for more optimization. A small optimized strategy that does not respect ramping can be formalized as seen in Listing 3.2:

```

1  minpower = min([u.minpower for u in self.units])
2  # only the smallest minpower is considered
3  maxpower = sum([u.maxpower for u in self.units])
4  # we aggregate max power of all our units here
5
6  min_cost = 0.8 * mean_cost
7  # lower cost for the min power, to keep a power plant running
8
9  bids = {}
10 bids.append({minpower, min_cost})
11 bids.append({maxpower - minpower, mean_cost})

```

Listing 3.2: Sample portfolio strategy without ramping.

Though the formulation of a [Linear Problem \(LP\)](#) is better suited to include the optimal ramping of such a portfolio. This is due to the optimal ramping becoming complex when avoided costs of additional cold start periods have to be considered as well. A formulation which also includes such behavior is given in [Section 4.3.1](#). The list of bids from one operator is then sent to the market agent concerning the open bidding interval and market closure. Following the introduction of the unit operator, which is responsible for setting bids for assets under its purview, the subsequent discussion will focus on the abstractions that prove useful in analyzing these assets.

Typically, one can divide these into two different categories from a modeling perspective – assets that can model a continuous demand/generation vs assets that have to charge or discharge and can not provide the same energy throughout a simulation. These two abstractions are called `SupportsMinMax` and `SupportsCharging` and provide a common ground for different use cases of explicit units such as `Demand`, `PowerPlant`, `Prosumers` and `Storage`.

For example, the `PowerPlant` does support basic ramping constraints, a minimum and a maximum power all of which are similarly useful when modeling `Demand`. One can, for example, model a power plant with a minimum power 300 MW, a maximum power of 800 MW and ramping constraints for 100 MW/h up and down. These constraints are then respected in the unit implementation and are not required to be reimplemented in every bidding strategy of a power plant.

Similarly, the `SupportsCharging` abstraction includes various settings related to the state of charging, a minimum and maximum discharge and charge constraint and separate ramping constraints for charging and discharging. Both implementations include methods to investigate the minimum and maximum constraints for a given time period, making it convenient for the bidding agent to query the bidding possibilities of all the assets it takes care of.

3.6 MODULAR SOFTWARE DESIGN

A substantial need of software projects is the possibility to expand and adjust behavior around core directives and provide useful abstractions. Failure to do so leaves projects focusing on a single use case or not being able to adapt to generalizations in a good way. In energy market simulations, it is therefore utterly important to find such useful abstractions, as done for the energy market configuration and the asset behavior in [Section 3.5](#). This abstraction offers parts to be defined as software interfaces, which only need to implement small parts of the functionality.

As the usage of design patterns and modular design is not a target by itself, one always needs to consider the target that is achieved by doing so. From a top-level perspective, this can often be argued through increasing cohesion and reducing coupling. More specifically, by increasing cohesion in the software design, configurable options belong together while reducing coupling makes it possible to keep testing, improve maintainability and reduce the scope required to understand core components [162, pp. 103–105]. From a novice user perspective, this can look more complicated than having a single source code file that contains all customizations, suited to a single given use case. However, the benefits come into play as well-maintained simulation software can be used and extended without a deep understanding of all core functionalities.

An important part of software science is handling complexity and reducing the required intellectual scope of the developer when using a part of the whole. Taking care of object-oriented design helps to do this by application of known core principles.

The common closure principle states how functionality that changes for the same reason should be found in the same component [153]. This generally holds for changes regarding the agent behavior or the market behavior and can be seen from the visualized architecture in [Figure 3.2](#), which is taken from the online documentation of the framework.

Modern programming languages enforce various patterns implicitly, such as the acyclic dependency principle, as the language parser errors on cyclic dependencies [152]. Using Python, it is mandatory to use explicit type hints for this, as a lack of typing can make such cyclic dependencies invisible. Overcoming cyclic dependencies can be done using the dependency inversion principle, which requires a dependency-injection framework or other factories and class registries, which increase the required scope and complexity of the software. Instead, the straightforward methodology to avoid cyclic dependencies is the extraction of common usage patterns to a common base unit. This keeps the natural workflow of being able to read through the source code.

Separation of concerns is another fundamental pattern, which reduces the required scope needed for implementation. This is not only useful for development, but also for testing, which is crucial for maintainability. It is common to therefore use a layered software design to decouple components in code [214]. The layered architecture of the simulation tool is shown in [Figure 3.3](#). An important part is the decoupling of stateful

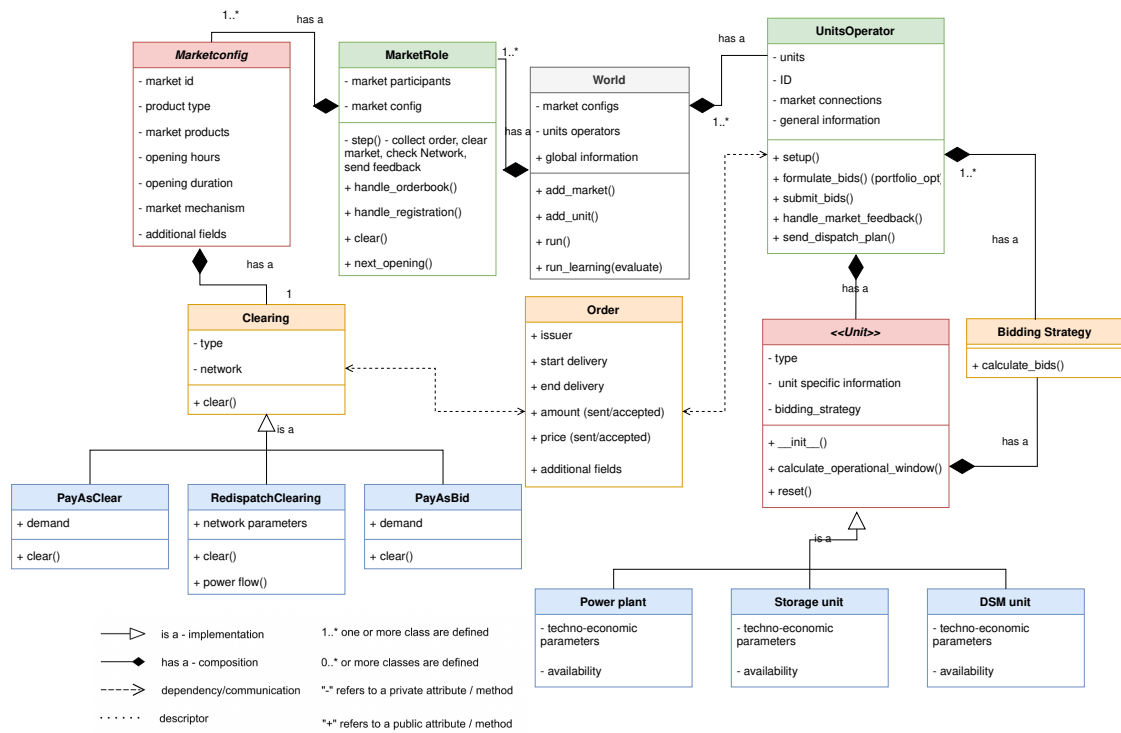


Figure 3.2: Visualized class diagram of the simulation framework – taken from the framework documentation

parts, which rely on externalities like files or database connections, typically referred to as I/O and are therefore considered impure [215]. Pure functions are much easier to test as they do not rely on the injection of external dependencies. It is required to move impure functions into wrappers that handle the impurity, hence the usage of the output role, which wraps writing to the database or file system.

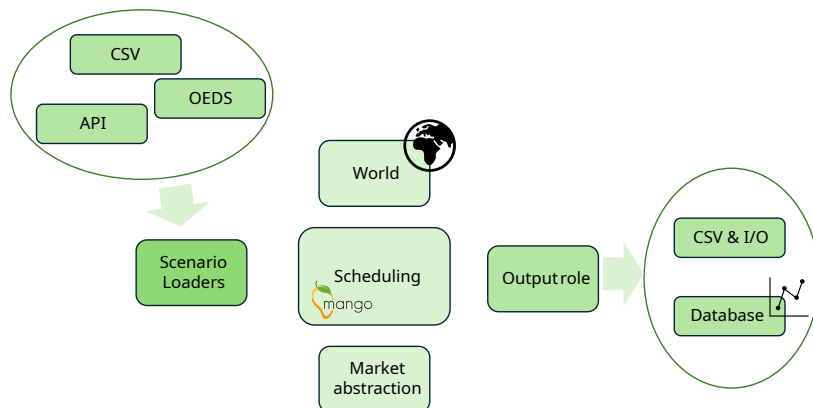


Figure 3.3: Visualization of acyclic depending code layers of the market simulation tool

The key parts that can be configured in the simulation include the agent types, the bidding strategies and the market clearing strategies. Those are put together in a structure defined through the input data of a simulation scenario.

This is supported by a builder pattern in the world object, which creates the simulation in an object-oriented way. All agents used in the simulation are configured before and used in the `World` object, which is finally run to start the simulation.

Examples where modular design comes into play is the possibility of changing one of the following:

1. A change in the input data config, adding or removing an agent
2. Parameters of a given agent in the simulation
3. Switching the bidding strategy of agents to analyze the impact
4. Changing the market framework used in the simulation
5. Adding new components to the framework to simulate

While modularity and reducing coupling generally provide high flexibility, it also includes the burdens of not having the whole simulation in the scope of the current execution context most of the time.

```

1  world = World(database_uri=...)
2
3  marketdesign = [
4      MarketConfig(
5          "EOM",
6          rr.rrule(rr.HOURLY, interval=1, dtstart=start, until=end),
7          timedelta(hours=1),
8          market_mechanism,
9          [MarketProduct(timedelta(hours=1), 1, timedelta(hours=1))],
10         additional_fields=["node", "max_power", "min_power", "
11             bid_type"],
12         maximum_bid_volume=1e9,
13         maximum_bid_price=1e9,
14         param_dict={"log_flows": True},
15     )
16 ]
17 pypsa_network = ...
18 bidding_strategies = ...
19 load_pypsa(world, "scenario_name", pypsa_network, marketdesign,
20         bidding_strategies)
21 world.run()
```

Listing 3.3: Scenario creation and adjustment through loader.

A typical solution to tackle this is the Inversion of Control pattern using Dependency Injection, which includes a lot of implicit complexity and does not always make up for

the effort.

The alternative used in this simulation is to have a scenario-building mechanism that knows about configurable dependencies, like strategies and agent types, creates these through stateless factory methods and modifies the world as a builder pattern, illustrated in Listing 3.3. This reduces scope in the execution, while still providing one method in which the whole set of options is available. After initialization, the simulation loop is started and progresses in the simulation time.

3.6.1 Scheduling Events in the Simulation Loop

In the following, a closer look is taken at three different kinds of simulation loops. Relying on the reduction of coupling and increasing cohesion, the most suitable method is then chosen.

BASIC SIMULATION LOOP OF EVENTS

The basic simulation loop method involves iterating through all events within the simulation straightforwardly. An example of this can be observed in the lemlab framework, where the sequence begins by reading input and creating agents, followed by successive simulation steps, and ending once the simulation criteria are met².

This method is advantageous due to its simplicity and ease of implementation shown in Figure 3.4. It offers a clear structure, making it straightforward to understand and debug. However, this approach requires that each agent and its ordering must be explicitly known to the simulation at every step. Consequently, adding or removing agents necessitates modifications across various parts of the simulation code, reducing flexibility and scalability. Additionally, this method can be inefficient, as it processes every step regardless of whether agents have actions to perform, leading to unnecessary computations depending on the used market design.

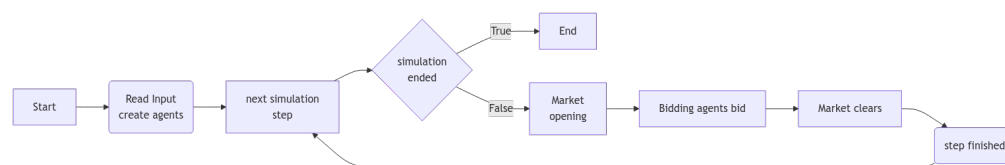


Figure 3.4: Flow of the basic simulation loop. For each step, a fixed order of hard-coded agents is executed.

SIMULATION LOOP CHECKING FOR AGENT ACTIONS

A more sophisticated approach is employed by frameworks using MESA such as ASAM

² https://github.com/tum-ewk/lemlab/blob/43670aa66a395f4ab703a8c4b6af757694d2e19e/lemlab/scenario_executor.py#L521-L540, visited on 11.12.2024

and Flexible, where the simulation loop checks if agents have actions to execute³. This model starts similarly by reading input and creating agents, but it then queries each agent to determine if it has actions to perform in the upcoming step, as can be seen in Figure 3.5. If no actions are needed, the simulation moves on, skipping unnecessary steps.

This method enhances flexibility by allowing agents to operate independently within the simulation, reducing the need for extensive modifications when agents are added or removed. It also mitigates inefficiencies by avoiding steps with no agent activity. However, it can still result in many steps where no actions occur, especially in simulations with sparse agent activity, potentially leading to inefficiencies in time and resource usage.

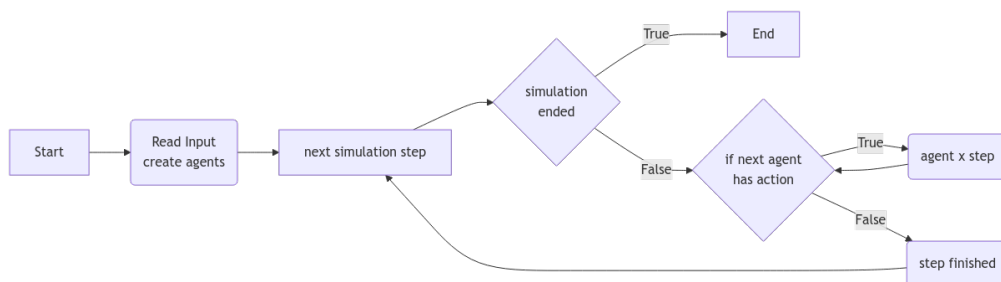


Figure 3.5: Flow diagram of the generic simulation loop. Each step executes each agent in a randomized or set order – independent of the number and action of each agent.

EVENT-BASED QUERY OF THE NEXT TIMESTAMP WITH AN EVENT

The most efficient and flexible method involves an event-driven simulation, where time advances based on the occurrence of events rather than fixed time steps. In this approach, agents inform the simulation of the timing of their next actions, allowing the simulation clock to skip directly to these events.

This method significantly enhances efficiency by eliminating periods with no activity, as the simulation only processes steps where events occur. It allows for a dynamic and responsive simulation environment, capable of handling irregular event occurrences effectively. This approach also simplifies the management of agent activities, as agents communicate their action times.

However, the event-driven method, pictured in Figure 3.6, requires a more complex implementation, including sophisticated event scheduling and handling mechanisms. Therefore, an event loop needs to be running, handling events and futures, which allocates additional resources in contrast to a simple indicative loop. Yet simulating only events that require processing has benefits if different time schedules occur. From a software design perspective, this makes it possible to decouple the world from

³ https://github.com/AncillaryServicesAcquisitionModel/ASAM/blob/c1a448ecd908ccd6bd6d7172aab2fe9791ff49b0/asam_classes/Main.py#L69-L70 and <https://github.com/INATECH-CIG/flexABLE/blob/3baea86e4716bd52b9017057ab02fdcc91ff2167/flexABLE/flexABLE.py#L119-L134>, visited on 19.02.2025

knowing everything about the simulation. Looking at existing examples, this is fairly similar to the way [AMIRIS](#) handles the simulation loop⁴, though AMIRIS does not handle injection of adjusted agent behavior equally well.

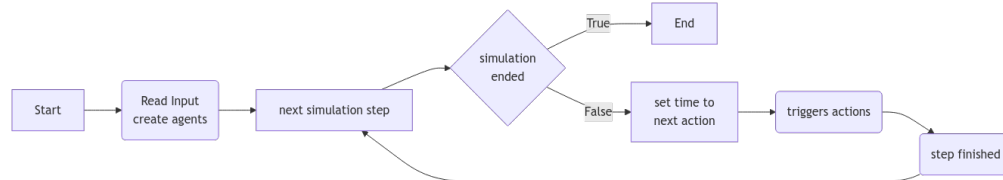


Figure 3.6: Flow of an event-based simulation. Each agent is queried for the next action they want to act upon. Only the time steps in which any of the agents act are simulated.

COMPARATIVE ANALYSIS

The choice of time iteration method greatly influences the simulation’s performance, scalability, and flexibility. The basic simulation loop, while easy to implement, lacks adaptability and can become inefficient with increased complexity and agent count. The agent-action checking loop offers improved flexibility but can still suffer from inefficiencies due to frequent inactivity. The event-driven method stands out by providing an optimal balance of efficiency and flexibility, particularly suitable for complex simulations with irregular event timings.

In conclusion, adopting an event-based simulation approach can substantially enhance the efficiency and modularity of agent-based models. By directly advancing to significant events, this method reduces unnecessary computations and offers a more streamlined simulation process, making it a preferred choice for sophisticated simulations requiring precise time management.

3.6.2 Orchestration and Choreography in Distributed Simulations

To run a simulation loop in a distributed way, it is needed to provide a way to communicate across different processes, which do not have access to the same memory. Typically, this intercommunication issue is either tackled through the use of a message broker, a central communication server or [Remote Procedure Call \(RPC\)](#) as used in [MPI](#) or [RePAST agent-based simulation toolkit \(RePAST\)](#).

The other possibility to run simulations on distributed servers is by running multiple independent simulations across servers and aggregating the simulation results to do Monte Carlo simulations. Yet, this is only feasible when there are randomized parameters in the input set. This option is typically done by individual scripts and therefore not respected in the core of the simulation. So the focus is further put on the orchestration and choreography of a single simulation run.

⁴ <https://gitlab.com/fame-framework/fame-core/-/blob/243f0fb58b8340915e4a71dede6f8a8349bb0e19/src/main/java/de/dlr/gitlab/fame/service/Simulator.java#L120-126>, visited on 11.12.2024

As described in Section 3.3, the main benefits of such a distributed simulation are to remove the barrier of the Python Global Interpreter Lock (GIL), allow distributed real-time simulations with hardware-in-the-loop and provide multi-GPU setups. The market simulation is implemented in the popular Python programming language, not only due to its advanced inclusion of reinforcement learning and low entry barrier. Yet, in Python, there is the GIL which ensures that only one thread of the Python interpreter process is acting at a time. Multi-threading is therefore only useful to offload I/O intensive tasks, but not CPU-intensive tasks. While this might change in the future, currently the best option for actual concurrency in Python is multiprocessing. Even with Python 3.13 – containing a free-threading variant that partially removes the restrictions of GIL – the performance and availability of free-threading is not yet sufficient. Using multiprocessing requires to start multiple instances of the Python interpreter, which can then run concurrently. This also comes with a separation of memory access and a multiplication of the required memory management for each process.

One has to denote the difference here between forking processes and spawning processes, as the former requires only copying the changed memory instances to a new instance, while the latter uses a copy of the whole process memory on multiple instances and has much higher startup times. The comparison of memory usage between spawning and forking multi processes in Python for a sample simulation is shown in Figure 3.7 for fork and in Figure 3.8 for spawn.

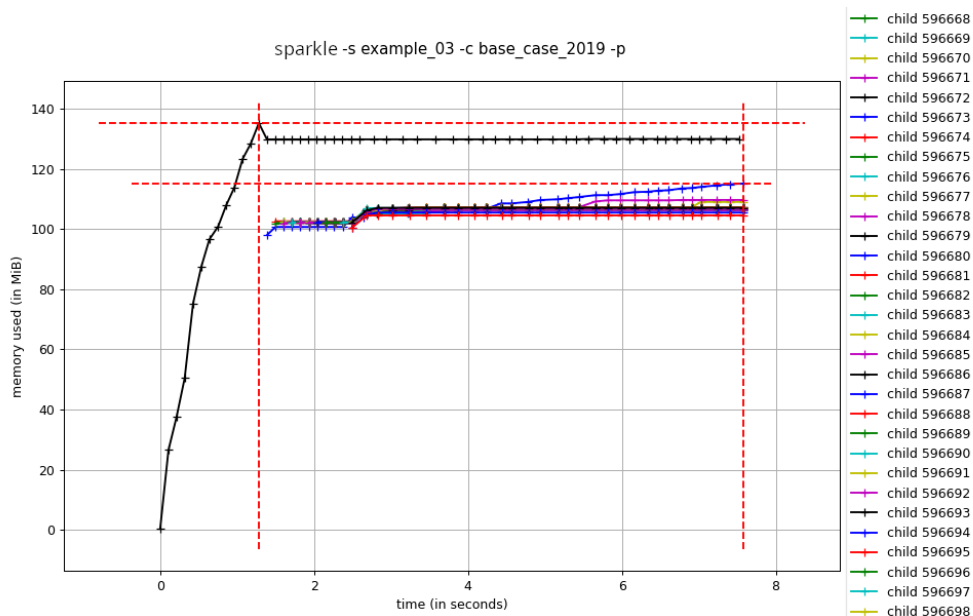


Figure 3.7: Memory usage using "fork" as a multiprocessing method for new processes – on a simulation of they year 2019 with 31 processes and 263 bidding agents in total.

The fork method is faster to start up and reduces memory consumption as it does not require copying the whole memory of the parent process. On the other hand, the spawn method is safer to use, as the forking multiprocessing tends to deadlock when using additional threading in the processes [230].

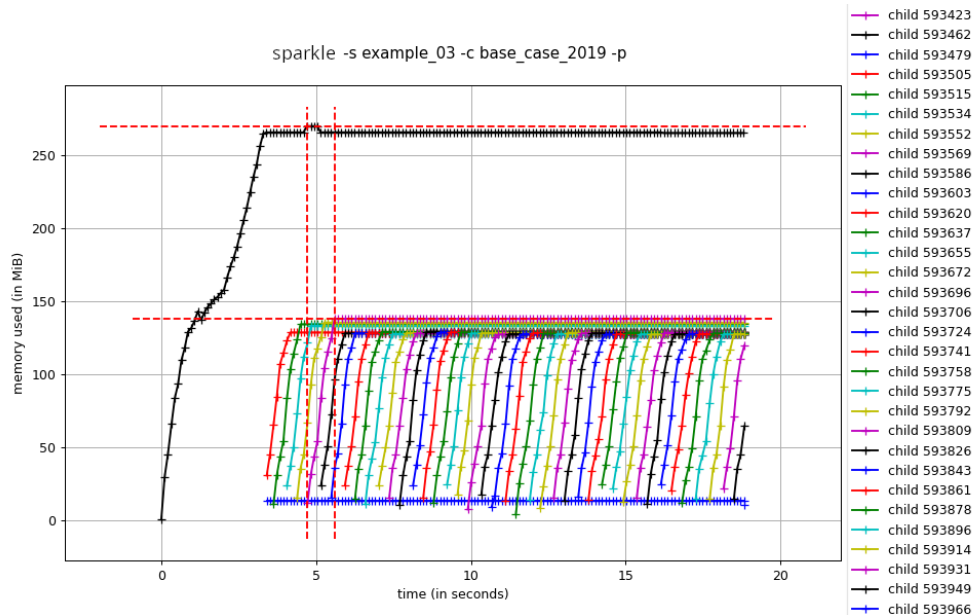


Figure 3.8: Memory usage using "spawn" as a multiprocessing method for new processes. The fork method references the same memory mappings, while spawn copies the simulation space into each process, as memory access is split per process.

Using the mango-agents framework provides a communication layer for inter-process communication through TCP Websockets or MQTT. However, it does not provide clock synchronization or task orchestration, so this is up to the simulation implementation to solve. The next section elaborates on the existing methods to synchronize execution order in distributed systems.

Execution Order in Distributed Systems

Simulations generally provide a clock that can run at a different speed than the wall clock. This is useful when different scenarios are evaluated comparatively. On the other hand, for setups that include simulated hardware like "hardware-in-the-loop" or digital twins, a clock that runs nearly in real-time is needed to co-simulate the market simulation in combination with actual grid operators and the like.

Still, in both scenarios, the question arises of how the simulation time is communicated throughout SPARKLE. The possibilities include letting each agent keep track of the time themselves, which can be done running in real-time and sharing the same interpretation of time. Yet, it is needed to synchronize the agents' view through a global timekeeper

for simulations that are run as fast as possible, making it crucial to know when the next action takes place and synchronize all agents to know about that time.

In distributed systems, it is often not needed to know the exact global time, but only if it is before or after a given action. This is known as partial causal ordering, which can be expressed through a happen-before relation.

This can be seen as a **directed acyclic graph (DAG)** of events, where each node represents an event or action, and edges represent the happen-before relationships. In this graph, parallel paths indicate events that can occur concurrently without affecting each other, while converging paths represent points where synchronization happens. Here, the order is not total as events happening at the same time might happen before or after each other. It is only needed to synchronize the next ready state. For this, one can reduce communication if the global simulation knows which actions influence other actions.

While one could assume to have this knowledge in a general simulation, a lot of flexibility is lost in the configuration of agents if all actions have to be known beforehand. This challenge is reminiscent of issues faced in distributed systems, where maintaining a consistent view of time across multiple processes is crucial. Two key concepts from distributed systems theory – Lamport clocks and vector clocks – offer valuable insights for managing the causality in complex simulations.

LAMPORT CLOCKS provide a method for creating a partial ordering of events in a distributed system. In the context of simulations, each agent can maintain a logical clock that is incremented with each local event and updated when receiving messages from other agents [143]. When an agent performs an action or sends a message, it includes its current logical timestamp. This approach ensures that causally related events are properly ordered without requiring perfect global synchronization. Here, only a single counter is stored per process and increased with every event taking place. When a message from a different process is received, the local clock is updated to the maximum of its current value and the message's timestamp and then incremented by one. The timestamps are not characterizing the happened-before relation; they only follow it.

$$C_i = \max(C_i, t_m) + 1 \tag{3.2}$$

VECTOR CLOCKS extend this concept further by maintaining a vector of logical clocks, one for each agent in the system [213]. Each agent keeps track of its own logical clock and its knowledge of other agents' clocks. When an event occurs or a message is sent, the entire vector is updated and transmitted as seen in [Figure 3.9](#). This provides more detailed information about the causal relationships between events, allowing for a more precise partial ordering. These concepts can be applied to simulation frameworks

to manage time more flexibly. Instead of requiring all actions to be known beforehand, agents can use Lamport or vector clocks to maintain a consistent view of simulation time without constant global synchronization. This approach allows for more dynamic agent behavior and easier configuration changes, as the system can adapt to new actions or interactions without requiring a complete overhaul of the time management system.

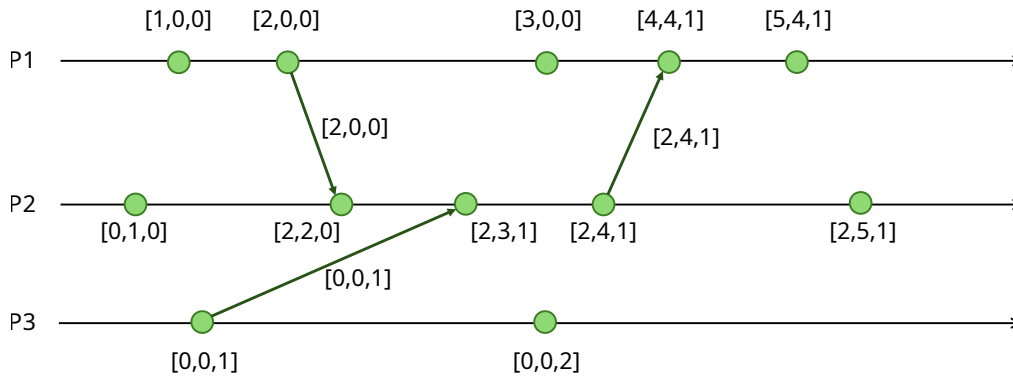


Figure 3.9: Visualization of vector clocks – the timestamps of other processes are tracked through individual process counters, creating a partial ordering.

For example, in a market simulation, agents using vector clocks could make decisions based on their local view of the market state, only synchronizing when necessary (e.g., when finalizing a trade). This would allow for more realistic modeling of decentralized markets while maintaining causal consistency in the simulation results.

Unfortunately, problems may still arise due to **First-In First-Out (FIFO)** or even causal anomalies. This happens if a message is received lately where a related reaction to that message has already been received before. While vector clocks allow the detection of these anomalies, avoidance is only possible for multicast scenarios, since a non-multicast receiver is not able to decide whether a message from a different process should be delayed because its content depends on another message.

Orchestration and Choreography

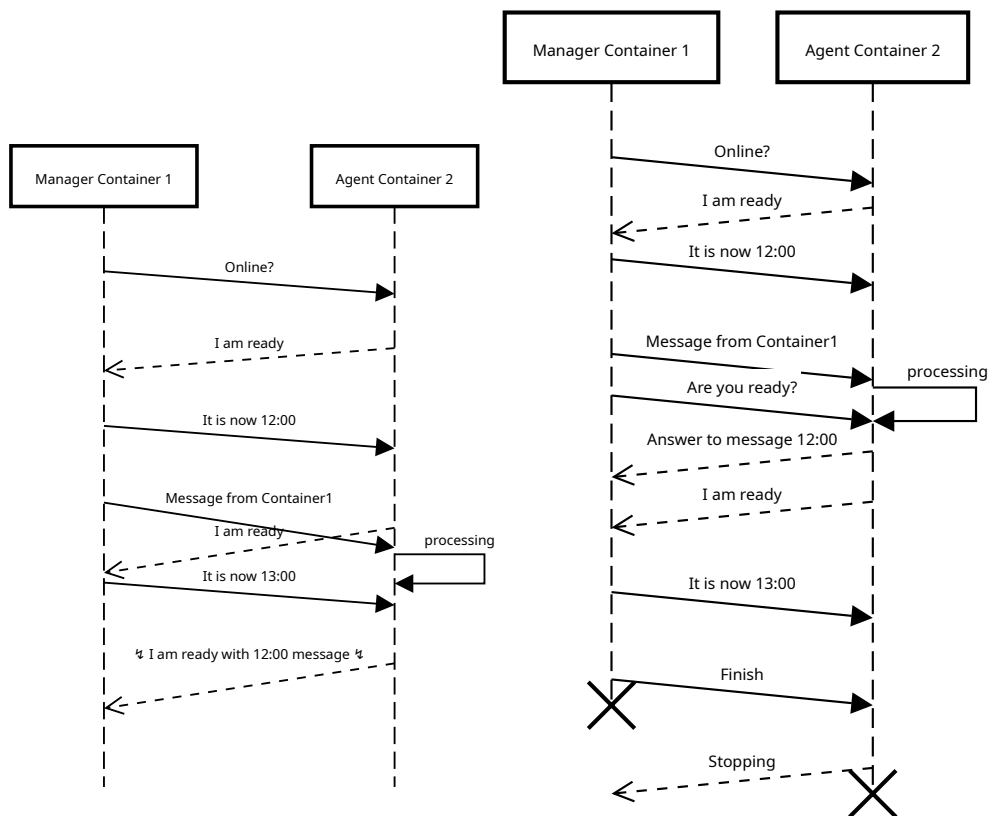
In the case of the market simulation, a holistic view of all agents that advance in time together is needed. One requirement is to orchestrate a centralized simulation clock, distributing time updates to the agents, which can then execute their behavior when it is due. As the clocks are independent of the messaging in the mango-agents framework, this is orchestrated while the behavior of the agents themselves is running as a choreography.

In **Agent-based Modeling**, the distinction between orchestration and choreography is very important. Generally speaking, orchestration provides individual tasks in a process that is executed in a defined order, while choreography handles message sequences between individual actors [183]. In software design, choreography can

be imagined as microservices communicating, while orchestration relates to a task execution service with a centralized orchestrator managing the tasks.

The market simulation joins the two approaches, as the agent’s behavior itself is not orchestrated but acts on its own when time is due to send or handle messages. On the other hand, one does not need to synchronize a simulation clock which is orchestrated centrally.

Fault tolerance of the simulation is not needed in general, as lost messages are resent through TCP on a transport level while missing messages due to software errors would render the results useless, as they are not reproducible or correct.



(a) Prior approach to distributed simulations with a single return loop. (b) Distributed simulations with a three-way message.

Figure 3.10: Sequence diagrams of agent communication without synchronization call and with additional readiness check.

3.7 SCALABLE SIMULATION

Scalability is defined as the ability to perform a greater workload when more resources are added. Being scalable requires adapting to changes in the demand of the workload. A distinction is made between the method of increasing resources by using a more

performant system (vertical scaling) and the usage of a higher number of systems in parallel to distribute the load (horizontal scaling). Vertical scaling reaches the limitation quite soon through the aforementioned `GIL` in Python; the requirements to scale horizontally are the same as using multiple cores on the same system.

The usage of a distributed simulation implicitly includes the synchronization of the simulation clock and can be applied to run on multiple cores on one machine, as well as in a completely distributed system through the use of a communication layer between simulation containers.

By using mango-agents, the two communication protocols, Websockets over `Transmission Control Protocol (TCP)` and `MQTT` are available to communicate between agent processes. Using TCP requires all agents to be on the same physical network and reachable by each other, as incoming messages are submitted to an open TCP port.

To evaluate the usage of the two options, two different use cases are benchmarked, which are run with TCP and MQTT. Both use cases show the sending of messages between multiple agents with one sending and one answering agent and 1000 sent messages between them. Results are shown in [Figure 3.11](#) The "direct ping pong" scenario runs a simulation without synchronization of an external clock. It therefore requires less time for the roundtrips, as each message is directly responded to. The "timestamp" scenario includes the synchronization of a clock in each container and therefore waiting for the termination of each execution step in the main container.

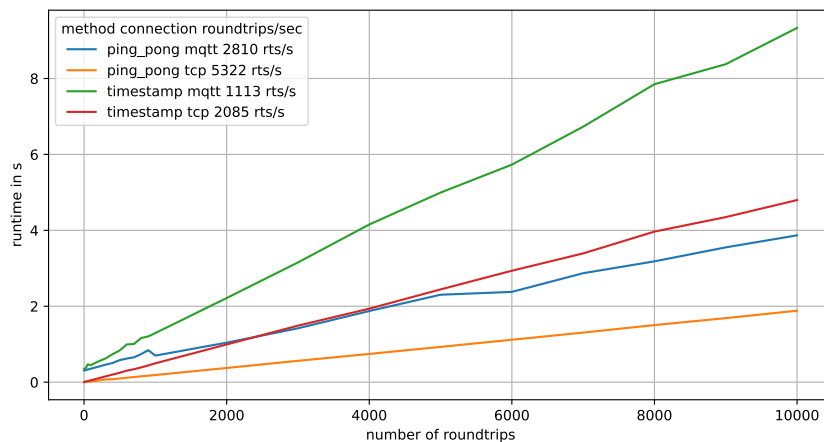


Figure 3.11: Duration graph for various counts of roundtrips for TCP and MQTT using a direct roundtrip vs synchronization with a clock in the timestamp scenario. TCP connection includes lower overhead, while MQTT has more flexibility in the connection handling.

In the simulation, time is spent in `wait_for_futures()` of `get_next_event` in the paho MQTT client library. This is due to the MQTT server aggregating publish requests if `TCP_NODELAY` is not set. When removing this delay through the config parameter `set_tcp_nodelay` of `mosquitto`, the round-trip time of MQTT connections can be

reduced from more than 40 ms to less than 1 ms⁵. A link to the test cases for this behavior is given in [Section 7.3](#).

3.8 INTEROPERABILITY WITH EXISTING ENERGY SYSTEM SIMULATION TOOLS

A major requirement for interoperability is the establishment of standards for the input and output of energy market simulations. For now, such a standard does not yet exist as input datasets can vary fundamentally throughout different simulation tools.

While most tools use a specialized format, which is incompatible with other solutions, it is technically possible to implement a compatibility layer between different input and output formats, making it possible to reuse datasets and scenario definitions from existing simulations.

Conceptually, many different well-defined input formats are available. A main driver for the diversity in formats lies in the complexity of having a tree-structured definition of the scenario and its agents while also providing the time series for the simulation, which are typically in tabular formats. Still, this can get very complex as seen in the Calliope framework, which includes various [Yet Another Markup Language \(YAML\)](#) files allowing overwriting and parameterizing through further configuration files [185]. The conceptually most important formats are included as scenario loaders in the simulation.

These include

- [PyPSA](#) (allows multiple inputs and outputs)
- [AMIRIS](#) (well-defines scenario.yml which references time series [CSV](#) files)
- [Calliope](#) (toml file which references related files and time series [CSV](#) files)⁶

As the constructed concept has additional flexibility through the used abstraction, a native scenario input is also useful to provide a configuration option that covers all the additional features of the simulation that are unique to it. They are therefore not available to the other interoperability layers. The native scenario input format is created based on a [YAML](#) file, which exposes all available configuration options and reads related time series data through [Comma Separated Values \(CSV\)](#).

⁵ <https://github.com/eclipse-paho/paho.mqtt.python/issues/874>, visited on 11.12.2024

⁶ <https://github.com/maurerle/sparkle/tree/calliope>, visited on 11.12.2024

3.9 PROSPECTIVE INTEGRATION OF COMMUNICATION TO COMPATIBLE SIMULATION TOOLS

Furthermore, if interoperability to the communication interfaces of simulation tools is required – as the case in cosimulation setups – the design allows to integrate this as well. Agents that are compatible with the [FIPA ACL](#) standard can communicate with agents from implementations that adhere to the ACL dynamics through serialized messages. This is supported for both of the two implemented communication protocols, [TCP](#) and [MQTT](#).

In this case, in contrast to the definition of inputs and outputs, a well-defined communication standard exists. However, the actual practical implementation is not standardized. Reasons include the tight target scope of simulation tools, which does not cover interoperability towards other simulation tools generally. Efforts to make other tools compatible are needed, which demands a deep understanding of the core components of both tools.

Moves in this direction are made by the TradeRES project [228] through the Spine Toolbox, which is an overarching workflow management tool, integrating independent usage of simulation tools [127]. However, this merely includes workflow management and pipelining of input and output data between different tools, formalizing preparation steps and the like. A different approach is the requirement to integrate different tools in the same software run, for example, to utilize the grid behavior from a separate software specialized in dynamic power flow calculation. For this, co-simulation frameworks like MOSAIK exist [178], which integrate the input and outputs of each simulation step.

Using [FIPA ACL](#), the practical requirements to implement such an integration into a co-simulation like MOSAIK in the future are fulfilled and a common interface exists.

4

MARKET SIMULATION ARTIFACT

They always say time changes things, but you actually have to change them yourself.

Andy Warhol, visual artist, film director
and producer [242]

The main artifact of the thesis is the simulation framework for agent-based research on energy markets. Here, the acquired requirements and concepts described in the previous chapters are implemented. The artifact allows modeling different energy market scenarios on its own but also contributes to research as a simulation framework, which can be integrated, extended and embedded into other simulations. Therefore, the final artifact *SPARKLE* can be seen as a framework, as well as a simulation tool with specific examples.

SPARKLE includes the developments done in this PhD and has a fixed feature set without ongoing development after this thesis.

Users of the tool are encouraged to use the maintained *Agent-based Simulation for Studying and Understanding energy Market Evolution and bidding behavior (ASSUME)* version. The features of *SPARKLE* have been contributed to the development version of *ASSUME*, which is a version with additional features and will be maintained throughout further research projects like *ADAPT*. This version receives updates on upcoming developments and includes the extension of *Deep Reinforcement Learning (DRL)* in agent strategies.

Furthermore, both parts rely on the *energy market library for Python (emarketlib)*, which contains the required market abstraction as described in [Section 3.5](#) and has been created throughout this thesis. *SPARKLE* utilizes the agent-based simulation framework *mango* [179] for the core dynamics, which also received numerous contributions throughout this thesis.

4.1 CHARACTERISTICS OF THE SIMULATION ARTIFACT

This section outlines the key characteristics of the market simulation artifact, focusing on its software design and functionality. The artifact is designed to facilitate agent-based research in energy markets. *SPARKLE* is an open-source simulation framework that allows researchers and practitioners to access, modify, and contribute to its

development. This openness fosters collaboration within the research community and ensures that the tool remains relevant and up-to-date with the latest advancements in energy market research.

One of the standout features of the simulation framework is its modular architecture. This design enables users to customize and extend functionalities according to their specific research needs. Researchers can easily integrate new components or modify existing ones without disrupting the overall system. This integration enhances the realism of simulations by enabling agents to adapt their strategies based on market conditions.

The simulation framework is equipped with tools for analyzing various market designs, mechanisms, and policies. Researchers can simulate different scenarios to evaluate how changes in market structure affect participant behavior and overall market efficiency. Supporting multi-agent simulations, the framework allows for the representation of diverse market participants, including generators, consumers, and storage operators. This capability enables a comprehensive analysis of interactions among agents in a competitive market environment.

Designed for interoperability with standard data formats, the framework facilitates seamless integration with other tools such as [AMIRIS](#) and [PyPSA](#). Users can easily import scenarios from these tools, enhancing flexibility in the simulation setup. To aid in result analysis, the framework features implemented Grafana Dashboards that allow users to visualize simulation outcomes effectively. These dashboards enable researchers to compare multiple simulations and gain insights into market dynamics. Additionally, the simulation framework includes an adaptable network representation feature, allowing users to model and visualize complex electricity networks. It is compatible with examples from PyPSA, making it easier for users familiar with that tool to embed existing simulation data into [SPARKLE](#). Overall, these characteristics highlight the flexibility and robustness of the simulation framework, making it a valuable resource for advancing research in energy markets.

Besides the core characteristics of the market framework, [SPARKLE](#) includes various features not directly derived from the functional and non-functional requirements. For example, the artifact provides good visualization capabilities of grid dynamics as well as a [FIPA ACL](#) compliant agent communication.

4.2 CONFIGURATION OPTIONS

[SPARKLE](#) offers a range of configurable components. The main configurable parts of the simulation include input data, energy market design, agent behavior, unit forecasts/availability and prices, visualizations, and [KPIs](#). An overview of these options is shown in [Figure 4.1](#). Users can specify various input data sources, including

historical market data, renewable generation profiles, demand forecasts, and other relevant datasets.

The simulation tool supports multiple data formats, enabling seamless integration with existing databases or external tools. The two major input formats are *CSV* and direct source code. While *CSV* makes it easy to configure agents through tabular data, quickly investigate an overview and attach time series data, an imperative simulation API allows programmatically defining, reading, and writing scenarios. Both options are available in the final simulation artifact.

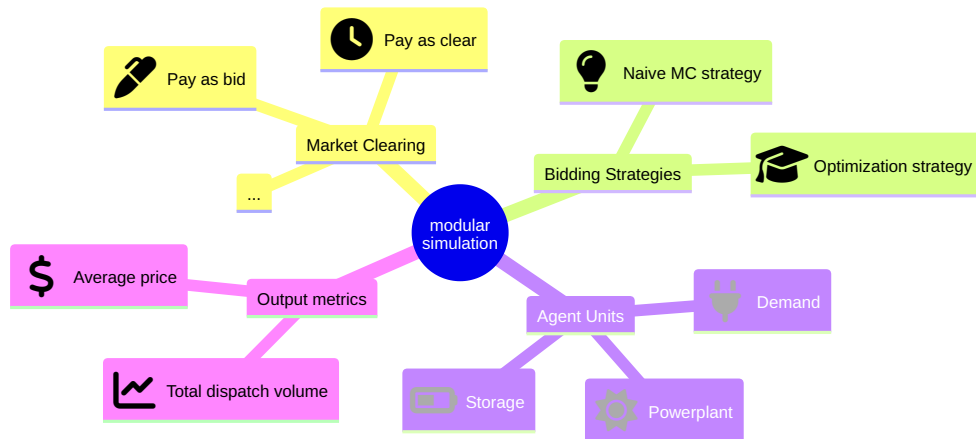


Figure 4.1: Overview of configurable elements of the simulation SPARKLE. Moving parts of a market simulation can be adjusted as required.

The simulation therefore allows for flexible configuration of different energy market designs. Users can define market structures such as day-ahead and intraday markets, as well as implement market coupling with other commodity markets (e.g., gas or hydrogen). This component also includes the ability to select and customize market clearing algorithms based on specific research objectives. Adding custom bidding strategies and markets is done by adding them to a registry in the world object, which makes the implemented class available to the market design as a market mechanism, shown in Listing 4.1. Here, just like in Listing 3.1 an eligible obligations lambda function is configured in the market design to only allow bids from participants with at least 10 MW maximum power. This is checked during the registration of the agents at the market. If a participant is not eligible to bid on the market, the market rejects the participation and does not include bids received from the rejected agent.

Additionally, each bid can have an additional field `eligible_lambda`, to only accept specific contracts of participants which fulfill extra requirements on a per contract basis. As the `pay_as_bid_contract` method requires the usage of additional parameters, this is individually configured in the `param_dict` of the market configuration.

```

1 world = World(database_uri=...)

```

```

2 world.clearing_mechanisms["pay_as_bid_contract"] =
    PayAsBidContractRole
3
4 world.bidding_strategies["support"] = SupportStrategy
5
6 marketdesign = [MarketConfig(
7     market_id="SupportEnergy",
8     opening_hours=rr.rrule(rr.MONTHLY, dtstart=start, until=end),
9     opening_duration=timedelta(hours=1),
10    market_mechanism="pay_as_bid_contract",
11    market_products=[MarketProduct(rd(days=28), 1, timedelta(days=0))
12    ],
13    additional_fields=[
14        "sender_id",
15        "contract",
16        "eligible_lambda",
17        "evaluation_frequency", # monthly
18    ],
19    product_type="energy",
20    supports_get_unmatched=True,
21    param_dict={"allowed_contracts": ["FIT", "PPA"]},
22    eligible_obligations_lambda: lambda u: u.get("max_power",0) > 10,
23    volume_unit="MW",
24    price_unit="EUR/MWh",
25    maximum_bid_price=9999,
26    maximum_bid_volume=9999,
27 )]
28 mo_id = "market_operator"
29 world.add_market_operator(id=mo_id)
30 for market_config in marketdesign:
31     world.add_market(mo_id, market_config)
32 ...
33 world.run()

```

Listing 4.1: Configuration of custom market mechanisms and bidding strategies in the world. Once added to the world - units and markets using the strategies can be added.

The framework enables users to configure the behavior of market participants through customizable agent strategies. Researchers can implement various bidding strategies, decision-making processes, and learning algorithms to model realistic agent interactions in the market. While the main focus is not put on the bidding strategies, different options are available, for example, a naive strategy based on **marginal costs (MC)**, a strategy requesting the amount from manual user input or a learning strategy. Additional behavior can be implemented as well, for example, a cartel strategy, which communicates prices to other bidding agents.

Users can define the availability and pricing of different generation units within the simulation. To apply uncertainties, a forecaster of availabilities and prices can be set for each unit. This forecaster can be configured to return the true values if no uncertainties are modeled, but also makes it possible to model increasing variability when values further away in the future are requested (see `FutureForecaster` class). Modeling uncertainties as a variable function has various advantages, as it also enables actual forecasts without any input data straight from past market results of the simulation. At first, this seems counterintuitive to provide a pre-known availability through some kind of forecaster, yet this can be interpreted as perfect foresight and therefore matches the same analogy. Forecasters include availability of renewable generation, maintenance schedules, market prices as well as fuel costs. Behavioral functionality can be, therefore, configured on every access of the forecaster, for example, to apply a given random noise as shown in [Listing 4.2](#).

```

1 def __getitem__(self, column: str) -> pd.Series:
2     noise = np.random.normal(0, self.sigma, len(self.index))
3     forecast_data = self.forecasts[column].values
4     noisy_data = forecast_data + forecast_data*self.percent*noise
5     return pd.Series(index=self.index, value=noisy_data)

```

Listing 4.2: Getter function of a `RandomForecaster` with randomized noise applied to the forecast data.

Furthermore, the framework provides options for configuring visualizations of simulation results. Users can create custom dashboards using Grafana or other visualization tools to analyze key metrics and trends over time, facilitating a better understanding of market dynamics. Finally, users can define and track various KPIs relevant to their research objectives. This includes metrics such as market efficiency, participant profitability, price volatility, and renewable integration levels.

Market Configuration

The market configuration from [Section 3.5](#) was implemented in the final simulation artifact. The definition of markets is done through an object-oriented interface and is separately available as the `emarketlib` software library. Through the usage of the event-based simulation, multiple markets can schedule events independently. The found abstraction makes it possible to implement various market designs. As there is no proof of completeness feasible for energy market designs, it is shown that the found abstraction is able to implement a wide range of market designs. A market design can, for example, be defined as a list of multiple markets as given in [Table 4.1](#) for the European Energy Market design.

name	EPEX DA	EPEX ID auction	EPEX ID trade	EEX Futures
product type	energy	energy	energy	energy
market products	[(HOURLY, next 24, starting next day)]	[(15m, next 96, starting in 15m)]	[(15m, next 96, starting next day), (30m, next 48, starting next day), (1h, next 24, starting next day)]	...
volume unit	MW	MW	MWh	MW
price unit	€/MW	€/MW	€/MW	€/MW
opening hours	daily at 12:00	daily at 12:00	every 5m (continuous)	every 5m (continuous)
opening duration	24 hours	every 15m	5m	5m
market mechanism	pay as clear complex	pay as clear	pay as bid	pay as bid
additional fields	baseid, linkid	/	/	/
query available offers	false	false	false	false
maximum bid	9999	9999	9999	9999
minimum bid	-500	-500	-500	-500
maximum volume	600	/	600	600
volume tick size	0.1	0.1	0.1	0.1
price tick size	0.1	0.1	0.1	0.1

Table 4.1: Overview of market configurations to simulate the European energy market. Selected markets are Day-Ahead (DA), the two Intra-Day (ID) markets and the Futures market.

This includes the Day-Ahead Market (DA), which trades one day ahead, the Intra-Day (ID) Auction, taking place. Through the definition of recurring openings, the overview of opening and delivery examples can be given. This is shown in [Figure 4.2](#).

A thriving topic is the modeling of market contracts in simulation software. The implementation of this topic is inspired by smart contracts, which enable the definition of contracts through source code. Yet, for the configuration of existing models, several preset contracts are available, while additional contracts can be added in a modular way.

All contracts shown in [Table 2.1](#) are implemented in the artifact. The distinction between market-based contracts like [CfD](#) and market premiums, to contracts solely based on the units dispatch, like [PPA](#) and [FIT](#) is quite important for the implementation. In the prior case, an additional request to the market is made during the execution of the contract.

This gives the first answer to the first research question:

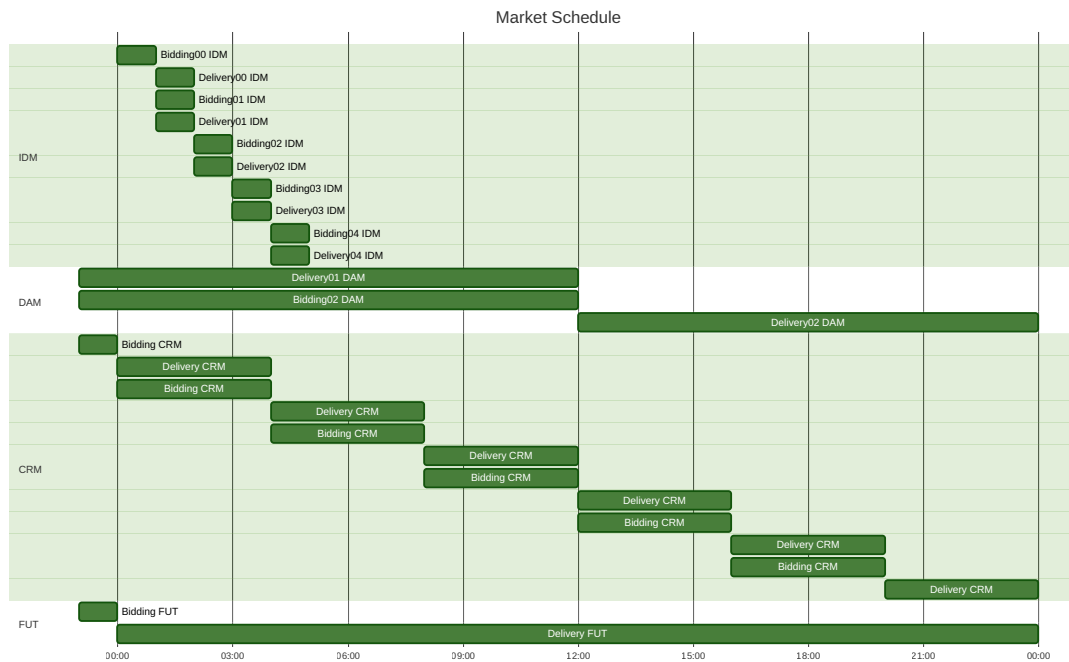


Figure 4.2: Schedule of multi-market dispatch using the simulation tool. Offset between bidding intervals and delivery are important when evaluating strategies for multi-market simulations.

Research Question 1

Which abstract description is able to characterize different market designs to guide their implementation within modular energy market simulation software?

The found description makes it possible to model the variety of existing markets and, while it is unclear what the future holds, is extendable in terms of the definition. It even allows to model more complex market mechanisms as shown in Listing 4.1 and in Table 4.1, which utilize the extended features.

4.3 COMPLEX BIDDING STRATEGIES

Besides the extensive simulation capabilities, a unique feature is the optimization for complex block bids. Such bidding behavior does not make up the majority of bids, but still allows for decreasing the operational cost of thermal power plants, as the actual ramping constraints are better represented in the market result [5]. For this, different market implementations are available, while the focus here is put on the optimization for block orders and exclusive orders.

4.3.1 Power Plant Optimization Module

In the following, an advanced power plant optimization module is provided, which implements the usage of ramping constraints for bids of multiple hours. It is introduced in SPARKLE as `DmasBiddingStrategy`.

The basic idea of the strategy is to solve the same optimization problem multiple times for different monotonously increasing price expectations and submit bids based on the increasing pricing level, relying on the existence of the previous layer.

This mechanism is visualized in Figure 4.3 as one can see that the previous stage of bids has to be accepted before the acceptance of bids for higher price levels. This is similar to the mechanism earlier described in Table 3.4.

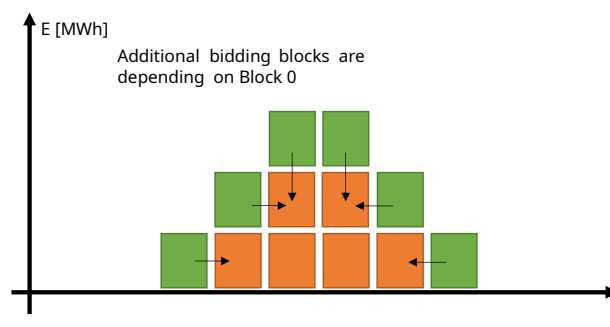


Figure 4.3: Complex bidding behavior for block bids of power plant. The black blocks can only be accepted by the market if the red blocks are accepted as well. This accommodates ramping constraints of power plants.

The basic optimization problem for day-ahead bidding is described below, and then the additional conditions needed to compute the best behavior when the day-after is included are added to investigate the avoided costs of keeping the plant on during the last hours of the bidding day. By calculating the expectation for profit from the next day, the power plant submits negative bids across the inefficient hours. Modeling this behavior by itself is unique to the artifact and not yet represented in other agent-based simulations. The typical approach to model the negative bidding comes from the addition of additional constraints to provide heat like a district heating market, cleared before the [Energy only market \(EOM\)](#) [193].

OPTIMIZATION MODEL

To model the basic optimization, a set of decision variables is needed, which are the actual power output and two helper variables for the additional and minimum power output. As well as three binary variables to indicate the start-up, shut-down and status indication. t specifies a timeslot of the market here, so an interval instead of a single point in time. Consequently, T defines the set of all clearing intervals that occur in the market.

DECISION VARIABLES

$p_{\text{out}}(t)$: Actual power output at time $t \in [0, p_{\text{max}}]$

$p_{\text{model}}(t)$: Additional model power at time $t \in [0, p_{\text{max}} - p_{\text{min}}]$

$z(t)$: Binary variable indicating whether the unit is on (1) or off (0)

$v(t)$: Binary variable indicating unit start-up at time t (1 if starting, else 0)

$w(t)$: Binary variable indicating unit shut-down at time t (1 if shutting down, else 0)

U : Current runtime/uptime duration (> 0 if on; < 0 if off)

PARAMETERS

Additionally, the optimization depends on various input parameters. These are listed in the following:

t : Time slot $t \in T$ (T ordered set of time slots per clearing)

$p_{\text{min}}, p_{\text{max}}$: Minimum and maximum power output

$\Delta = p_{\text{max}} - p_{\text{min}}$: Difference between maximum and minimum power

$R_{\text{up}}, R_{\text{down}}$: Ramp-up and ramp-down limits

$U_{\text{up}}, U_{\text{down}}$: Minimum uptime and minimum downtime of the power plant

η : Efficiency of the unit.

E : Emission factor.

C_{start} : Cost of starting the unit.

$C_f(t)$: Fuel price at time t

$C_e(t)$: Emission price at time t

$C_p(t)$: Electricity price at time t

p_0 : Initial power output

OBJECTIVE FUNCTION

To maximize the economic usage of the power plant, the optimal costs are calculated:

$$\max \sum_{t=0}^{T-1} \left[C_p(t) \cdot p_{\text{out}}(t) - \frac{p_{\text{out}}(t)}{\eta} \left(C_f(t) + E \cdot C_e(t) \right) - v(t) \cdot C_{\text{start}} \right] \quad (4.1)$$

CONSTRAINTS

The optimization is constrained through the helper variables, which determine the actual p_{out} , which is composed of the minimum power plus the additional power:

$$p_{out}(t) = p_{model}(t) + z(t) \cdot p_{min} \quad (4.2)$$

The power output should be in the bounds of 0 and the $p_{max} - p_{min} = \Delta$:

$$0 \leq p_{model}(t) \leq z(t) \cdot \Delta \quad (4.3)$$

Additional ramping constraints ensure:

$$\begin{aligned} \text{For } t = 0 : \quad & P_0 - R_{down} \leq p_{out}(0) \leq P_0 + R_{up} \\ \text{For } t > 0 : \quad & p_{out}(t) - p_{out}(t-1) \leq R_{up} \cdot z(t-1) \\ & p_{out}(t-1) - p_{out}(t) \leq R_{down} \cdot z(t) \end{aligned}$$

State Transitions:

$$z(t-1) - z(t) + v(t) - w(t) = 0, \quad \forall t > 0 \quad (4.4)$$

Minimal Run Time:

$$z(t) \geq \sum_{k=t-U_{up}}^{t-1} v(k), \quad \forall t \geq \text{MinRunTime} \quad (4.5)$$

Minimal Stop Time:

$$1 - z(t) \geq \sum_{k=t-U_{down}}^{t-1} w(k), \quad \forall t \geq \text{MinStopTime} \quad (4.6)$$

Initial Runtime Constraints:

$$\begin{aligned} \text{If } U > 0 : \quad & z(t) = 1, \quad \forall t < U_{up} - U \\ \text{If } U < 0 : \quad & z(t) = 0, \quad \forall t < U_{down} - (-U) \end{aligned}$$

4.3.2 Addition of Avoided Start Cost Calculation

A unique feature of this implementation is the inclusion of calculating the avoided start cost based on a forecast for the next day and the expected benefit of keeping the power plant running in contrast to a shutdown, which would have the consequence of keeping it turned off during the minimum downtime hours.

For this, two additional parameters and one decision variable are required, which are:

ADDITIONAL DECISION VARIABLE

$p^*(t)$: Hypothetical output power if the plant operates continuously without shutting down for certain hours.

ADDITIONAL PARAMETERS

Δ_{Eff} : Economic efficiency improvement from preventing starts

ADDITIONAL VARIABLES

$A(t)$: Set of hours where a start is prevented if it would improve efficiency

ADJUSTED OBJECTIVE FUNCTION

The objective function remains focused on maximizing cash flow but incorporates the evaluation of the efficiency delta when avoiding starts. To do this, an additional term is added to the existing function, which calculates the benefit for the next day we have from having the power plant turned on.

$$\max \sum_{t=0}^{T-1} \left[C_p(t) \cdot p_{\text{out}}(t) - \frac{p_{\text{out}}(t)}{\eta} \left(C_f(t) + E \cdot C_e(t) \right) - v(t) \cdot C_{\text{start}} \right] + \sum_{t \in A(t)} \Delta_{\text{Eff}} \cdot p^*(t) \quad (4.7)$$

The additional term ensures that the model considers potential efficiency gains from preventing starts.

ADDITIONAL CONSTRAINTS

Hypothetical Continuous Operation Power for hours where starts might be avoided

$$\forall t \in A(t) : p^*(t) = p_{\text{out}}(t) \quad (4.8)$$

For other hours:

$$p^*(t) = 0 \quad (4.9)$$

Prevented Start Logic: If preventing the start of the power plant is more efficient ($\Delta_{\text{Eff}} > 0$), ensure the plant runs continuously:

$$z(t) = 1, \quad \forall t \in A(t) \tag{4.10}$$

Consistency with Prevented Start Analysis works as follows:

- After solving the model with a baseline set of prices:
 - Identify hours where $p_{\text{out}}(t) = 0$ (the plant would normally shut down).
 - Simulate the operation with prevented starts and compare cash flow (Δ).
- If $\Delta > 0$, modify $A(t)$ to include these hours in the subsequent model iteration and set negative prices for such hours.

EXECUTION OF ITERATIVE OPTIMIZATION

First, the optimization model is executed and stored for the time slots in T for a given price assumption of the forecast price. Optimization with the increased price horizon is done for the prevented starts calculation and then compared to the simulation with the smaller forecast. If the cash flow of the prevented simulation is larger, the shutdown is prevented by setting negative bids, equal to the avoided cost. This is then repeated for higher price assumptions to calculate the different blocks in the market.

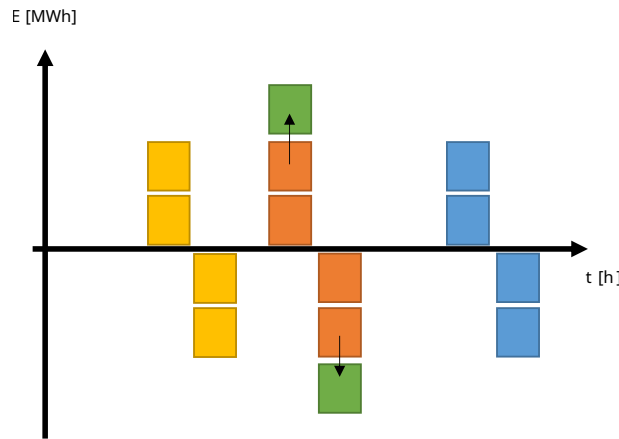


Figure 4.4: Complex Bidding behavior of for exclusive bids of storages. Only one color of the provided blocks can be accepted by the market. The bids differ in the charge time, as well as the maximum power that can be charged or discharged.

A similar model, containing the evaluation of different price potentials and solving a linear problem for each is done for storages to investigate exclusive bids. These bids include multiple dispatch options. Typically, different variations are possible by moving the whole charge and discharge blocks across the time blocks, as shown in Figure 4.4.

4.3.3 Market Model for Linked and Exclusive Orders

The presented advanced bidding strategies require the usage of a capable market mechanism. It is possible to check the eligibility of a market and its requirements by respecting the market requirements as described in Table 4.1.

The optimal solution to a market with complex orders, like linked orders and exclusive orders, requires solving a mixed integer linear optimization problem as various combinations of power plants can be selected while each dispatch has specific constraints. As the above-introduced strategy is used in the evaluation simulations, the corresponding market problem is given in the following.

DECISION VARIABLES

In the following the decision variables of the market problem are described

S_t	the magic source/sink required to adjust for floating point deviations
$V_{block,t,name}$	the accepted volume of each bid
$u_{block,t,name}$	boolean if the block is used
$ul_{block,t,name}$	boolean if the linked block is used
$um_{block,t,name}$	boolean if the mother block is used

PARAMETERS The following model parameters can not be changed by the optimization but are required as inputs to the model.

order_types	(linked, exclusive, standard)
orders	dictionary of orders for every order type
parent_blocks	parent block
T	$\{0, 1, 2, \dots, t_{max}\}$
c_{max}	$\in \mathbb{R}^+$ - maximum bidding price
$c_{block,t,name}$	$\in \mathbb{R}^+$ - the bid price
$V_{max(block,t,name)}$	the bid volume

OBJECTIVE FUNCTION

The objective function minimizes the total cost over all time steps. An additional magic source/sink is available to compensate for small deviations, without which the problem would be infeasible:

$$\min \sum_{t \in T} \left(\sum_{ot \in \text{order_types}} C(ot, t) + |S_t| \cdot c_{max} \cdot 10 \right) \quad (4.11)$$

Here, the costs for each order type in a given time slot t are:

$$C(\text{order_type}, t) = \sum_{block, name \in \text{orders}[\text{order_type}][t]} c_{block, t, name} \cdot V_{block, t, name} \cdot u_{block, t, name} \quad (4.12)$$

This is used to calculate the overall cost later on.

CONSTRAINTS

First of all, all bids can only be accepted between 0 and the maximum available amount submitted in the bid.

$$\forall (block, t, name) : 0 \leq V_{block, t, name} \leq V_{max, block, t, name} \quad (4.13)$$

The child block constraint enables that a parent block has to be used entirely:

$$\sum_{t \in T} u_{block, t, agent} \leq 2 \cdot \sum_{h \in \text{parent_blocks}} u_{parent_id, h, agent} \quad (4.14)$$

If the current block is a linked block, an additional constraint is added for it to only be used if the dependent block is set. Here the *mother_bid_counter* equals the count of depending blocks, creating an all-or-nothing situation of depending blocks:

$$\sum_{t \in T} u_{block, t, agent} = \text{mother_bid_counter} \cdot u_{block, agent} \quad (4.15)$$

Regarding the exclusive blocks, only one of the collections of blocks is allowed to be set. As the u variable is binary, this can be expressed as follows, ensuring that only blocks of one section of exclusive blocks can be used:

$$\sum_{block \in \text{exclusive_blocks}} u_{block, *, agent} \leq 1 \quad (4.16)$$

Finally, the sum of the volumes per order type should match zero for every time slot, with the opportunity to use the magic source instead. The additional expenses from the magic source are covered by the optimization function:

$$\forall t \in T \quad \sum_{\text{order_types}} V(\text{order_type}, t) + S_t = 0 \quad (4.17)$$

The market model, therefore, maximizes social welfare by optimizing the unit dispatch within the given constraints of complex bids through block orders and exclusive orders. Typically, the requirement for the magic source is nearly zero. Due to floating point calculations, this might as well be off by an amount less than 10^{-10} . In cases where the clearing is not feasible due to missing generation, the magic source will step in to create a feasible solution.

The extended market optimization as well as the power plant optimization is part of SPARKLE and is used in Chapter 5.

4.4 SCHEDULING

As noted in Section 3.6, the usage of an event-based simulation design allows for the dynamic creation of additional agents, without changing core workflows. Luckily, this decoupling of the agent logic from the world and simulation behavior is also beneficial when scheduling in a distributed simulation. The usage of mango agents made it possible to create a distributed simulation as it already brings core elements of communication to it.

This supports various use cases:

- manual simulation using market games
- digital twin co-simulation
- real-time simulation

A future use case for such market simulations – besides their current usage researching future scenarios – is gamification in lectures. Typically, market games are used to create a better sense of market dynamics. Through the usage of an `ExternalClock` which advances in predefined steps, the market simulation artifact rudimentary supports such use cases as well¹. A manual strategy would wait for user input to set the bids, creating an interactive version of the market. This, of course, halts the simulation, which waits for the slowest agent in the simulation.

The other criteria, running real-time, is also covered by the simulation tool by providing a clock that is set in real-time from the system clock, available as `AsyncioClock` in

¹ https://github.com/maurerle/sparkle/blob/maurerle/docs/source/manual_simulation.rst, visited on 13.02.2025

mango. In this case, no synchronization of agents happens in the simulation, and all agents are required to rely on the accuracy of the system clock.

The agent framework **mango** is developed at the University of Oldenburg, while various fixes and features have been contributed to it throughout this thesis. Features implemented on top of the existing framework, which were integrated into the upstream version, include the distributed clock mechanics, functionality to query a role of an agent, recurrency-based schedules and improvements to **MQTT** and parallel execution. The distributed clock works as follows, by creating a simulation with each **mango** container. While the whole simulation typically also runs in **Open Container Interface (OCI)** containers for separation of privileges and fixed dependencies, each simulation is also contained in a **mango** runtime container, which includes the scheduler and all agents running in a given process. The distributed clock then creates a clock agent in each **mango** container and uses the clock manager to send and update the current simulation time in the main container toward the clock agent containers. The feature of distributed clocks was contributed to **mango** throughout this thesis and is used for distributed simulations of **SPARKLE**.

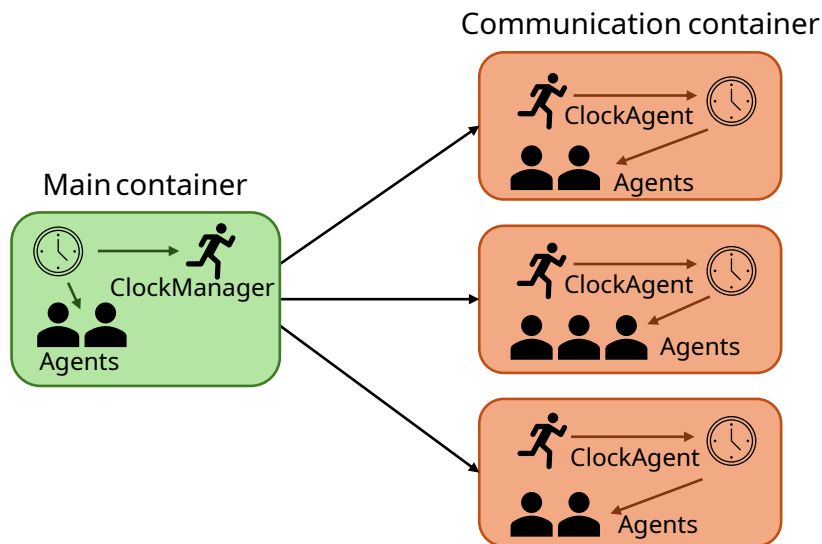


Figure 4.5: Interplay of the distributed clock in a **mango** simulation. **Mango** containers require some kind of synchronization, as each has a separate clock. Instead of an external signal, these clocks are synchronized through updated timestamps from the manager.

Research Question 2

In what way can different market mechanisms be represented in the simulation?

The second research question handles the actual implementation of the abstraction in software. Actual simulations have very heterogeneous demands regarding the time schedules, complexity and implementation. Additional ramping constraints are

implemented in the market and power plant optimization, which serves as a showcase of different market and bidding strategies. The usage of complex market mechanisms requires the implementation of suitable bidding strategies that mutually take advantage of the market characteristics. This is also the case for the implemented contracts and real-time features of the market abstraction. The different market mechanisms can therefore be successfully applied in the simulation software, which requires much more than the plain representation of the market abstraction from the first research question into a source code equivalent.

4.5 VISUALIZATION OF OUTPUTS

SPARKLE supports two different output formats, *CSV* and any database supported by SQLAlchemy [46]. The data is aggregated in the simulation from an output role, which then handles the writing, providing an abstraction to the externalities, just as described in the Section 3.6 of conceptualization. The output can be used to attach the output to an interactive visualization tool. For this purpose, Grafana dashboards are available with the software, providing an intuitive web interface to the results in real-time. Therefore, results can be analyzed on the fly, users can create new graphs by using an existing prominent open-source interface, while still having the choice of usage and direct access to the database. As not all users have the possibility to run a Database management system (DBMS) like PostgreSQL on the computer, export to *CSV* allows further analysis of the results. Depending on the simulation

Technically, this is implemented by utilizing a PostgreSQL database, which is set up with the Grafana dashboard in OCI containers (using podman or docker). Preconfigured dashboards are available in the repository of **SPARKLE** while each dashboard serves a separate function.

While there are dashboards for specific investigations of linked bids or redispatch, there is also the option to visualize the difference between two simulation runs or investigate the individual agent behavior, dispatch and economic key performance indicators. As *KPIs* can be extended in the software easily, as shown in Chapter 3, the calculated results also show up in the simulation interface. One possible visualization of the economic profitability of power plant units is shown in Figure 4.6.

The evaluation of *KPIs* is possible in the simulation through the definition of an aggregation subset of the output agent. By adding entries to the output roles `kpi_defs`, additional calculations can be added.

From the various options of integrating the calculation of *KPIs*, this methodology allows the adjustment of only one configuration, to have the additional *KPI* calculated for every simulation run which includes this adjustment. Making it available in the output database as well as directly on the dashboard to compare different simulations interactively. Therefore, the third research question is answered in this section.

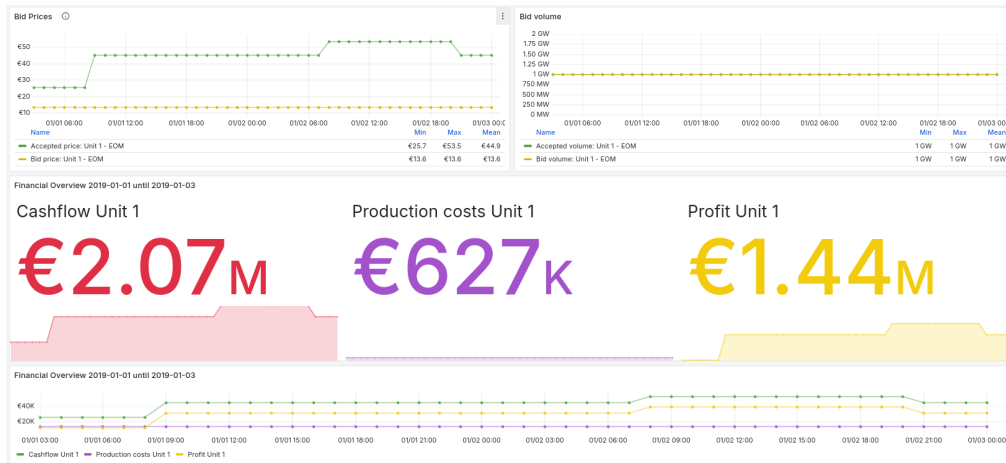


Figure 4.6: Calculation of economic parameters for example01a of a selected power plant. Besides the aggregated values, an inspection of when which cost or profit occurred is shown.

Research Question 3

How can indicators of market mechanisms be used to evaluate specific market designs?

In this chapter, the final software artifact **SPARKLE** is presented. The design choices described in Chapter 3 met the expectations and allowed successful modeling of market mechanisms and execution in a market simulation. Finally, the focus is put on the evaluation of results, where a methodology to freely define customized visualizations of the results is equally possible as the calculation of **KPIs** directly in the simulation framework.

5

EVALUATION

Truth (...) is much too complicated to allow anything but approximations.

John von Neumann in "The Mathematician" (1947) [239]

The examination of the complex field of market modeling is an important step in evaluating the characteristics found in the previous conceptual exploration. This key section evaluates the proposed model from [Chapter 4](#) according to the functional and non-functional requirements from [Chapter 3](#). It navigates the landscape of evaluation methodologies and provides a structured framework for assessing the effectiveness and robustness of the market modeling strategies under review. Finally, leading back to the overarching research question of this thesis:

Overarching Research Question

How can different energy market designs be evaluated in a simulative comparative manner?

While a single answer to the research question is not finite and will be extended through future research, a step forward towards evaluating different energy market designs is given through the tools and results of this thesis.

The evaluation of the simulation tool with regard to the research questions is split into three parts, as categorized before, first focusing on the [functional-requirements](#) and then on the [non-functional-requirements](#) again before evaluations and showcases are presented.

In general, the evaluation is done by examples, which showcase the flexibility and usage of the simulation, as well as the usage with different simulation datasets. The main idea is to give examples of how the final artifact behaves and make sure, that the results match the simulation expectation. In particular, the system under test fills the research gap for energy market simulations.

As a bottom-up agent-based simulation model, it includes a variety of possibilities, which are not covered in this thesis, especially regarding optimized agent behavior of simulated market participants. So the following section is given as an excerpt of the possibilities, covering the main advancements of energy market simulations.

5.1 FUNCTIONAL REQUIREMENTS

As outlined in the research gap in [Section 3.1](#), the main missing requirement is a tool to compare different energy market design choices in simulations. The required functional requirements were then derived in [Section 3.2](#). These are now analyzed further in showcase scenarios, which explain the applicability of simulations.

5.1.1 Agent-Based Simulation

Through assessing related agent-based simulations, a new approach for agent simulations has been established. While simulation tools often handle input data solely from reading files in a given format (e. g. Calliope and AMIRIS), the agents can be configured in the final simulation artifact more interactively. While the whole scope is handled in the world instance, one can add agents to it programmatically as shown in [Listing 5.1](#). This is also possible when loading an initial scenario from CSV and adjusting it before running the simulation.

```

1 world.add_unit(
2     id = "demand1",
3     unit_type = "demand",
4     unit_operator_id = "my_demand",
5     unit_params = {
6         "min_power": 0,
7         "max_power": 1000,
8         "bidding_strategies": {"EOM": "naive_eom"},
9         "technology": "demand",
10        "price": 20,
11    },
12    forecaster = NaiveForecast(index, demand=1000),
13 )

```

Listing 5.1: Addition of an agent to the simulation world through the object-oriented interface.

The agents have common parameters that can be configured, where parts of the `unit_params` are only respected when selected bidding strategies are used. This way, one can define a new bidding strategy, which takes additional parameters from the unit instantiation into account. The units, therefore, only manage the current state, while the decision logic of the behavior is separated from the actual runtime and generation properties of the simulated market participants.

The use of an agent-based simulation framework fits the use cases of more complex and specialized market simulations with multiple market and bidding options. It also allows to explore future fields of application like real-time simulation, cosimulation

or gamification. The object-oriented approach manages to decrease coupling of the simulation internals and maintain understandable client logic.

5.1.2 Power Flow

Respecting grid constraints through a power flow is one of the requirements outlined in the prior research, which has not been covered by other openly available market simulation tools. With `PyPSA`, an open-source library for power flow calculation exists, which is integrated into the final software artifact. Conceptionally, different possibilities of integrating power flow into a market calculation exist. The core decisions in the concept phase is the question of where the grid model exists – in the market model or in a separate power flow model? As this discrepancy exists in different real-world energy markets as well, an approach to both methodologies has been made. Specifically, three different methodologies are available for the simulation of power flow.

The first option handles a separate redispatch "market", taking place after an `EOM`. For the redispatch market, all agents transmit the ramping flexibilities and accepted volume from the `EOM` – the market then computes the congestions using `PyPSA` and calculates the least costly changes to the dispatch to adhere to the grid limits. The resulting deviations are then communicated as the result of the redispatch market. This, of course, assumes that the agents behave truthfully and do not communicate wrong information to the redispatch market.

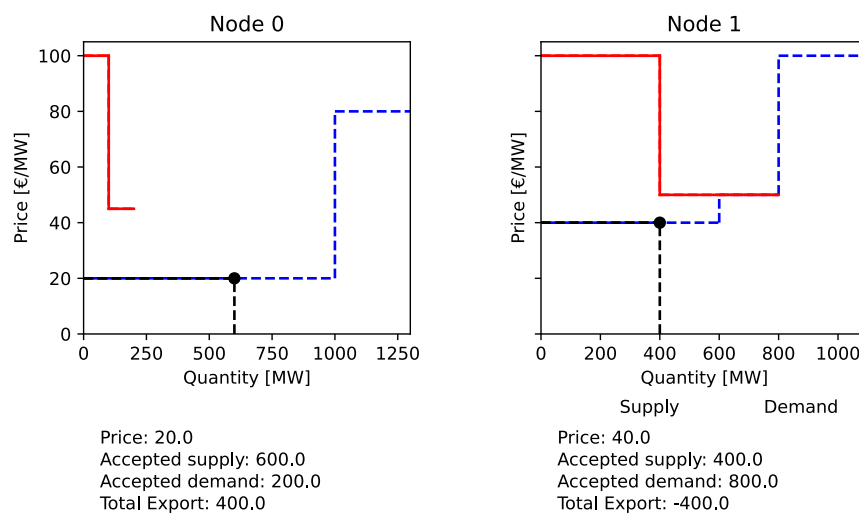


Figure 5.1: Market result for two-node nodal clearing example of a single clearing using `emar-ketlib`. Demand (red) is lower on the left side, so there is more generation (blue) available to be transferred to the right side. The line capacity between the two nodes is 400 MW. It is fully utilized, transferring 400 MW from node 0 to node 1 to reduce the price at node 1 to 40 €/MW.

Additionally, a nodal market using `PyPSA` is available, which directly calculates dispatch adjustments through the set marginal cost of generation for each bus and line of the simulation model. A single clearing result of this market is shown in [Figure 5.1](#), where the left node clears much more generation to make up for the expensive generation in node 1. However, as `PyPSA` does not support marginal costs for demand, one can only model inflexible demand, which has to be fulfilled at any cost.

This restriction is removed through the third method for power flow calculation, which includes a nodal market configured through the `ComplexClearingRole` as a market. It is based on a `LP` formulated in `Pyomo`. Having the different options for integrating power grid constraints makes it possible to model redispatch as well as `LMP`, which is more common in energy markets of the United States of America [27].

5.1.3 Market Design Configuration

The implementation of different market design choices has been verified through the `emarketlib` as well as unit tests of the final artifacts. This includes the edge cases of the clearing, in which multiple options are effectively possible, yet there exist cost-minimizing options of the intersections shown in [Figure 5.2](#).

The upper left and lower right images show situations where the accepted volume or price overlaps with another bid, as also shown in literature [217]. In these cases, the market mechanism correctly maximizes the cleared volume while selecting the lowest price for this amount.

Modeling of entry barriers is possible through the eligible obligations lambda expression as described in the concept. This can be set to add constraints on market participation by checking the properties of each agent at registration of the market. The modeling of the registration of agents at the market enables the creation of a realistic setting and also allows for extension towards a simulation, where a market can receive arbitrary messages from a learning agent to evaluate the potential for cheating. To create a limit for the entry barrier, one of the preset expressions to only include CO_2 neutral plants, requires specific technologies or a minimum capacity can be used. Other requirements can be formulated by providing a function reference in the market design.

This is similar to how new market mechanisms, bidding strategies or market contracts can be established.

5.1.4 Comparison of Market Design Changes

The main objective of the simulation is to provide a tool that makes it possible to simulate different market designs with the same input and scenario dataset and compare them through the change of the market design and strategic behavior. To

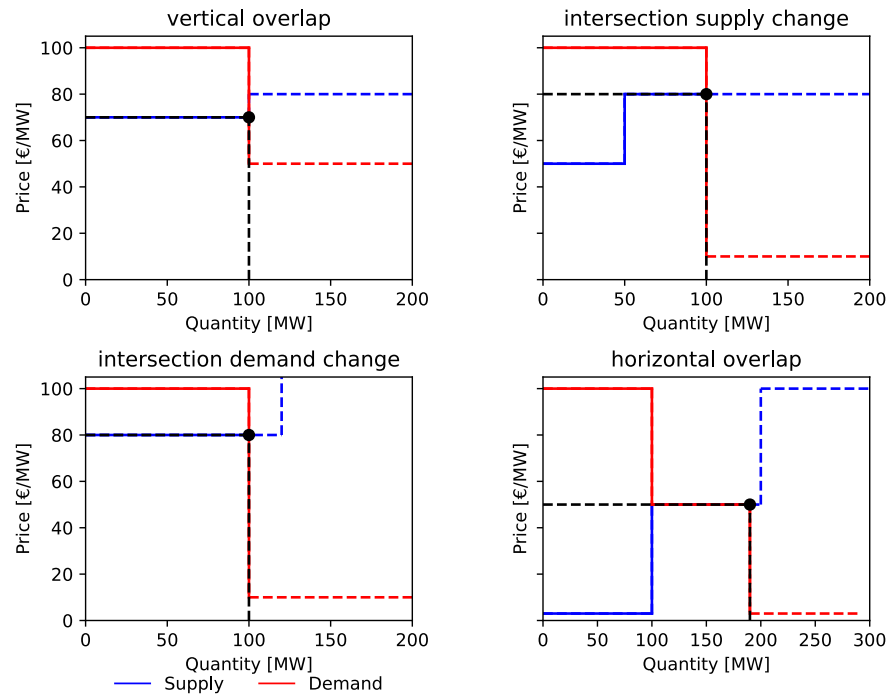


Figure 5.2: Validation of optimal clearing of the implemented pay-as-clear market mechanism in edge cases of typical clearing behavior in pay-as-clear. The market minimizes the total cost while maximizing the possible dispatch.

apply a comparison of market designs, the major difference is that the same tool supports the configuration of different market designs. This enables the simulation of different market designs while keeping the agent behavior, input data and scenario settings.

A rather understandable situation is the comparison of a market design consisting of a typical **EOM** to a simulation with a market design with an additional **Long-Term-Market (LTM)** to hedge against the risk of rising prices. In this scenario, the contract trading takes place for seven days, while the energy-only market places bids every hour, visualized in [Figure 5.3](#).

While the **EOM** uses a pay-as-clear pricing mechanism throughout both scenarios, the contract market uses pay-as-bid. All agents bid the maximum continuous supply quantity, which can also be interpreted as base load or firm capacity. Some agents, like solar power plants, do not have any firm capacity and therefore do not bid on the contracts market.

In this scenario, all agents bid their naive marginal cost. For the contract market, a physical contract for delivery is made for the duration of seven days. This contract is cleared using pay-as-bid, creating a meaningful reduction of the dispatch cost as shown in [Figure 5.4](#). This, of course, is mainly caused by the change of the market design only,

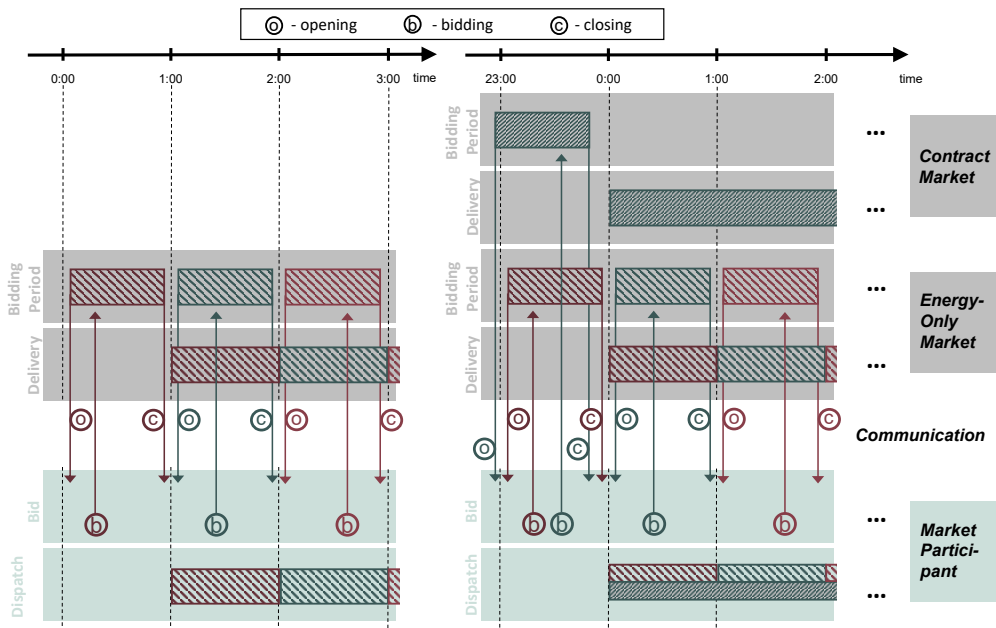


Figure 5.3: Schedule of the two market designs under comparison. One includes the EOM with pay-as-clear only, which is compared to the addition of a contract market with 7d products with pay-as-bid. Also published in prior work [159].

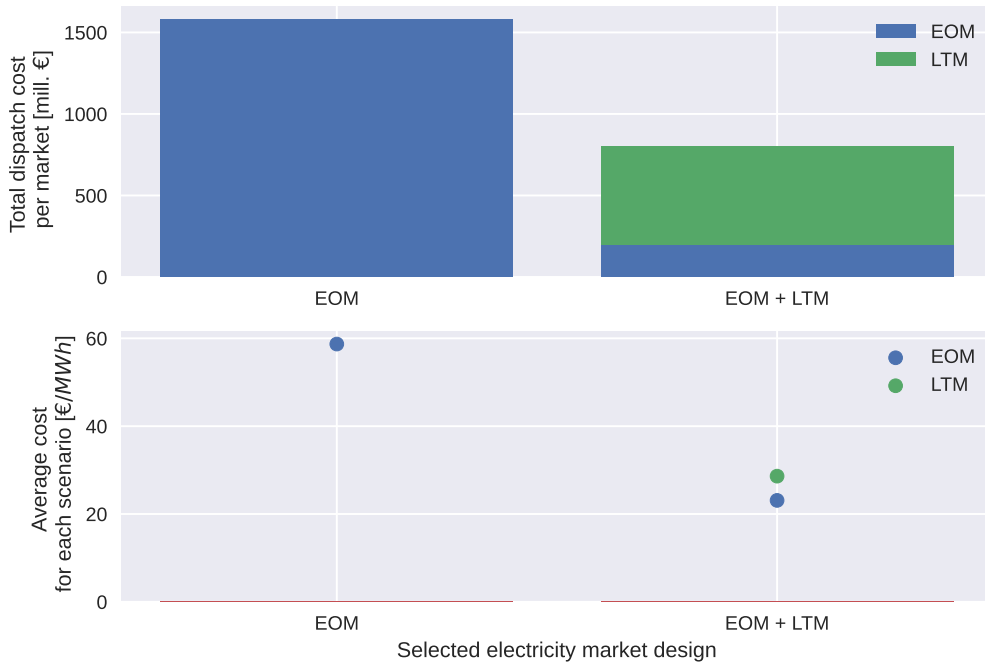


Figure 5.4: Results from market comparison of the laid out design. Total dispatch costs vary, as more energy is sold for the bid price, instead of the clearing price. The average price of the EOM is decreased as well. Also published in prior work [159].

without adjusting the agent's behavior. In real-world scenarios, the bidding behavior on pay-as-bid markets would differ from the plain marginal cost bidding by an unknown margin.

This is the case, as in pay-as-bid scenarios the actual agents need to anticipate the market price and try to set the bid near the expected market price. Useful forecasts are therefore a requirement in such settings, making it harder to simulate the behavior of real agents, as their forecasts are not known.

This small study shows that adjustments to the market design can be compared, be it a change of one market or the addition of other bidding or contract opportunities. During the creation of the market design, one has to carefully evaluate which market takes place before the other market, as a submitted volume on one market might not be available on the other market anymore. The evaluation of the simulation output is either directly possible through the dashboard or by querying the simulation database for more complex analysis.

5.2 NON-FUNCTIONAL REQUIREMENTS

The non-functional requirements defined in [Section 3.3](#) are revisited in this section. The first two requirements, modularity and open-source, can not be measured directly. However, the requirements for fulfillment defined before were met. The implementation also contains a few exciting details that should not be withheld here.

Open Source

Regarding the open-source way of development, it is important to mention that the simulation framework has already received contributions from 15 developers and is known in energy market research. To still make sure that the functionality of the system can be provided, unit tests and integration tests are implemented for [SPARKLE](#), providing a test coverage of more than 75 %. All final artifacts have a permissive license and comply with the REUSE specification [66]. This includes the market abstraction itself in the [emarketlib](#), as well as the agent-based simulation [SPARKLE](#). Both is available as part of the software distribution specified in [Section 7.1](#) of the appendix.

Modularity

The implementation of modular software design has been described in [Section 3.6](#), which was incorporated in that manner. The moving parts of the final artifact were shown in [Figure 4.1](#), providing functionality to inject additional behavior into the framework. Yet, modularity is especially important when adding new market participants, market mechanisms and bidding strategies.

These two requirements are hard to quantify with a benchmark but are nevertheless crucial for the success of sustainable software development.

The integration of various existing simulation tools like [PyPSA](#) and [AMIRIS](#) shows that modularity enables to have loosely coupled decisions and integrations. Furthermore, by including core functionality into the mango agent framework, the market abstraction into [emarketlib](#) and the simulation tooling into [SPARKLE](#), a foundation to future software development in energy market research has been made, which can be used as a whole or with individual parts.

Scalability

Scalability allows the simulation of larger studies using an approach to scale out, by using multiple cores for the simulation. This is either possible through concurrent subprocesses in Python on the same machine or by using to distribute a simulation horizontally across multiple compute nodes.

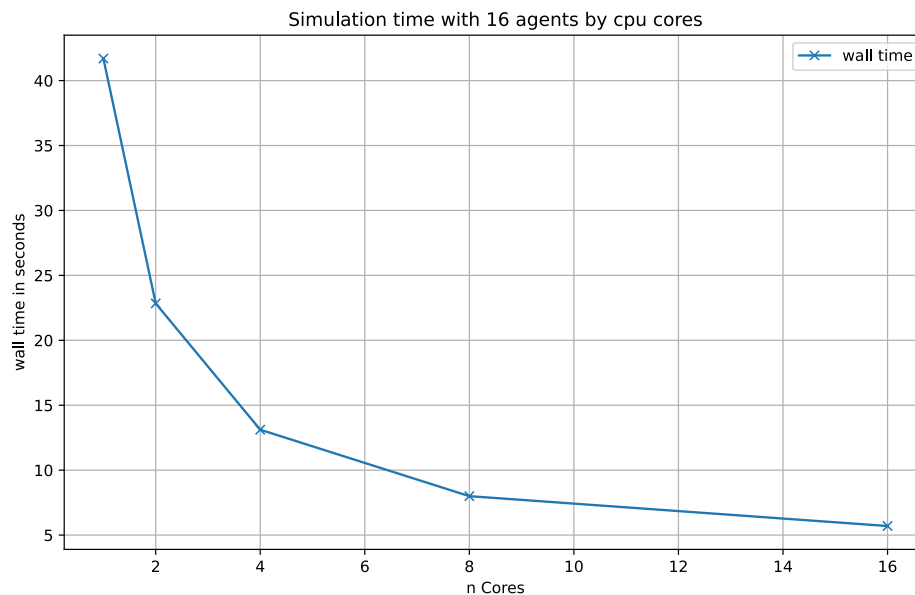


Figure 5.5: Number of cores visualized to the reduction of the runtime of a simulation with 16 market participants.

While small scenarios are slowing down through the distribution of agents across multiple cores, as the start time and resource allocation increase, a substantial benefit can be seen for the simulation time of larger simulations. A scenario with 16 agents distributed across different numbers of cores is shown in [Figure 5.5](#). It can be seen that nearly a halving of the runtime is possible through the allocation of more resources. Furthermore, a methodology to run a simulation across a larger cluster is given in the documentation of the artifact. Using Docker Swarm as an orchestration engine

allows to connect multiple containerized independent instances of the program across computational borders using TCP or an MQTT broker.

```

1 docker stack deploy -c compose.yml -d sparkle
2 docker service logs -f sparkle_simulation_mgr

```

Listing 5.2: Deployment and monitoring of the docker swarm to a cluster using the generated compose.yml.

This makes it feasible to run a swarm of agents with distributed communication. Scaling towards 1000 or more containers is efficiently possible as shown in Table 5.1. As every container uses the overlay file system of the same container, the actual storage requirements of multiple containers are not increasing linearly. Still, as each execution environment includes a separate network stack and Python execution context, each container consumes about 300 MB RAM and the initial provisioning of the container across multiple nodes is not parallelized and can take a few seconds per container. Using the comparison dashboard of SPARKLE makes it possible to show that for agents bidding normally distributed random prices, the average price decreases the more agents are used in the swarm, as liquidity increases (see Table 5.1). A trivial example, which shows how a higher amount of liquidity in a market reaches more optimal prices.

simulation	avg price	total cost in million €	total volume
swarm simulation2	9.86 €/MWh	13.73 €	1392 GWh
swarm simulation5	9.71 €/MWh	13.52 €	1392 GWh
swarm simulation10	9.61 €/MWh	13.37 €	1392 GWh
swarm simulation25	9.50 €/MWh	13.23 €	1392 GWh
swarm simulation50	9.44 €/MWh	13.14 €	1392 GWh
swarm simulation75	9.40 €/MWh	13.08 €	1392 GWh
swarm simulation100	9.37 €/MWh	13.04 €	1.39 TWh
swarm simulation200	9.32 €/MWh	12.95 €	1.39 TWh
swarm simulation500	9.24 €/MWh	12.84 €	1.39 TWh
swarm simulation1000	9.11 €/MWh	12.66 €	1.39 TWh

Table 5.1: Overview of simulations with increasing liquidity as the number of agents increases. The average prices decrease with increasing liquidity, analogous to the total cost. As the demand is similar between the simulations, the total volume stays the same.

Interoperability

The requirement of interoperability allows for seamless data reusing of existing studies, by providing a common interface. From existing research, it can be seen that the preparation of input data takes up a recognizable amount of time, as most data scientists spend more than 25 % of the time preparing and cleaning data [56]. Therefore, it helps

to be able to reuse existing datasets from top-down models for other implementations as well.

This kind of interoperability improves using data and also allows for comparing frameworks on the same input data, as shown with [AMIRIS](#) in [Section 5.3.2](#).

The simulation artifact includes five different interaction methods:

- Object-oriented API
- [CSV](#) scenario loader
- [OEDS](#) scenario loader
- [PyPSA](#) scenario loader
- [AMIRIS](#) scenario loader

The core dynamic behind this is, of course, that the object-oriented API can be used to write converters for any other input format. Typically, such external input formats do not include all requirements available in the simulation framework – for example, bidding strategies that are not available in [PyPSA](#). Most scenario loaders, therefore, allow defining additional information, like bidding strategies.

This makes it possible to model arbitrary [PyPSA](#) networks using the simulation model. When simulating the [scigrid](#) example from [PyPSA](#), additional logging of flows is available in the [Grafana](#) dashboard, shown in [Figure 5.6](#). Here, the color of the lines resembles the grid congestion at a selected hour, allowing deeper market analysis in such nodal markets. Concluding, the interoperability of the artifact is given through a variety of existing simulation options, while further ideas regarding the interoperability through the integration of communication interfaces can be extended in the future. This enables usage of the provided artifact in combination with co-simulation software, such as [MOSAİK](#) [178].

5.3 CASE STUDIES

This section covers case studies, where parts have already been published in reviewed conferences and papers. The first study utilizes the [OEDS](#) interface to use recent weather data and consumption from Germany. The second study is about a comparison of the simulation tool [AMIRIS](#) to the simulation artifact of this thesis, published in [160] with collaborative feedback from the developers of [AMIRIS](#). The results of this thesis have been developed within [SPARKLE](#) and are integrated into the [ASSUME](#) market simulation for broader accessibility. The features used were mostly developed within this thesis and are available for both frameworks, but for a common presentation of the tool to the public, the case studies were done with the [ASSUME](#) version in the released literature.



Figure 5.6: Visualization of simulation grid from a given PyPSA input dataset. Utilization of grid lines is visualized from power flow calculation in market results (green – low utilization; yellow – medium utilization; red – high utilization).

5.3.1 Evaluation of German Energy Market Scenario

Modeling market scenarios requires a good evaluation of the data used to calibrate and evaluate the model. Often, only partial data is available for simulations, through specifically extracted parts from different energy system datasets. This study provides a broader approach that allows to model any year for which historical data is available and tries to provide a benchmark tool for future simulations as well. Generally, a market simulation is based on different types of datasets, which are the set of power plants, time series for renewable power plants, prices and demand series.

Demand Series

Using existing open source studies of energy demand usage in Germany, one approach to creating an artificial demand series is to use a forecast of total energy demand for a period and create a series from the BDEW standard load profiles. This requires the

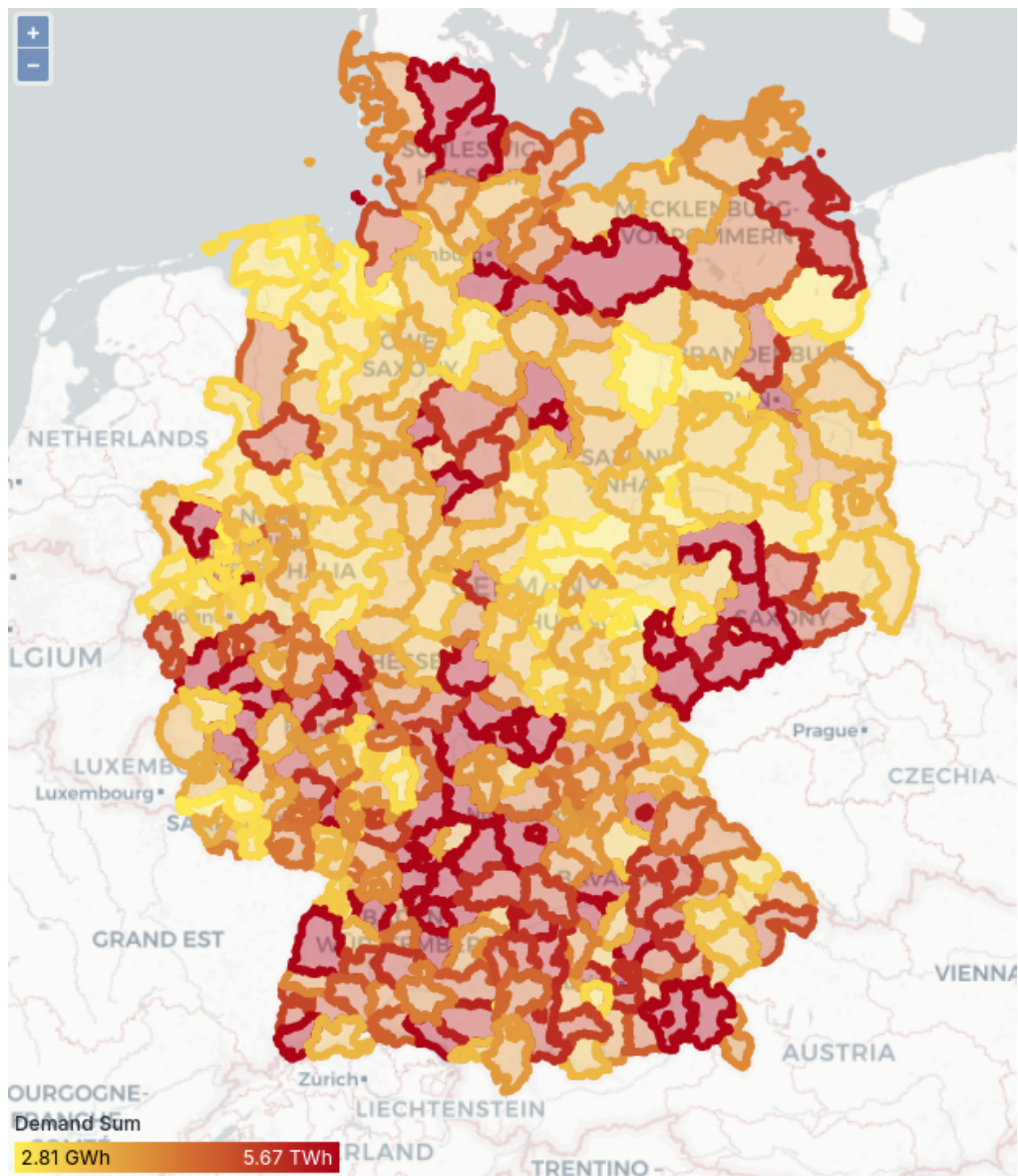


Figure 5.7: Heatmap of yearly energy demand per NUTS3 area for Germany, publicly available from OpenEgo project, based on synthetic data generated with OpenStreetMap.

availability of total energy demand per Nomenclature of Territorial Units for Statistics (NUTS) area, as areas differ in their energy consumption. This can be done using the demand calculation from openEgo¹, which includes aggregated demand for each NUTS area. This has been calculated through a synthetic dataset using OpenStreetMap² data. Energy demand varies from region to region, as can be seen in Figure 5.7, which shows the synthetic data per NUTS3 area of Germany.

¹ https://github.com/openego/data_processing, visited on 19.02.2025

² <https://openstreetmap.org>, visited on 19.02.2025

To create a demand time series from these total values, one can use BDEW data by adding up the time series for the specific sectors³. This is done through the open-source tool `demandlib` [136].

There are distinct load profiles for industry, agriculture, and households. While the BDEW standard load profiles are frequently employed for estimation purposes, they offer limited utility in generating actual yearly time series for the nation's demand in its entirety.

One approach to this problem involves the use of a linear regression model to fit the best coefficients, a_1 to a_{10} , of all standard load profiles to match the actual historic demand.

$$y = a_1g_1 + a_2g_2 + a_3g_3 + a_4g_4 + a_5g_5 + a_6g_6 + a_7g_7 + a_8h_0 + a_9l_1 + a_{10}l_2 + \epsilon \quad (5.1)$$

The model therefore calculates the best coefficients to the standard load profiles for industry g_1 to g_7 , h_0 for households and l_1 and l_2 for agriculture.

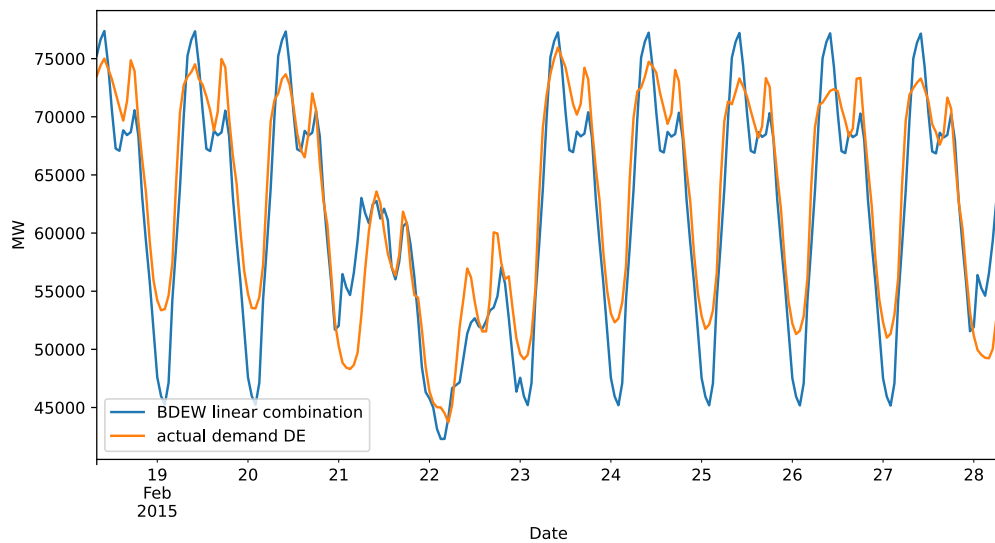


Figure 5.8: Comparison of best linear combination from BDEW profiles to the actual power demand of Germany in 2015. Actual values deviate from the best linear combination, highlighting the requirement for updated standard profiles.

This gives an overall acceptable fit, as seen in Figure 5.8, but makes clear, that the actual demand forecasting for future scenarios is improvable and might not resemble the actual outcome that well. An improvement to this might be made using the latest BDEW released standard load profiles from 2025 [21], but is left out for now.

³ <https://www.bdew.de/energie/standardlastprofile-strom/>, visited on 19.02.2025

Power Plants

The existing power plants are taken from the German Register of existing power plants, the Marktstammdatenregister [38]. This dataset contains the commissioning and decommissioning dates of power plants as well as various technical power parameters. Using the OEDS⁴, the power plant database can be efficiently queried according to different scenarios and filtered according to generation technologies. The market data register contains location information in the form of postal codes, which can be translated into NUTS areas and used in the simulations.

This capability enables the creation of customized simulations for specific NUTS areas or partial regions, thereby facilitating a more nuanced analysis.

Renewables Time Series

Similarly to the usage of demand series, typically only the national generation series exists for renewable power production of wind and solar. One can disaggregate this into individual NUTS areas using a bottom-up approach. Individual weather data on a 10km per 10km grid is available from ECMWF, which makes it possible to calculate the solar and wind generation from irradiation and respective wind speed.

The conversion of meteorological data and documented power plants to a renewable generation time series is accomplished through the utilization of two prominent Python libraries: windpowerlib and pvlib. Pvlib utilizes disparate diffusion models, thereby enabling the calculation of direct normal irradiation (DNI) and direct normal irradiation (DHI) from the global horizontal irradiance (GHI) provided by ECMWF [10]. Therefore, the Erbs diffusion model is utilized [64] as a baseline, aiming to create realistic solar generation from the GHI weather information provided in the ECMWF dataset [47].

Similarly, the wind speed at 10 meters height is calculated from the meridional wind speed and zonal wind speed from ECMWF at 10 meters height through Equation 5.2.

$$V_{wind} = \sqrt{V_{zonal}^2 + V_{meridional}^2} \quad (5.2)$$

Which is then used with windpowerlib to calculate the wind speed at a known height using the Hellman equation. The interpolation of the wind power curve is finally derived from the wind power equation in Equation 5.3 or empirical model data derived from the turbine type where available [91].

$$P_{wind} = \frac{1}{2} \rho A v^3 \quad (5.3)$$

⁴ <https://github.com/open-energy-data-server/open-energy-data-server>, visited on 19.02.2025

Market Results

The simulation studies from FlexAble [193] did show that the addition of modeling heat demand increases the realism of electricity simulations quite a lot [193]. For simplicity, this is left out in this example and a focus is put on the simulation of different renewables resolutions.

The integration of input series is established through the Open-Energy-Data-Server, which holds weather data and power plant data, as well as validation time series in different geospatial resolutions. A fundamental component is the ad-hoc investigation of market scenarios and outcomes, which facilitates comparison with the actual results of the EPEX spot auction, as illustrated in Figure 5.9 for the case of Germany in 2023 for NUTS1. This figure reveals a cost structure analogous to that of the EPEX spot market

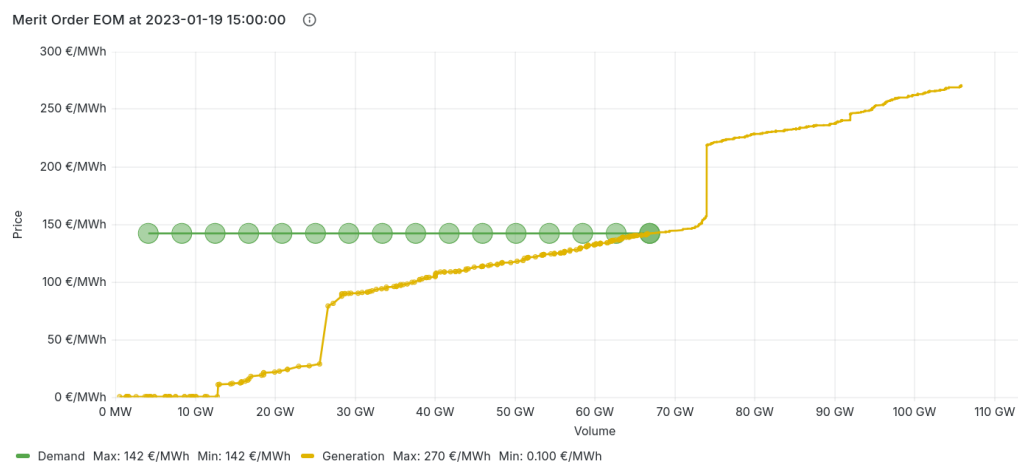


Figure 5.9: Merit order visualization of the market result of a given hour from the simulation dashboard of Germany 2023 NUTS1. Results for other NUTS aggregation vary only slightly.

results, although the volume that has been cleared differs. This disparity arises because the market simulation clears the entirety of the volume in its single spot market, instead of multiple different market options.

Finally, in Figure 5.10 the correlation coefficient of all the modeled simulations with the respective NUTS areas is shown. It is evident that the impact of employing different resolutions for modeling renewable energy sources, as implemented in this study, is negligible, as the variations observed are minimal. A fixed pattern of which aggregation provides the best results can not be fully estimated, though, due to the reduced complexity, simulations with a higher aggregation or lower resolution can be handled more easily. On the other hand, simulations employing higher resolutions do offer enhanced individual bids within the market, thereby enabling a more comprehensive examination of bidding behavior. Concluding it is shown that the market model enables acceptable results of modeling the German energy market on all aggregation levels, while years including the gas crises have a lower correlation factor. In conclusion, it has



Figure 5.10: Summary of correlation coefficient with historical benchmark dataset of ENTSO-E between market simulation with different NUTS aggregations. One can see that the focus on correct price modeling and bidding behavior has a higher influence on the results than the aggregation, while all simulations provide good out-of-the-box results.

been demonstrated that the market model is capable of producing satisfactory results in the modeling of the German energy market across all aggregation levels. However, it should be noted that years including the gas crises exhibit a lower correlation factor.

5.3.2 Comparison to Other Simulation Models

The comparative analysis of electricity price simulations using AMIRIS and ASSUME reveals nuanced insights into their performance and limitations.

Figure 5.11 illustrates the electricity price dynamics for an exemplary week, demonstrating that both models exhibit reasonable alignment with the historical ENTSO-E time series. However, significant differences emerge in their ability to capture price fluctuations.

The proposed simulation model displays heightened sensitivity to renewable energy-induced price drops, which can be attributed to fundamental differences in storage operation logic:

- ASSUME bases storage forecasts exclusively on historical data
- AMIRIS generates prospective price series beforehand

Notably, the models struggle to reproduce price spikes on January 24th and 27th, with these discrepancies traceable to divergent storage operation strategies.

Table 5.2 provides an overview of the models' performance:

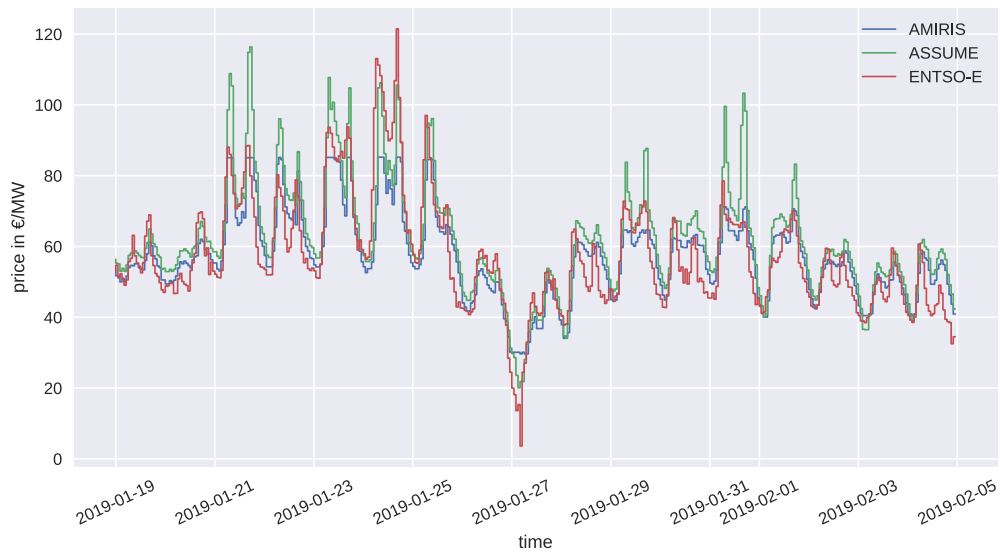


Figure 5.11: Comparative electricity price simulation for the German Market (2019).

Model	MAE	RMSE	Max	Min	Mean	Std
AMIRIS	5.55	8.97	85.21	0.00	38.13	13.41
Proposed Model	6.38	8.18	116.36	0.00	41.03	14.56
Historical	-	-	121.46	-90.01	37.56	15.08

Table 5.2: Quantitative Performance Metrics from the Comparison of the created simulation model towards AMIRIS.

This section contains the evaluation of the proposed model in the form of ASSUME to the energy market simulation tool AMIRIS [194]. Most of this has also been presented in [160]. To cover the comparison to the behavior of other energy market models, a comparison with AMIRIS has been performed. This has been accomplished by creating interoperability functions that can read an arbitrary scenario from the AMIRIS format and load a simulation for these.

Figure 5.12 shows the correlation of the simulation prices with the historical prices. It can be seen that both simulations have a good correlation with a Pearson correlation coefficient of the price time series of 0.8437 for AMIRIS and a slightly higher correlation of 0.8458 for ASSUME. This graph also shows that in AMIRIS the storage operation cuts off prices above 85 €/MWh. Both models failed to correctly reproduce the negative prices of the historical data, due to a lack of incentive to keep power plants running throughout situations with a high renewable share in the simulation.

The price duration curve, shown in Figure 5.13, provides additional insight by displaying prices in descending order. This visualization shows that simulated prices tend to be slightly higher than actual prices for the majority of hours. The important takeaway of this representation is that most of the time, a good match to the historical prices can

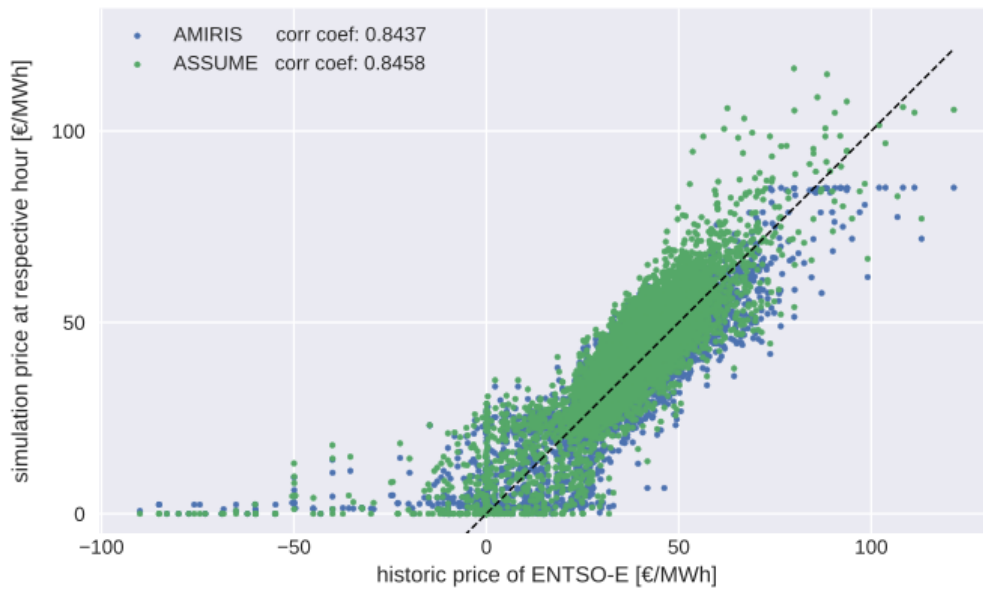


Figure 5.12: Scatter plot of the price simulation from ASSUME and AMIRIS on the y-axis, with benchmark prices from ENTSO-E on the x-axis. One can see that a high correlation between the two exists. Published in [160].

be made, with a high interest on the prices between 0 and 30 €/MWh. The models accurately capture the price spike below 30 €/MWh, which can be attributed to the retirement of conventional power plants.

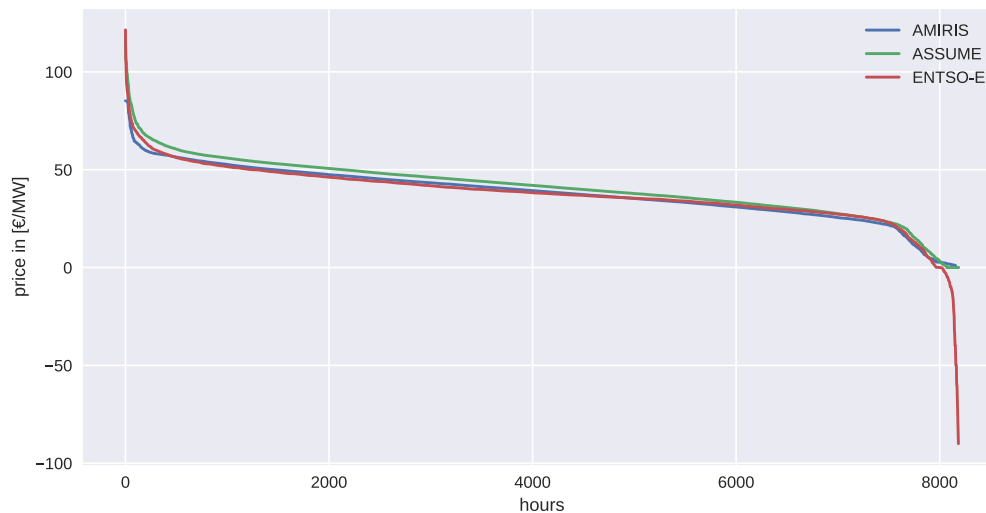


Figure 5.13: Price duration curve for AMIRIS, ASSUME and the historical data from the 2019 Germany dataset. Despite the good overall fit, the simulations do not fit negative prices well. Published in [160].

To summarize, one can see that both market simulation models generate a good fit of the historical prices. Research shows that the correct representation and adjustment of the bidding prices per technology are crucial for the correct representation of market results. However, it is noteworthy that neither simulation reproduces negative prices correctly. This discrepancy is due to the exclusion of must-run conditions in the given scenario, a consequence of the use of simplified bidding strategies. Furthermore, improvements can be made concerning the bidding strategy of storages, which have an important impact on market results and make up for most of the differences between AMIRIS and ASSUME.

This study shows that the proposed framework is largely consistent with the results of existing market simulations, while the existing strategies leave room for future improvements in the nature of portfolio management and [strategic bidding](#).

5.3.3 Two-stage Local Energy Market

A topic which is often addressed in literature regarding novel energy markets is the usage of layered markets [50, 121]. Such concepts include a downstream market where local trades are settled, while remaining volume, both on the bid and ask side, is pushed into the upper market. The upper market then clears the remaining bids.

Such scenarios often resemble energy communities or local energy markets[122]

The schedule required is shown in [Figure 5.14](#), where one can see that the schedule of the upper market takes place between the clearing of lower markets, so that the results of the upper market are integrated into the clearing of the lower markets, which takes place at the end of their bidding period. The intermediate markets calculate a clearing to decide which bids will be left over and send all rejected bids to the upper market. This setup requires fine adjustments to the bidding periods, as the upper market does not have any bids at all or only receives bids for the wrong time period if configured inconsistently.

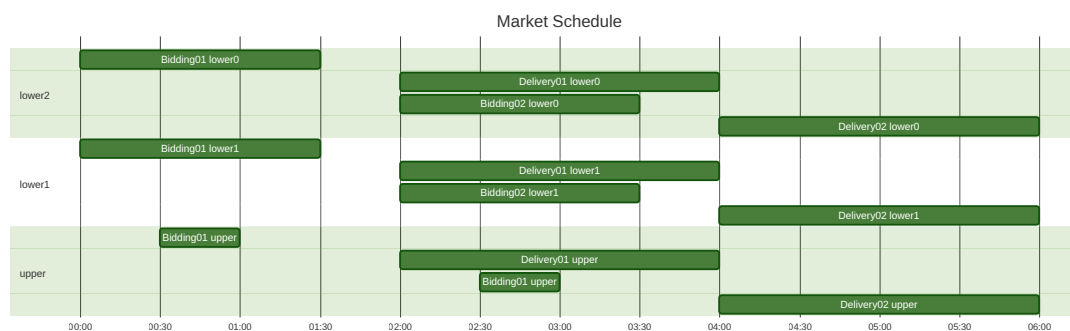


Figure 5.14: Schedule of two-stage market dispatch. The lower markets have a longer duration, as they are waiting for the result from the upper market auction and reintegrate this into the lower market clearings.

The two-stage simulation includes a single power plant and demand at each lower market with varying prices and volumes. A cheap power plant is available at the lower2 market, which can generate more energy than required by the demand of lower2. The remaining volume is traded to the upper market and is settled there.

An excerpt of a selected graph from the simulation dashboard is shown in Figure 5.15, where the total dispatch cost and dispatch volume of each market is shown. The

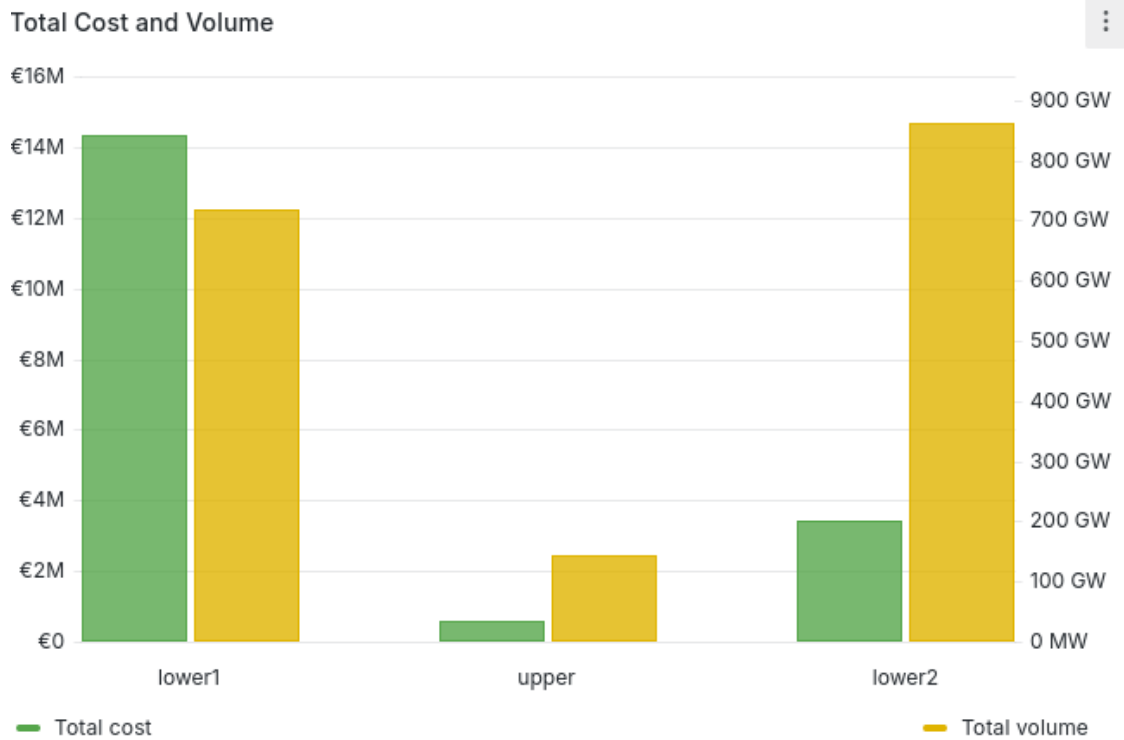


Figure 5.15: Results from Grafana dashboard showing different markets of the twostage simulation. Prices for lower1 are higher, while the leftover volume is traded from the lower2 market to lower1 through the upper market.

average market price of the lower1 is 20€/MWh, and 4€/MWh for lower2 and upper. The simulation KPIs from one month shows results for the different markets and allows to compare the result to a simulation with two separated markets, in which the volume of the upper market is therefore not traded, or a nodal clearing, in which all bids are respected in a single clearing. This design differs from nodal clearing in the way, that more expensive bids are accepted directly on the intermediate market in the pre-clearing and only remaining bids are available for trading to other zones. On the other hand, nodal clearing respects the zonal capabilities in a single clearing to minimize the total cost.

This shows the flexibility of the framework and its capability to simulate local energy markets. The source code of this example is given in Section 7.4.

5.3.4 Fuel Market Coupling Scenario

Market coupling includes the investigation of multiple markets, which have an influence on one another. In this case, an additional market simulating the trading of gas prices is implemented using synthetic randomized data.

The scenario focuses on the evaluation of the capacity factor and total emissions. Therefore, the additional KPI `total_emission_tons` is defined as given in Listing 5.3.

```

1 additional_queries = {
2   "total_emission_tons": {
3     "value": "sum(power*emission_factor)",
4     "from_table": 'unit_dispatch ud join power_plant_meta um on ud.
5       unit = um."index" and ud.simulation=um.simulation',
6     "where_clause": "ud.simulation = '%simulation%'",
7     "ident": "unit",
8   }
9 }
10 world.additional_kpis = additional_queries

```

Listing 5.3: Definition of additional KPI query for a given simulation in the construction of the simulation world.

The KPIs are evaluated at the end of the simulation and are written to the database using a unified format. The definition of such KPIs has enough flexibility to make complex queries using SQL possible, while maintaining the required structure of a measurand (value) and an identifier (ident) specifying the relation.

This scenario makes clear that not only can energy in the form of electricity be traded, but also other commodities, on which the energy market depends.

Here, a coal power plant and a gas power plant are simulated, including the ramping constraints and minimum downtime between starts using the optimization in Section 4.3.1.

For the communication of the resulting price signal from the gas market towards the energy-only market of the simulation, a special bidding strategy can be used. This strategy adjusts the fuel cost component in the forecast to match the result from the gas market. That way, the results from the gas market are accessed when calculating the marginal cost on the EOM. It should be noted that the schedule between these two markets is very important, as the fuel market has to be scheduled with enough time to the EOM clearing so that the results of the gas market are available when the EOM auction opens.

Otherwise, an additional forecast for the expectation of market results would be required, which is currently not implemented in the simulation.

Practically, other fuel markets and CO₂ market prices can also be modeled if a solid bidding strategy for these markets is given. This allows for investigating coupling behavior of different systems, for example, heat, hydrogen or gas demand.



Figure 5.16: Visualization of hourly market dispatch and actual feasible dispatch using clearing mechanism and bidding strategies described in Section 4.3.1 for the fuel market scenario. The tooltip shows a deviation due to a ramping constraint, which the market did not respect, leading to a reduced dispatch.

6 | CONCLUSION

Research that produces nothing but books will not suffice.

Kurt Lewin [144]

This chapter summarizes the contributions of the PhD project to the research area. The major contribution is the definition of a market abstraction, which provides a generalized form of bids to include various special cases, like P2P and Contracts. The abstraction is implemented in the market simulation framework SPARKLE, which can be applied to market research questions and is publicly available to be used and improved by the research community. Evaluation of scenarios and inspection is possible through a simulation dashboard, while also including a variety of flexibility of the analysis. The effective calculation of preconfigured KPIs provided to compare key figures conveniently in an adjustable way. Finally, application scenarios and an assessment of the requirements are provided in the evaluation of this thesis. To conclude the thesis, the main contributions are outlined, followed by a description of limitations and possible improvements. And finally providing an outlook for future developments and research.

Regarding the availability of data, many things have changed in the field of energy system modeling in recent years. Many basic principles and data have been added that were previously unavailable. The areas of energy system modeling can be divided as follows:

1. Public data from organizations
2. Institutes/associations/groups that process data
3. Libraries for the use and simulation of energy systems
4. Knowledge collections/wikis

This work would not have been possible without open data and open source developments, while the results of this work also contribute to the availability of high-quality simulation tools and the use of open data.

6.1 RESULTS AND CONTRIBUTIONS

The results of the thesis are multifaceted in multidisciplinary fields, ranging from data availability to software simulations and market mechanisms.

The overarching research question, "How can different energy market designs be evaluated in a simulative comparative manner?" is answered through a software framework covering the requirements created from the three research questions of this thesis:

1. Which abstract description is able to characterize different market designs to guide their implementation within modular energy market simulation software?
2. In what way can different market mechanisms be represented in the simulation?
3. How can indicators of market mechanisms be used to evaluate specific market designs?

After the introduction to the topic in [Chapter 1](#) and the investigation of requirements and existing tools in [Chapter 2](#), a conception for a simulation is provided in [Chapter 3](#). This concept has been realized and described in [Chapter 4](#) and evaluated according to the requirements in [Chapter 5](#). This section describes the results and summarizes the contribution of the PhD project.

6.1.1 Market Abstraction

[SPARKLE](#) utilizes the market abstraction from [Section 3.5](#) to simulate the bidding behavior on arbitrary markets. For this, a market abstraction was found which describes a market design, consisting of multiple individual markets, with their properties. This market abstraction has been presented at different events and discussed in literature as well. It is currently available as a separate software library `emarketlib`. Through this, it can be included independently to model different markets. For example, to analyze game-theoretic behavior in individual auctions, without considering a simulation clock.

Besides the formalization of energy market designs, the library includes different algorithms available for market clearing. The following market mechanisms are available in the `emarketlib`.

- Pay as clear/Uniform pricing
- Pay as bid
- Pay as clear (all-or-nothing)
- Pay as bid (all-or-nothing)
- Complex Clearing with block orders and exclusive orders
- [VCG](#)
- [McAfee \[161\]](#)
- [Trade Reduction \[161\]](#)
- Two-Step Market with intermediate market layer
- Contract clearing with execution of contracts like [FIT](#), [PPA](#), [CfD](#)
- Fuels market used for supply-chain auctions [\[14\]](#)

- Nodal pricing
- Redispatch (in combination with a pay-as-clear market)

This is a useful reference implementation of market clearing mechanisms, which have not been available before in an energy market related library.

6.1.2 Market Simulation SPARKLE

The market simulation [SPARKLE](#) has been developed to answer the research questions of this thesis.

It is a tool that is modular for changes on the one hand, but provides useful abstractions of behavior and simulation objects on the other hand. The conception did consider the non-functional and functional requirements derived from existing energy market simulations to create a sustainable artifact that can be used for further research in the field. The research presented is therefore a contribution to the field and surpasses other solutions in modularity and interoperability. Taking a look at the bidding agents, the addition of different strategies per market is possible through a reusable interface. An abstraction for systems that support a conversion to energy under some constraints (`SupportsMinMax`) as well as storage-like (`SupportsCharging`) are used to provide differentiation to market participants. Strategies are typically suited for a specific type of market and match either of the two unit abstractions. Here, changes in generation prices, availability and forecasting enable realistic market simulations. [SPARKLE](#) has been used in different scenarios and can therefore be considered a state-of-the-art energy market simulation tool.

6.1.3 Evaluation

While the main focus of the simulation framework is on electricity markets, other modalities can be simulated as well. A showcase of a separate market showing fuel markets is shown in [Section 5.3.4](#). This scenario shows how multiple markets can influence the behavior of one agent towards the bids to a second depending market. Additionally, simulations of multiple different markets with varying time schedules are possible [\[159\]](#) as also shown in [Section 5.1.4](#). The usage of hierarchical market mechanisms was analyzed in prior work, as well as the integration of grid capabilities through nodal or zonal clearings.

To harden the usage and correctness of the simulation, a comparison to an existing energy market simulation tool is provided in [Section 5.3](#) which references the work done in [\[160\]](#). Here, the simulation tool has been compared to [AMIRIS](#) as well as the targeted prices of [ENTSO-E](#), resulting in a successful representation of historic market behavior most of the time.

Simulations to showcase the distributed capabilities and dynamics of the simulation were described and benchmarked in [Section 3.6](#). This did show that [SPARKLE](#) can be run distributed across multiple machines, enabling real-world cosimulation scenarios.

6.1.4 Agent-based Simulation Tool Mango

Besides of the development of the market simulation tool [SPARKLE](#), various contributions to the open-source agent-based simulation framework mango-agents have been done throughout the thesis. This makes it possible to simulate distributed agents with a common consistent monotonic clock. Mango-Agents is an important project for this thesis as it is the agent-based simulation core used as a foundation for the specific subject-related agent-based *market* model. The event-based nature of this tool reduces the scope of a single agent to the properties required in this agent. Improvements to the [MQTT](#) communication in the framework were required to enable the distributed simulation in [SPARKLE](#). The default configuration of MQTT is not set up for simulations running locally, as the server buffers received messages before sending. Contributing fixes to the upstream project simplifies ongoing software maintenance. This way, people using the upstream project mango can benefit from the improvements without relying on patches in the market simulation. Collaborating, therefore, shares important improvements with the wider [ABM](#) research community.

6.1.5 Data Preparation and Accessibility using OEDS

A lot of effort has been put into the preparation of input data from open datasets as well as the preparation of the simulation outputs. Especially regarding the preparation of input data for scenarios for whole of Germany as used in [[maurerInvestigationEndogenousRenewables2025a](#)]. This makes it possible to not only reproduce the results of the research using publicly available data, but also provides the tools needed to run updated simulations with the most recent data. The method to prepare this data has been published as [Open Energy Data Server \(OEDS\)](#), which can be used independently from the market simulation efforts of this thesis.

High interest from different research facilities to reuse the [OEDS](#) was mentioned to maintain an internal database for research, which automatically contains the latest updates of open-data publications.

The same methodology of a structured database for inputs has been adapted for the results of the simulation. The results can be visualized interactively through a Grafana dashboard. This way, not only the dispatch results but also economical parameters and preconfigured and calculated [KPIs](#) are distributed.

6.2 LIMITATIONS

While various use cases and unique features of an open-source market simulation tool are shown, one also has to make notes of the limitations of the simulation capabilities. This is also important to make clear what can be expected from [SPARKLE](#) and what is beyond its scope.

6.2.1 Bidding Strategies

As the focus of this PhD thesis is put in the creation of a market abstraction to cover different market mechanisms, the focus on bidding strategies is limited. As the optimality of bidding strategies is defined out of scope for this thesis, no guarantees of optimality outside of the solved linear problems can be made.

While naive strategies for single and multi-markets exist, forecasts and portfolio management are still open issues that should be covered by future research. With portfolio management, one would need to consider the risks of bidding a combination. This would also allow for anticipating a fluctuating forecast which includes uncertainty. Having a bidding strategy for truthful market mechanisms like pay-as-clear is much easier than other market clearings. If a market mechanism is not truthful, the bidding behavior needs to derive from the marginal cost to be profitable. This strategic optimization is a well-known part of economics and has been discussed extensively in other research fields. In the current state it is left out of the simulation, as these scenarios also provide a lot of complexity and make simulations less understandable. Further additions to study complex behavior are needed for a better understanding of the [DAM](#) and similar real-world markets.

The modular design of [SPARKLE](#) makes it easily possible to integrate such new strategies into the framework. It only requires the registration of a new bidding strategy in the simulation world and referencing this strategy at the desired agent.

6.2.2 Runtime Improvements

The development of the simulation tool takes extensive efforts to reduce the runtime for full-year simulations. This includes the move away from high-level libraries like `pandas` towards own implementations of index-based accessing of time series. The benefit of such changes has also been documented in other projects like [lemlab](#) as well. An internal replacement library called "fast_pandas" is implemented, providing performance benefits of a factor of 100 for specific datetime index operations. Furthermore, concurrency is used where possible to separate storing data from the actual runtime. Also included is a new feature in mango-agents, making it possible to ignore schedules

marked with "no_wait" to not limit their runtime. An overview of the occurred runtime challenges and their solution is shown in [Table 6.1](#)

Runtime challenge	solution
str eval	usage of python logging
MQTT send delay	TCP_NODELAY
Slow pandas datetime series indexing	fast_pandas module
Some jobs should not be waited for	"no_wait" src in mango
GIL blocking parallelization	multiple subprocesses

Table 6.1: Overview of challenges limiting runtime of the simulations and the found solution

While the simulation tool did take different efforts to be scalable and usable in large-scale scenarios, the overall runtime for simulations of a full year is still not optimal. Extensive efforts in runtime optimizations have been made to inspect and improve the performance of the simulation. However, the focus on interoperability and ease of use, through the usage of the Python programming language, limits the possibilities of multiprocessing and low-levelness. On the other hand, this provides a good foundation for the implementation of reinforcement learning-based bidding strategies. In general, the time required to improve the performance and relation of time spent on programming the simulation has to be put into relation to the time spent doing market studies and creating additional scenarios. The framework as is therefore provides a justifiable trade-off. Rewriting parts of the simulation in a low-level language could further increase performance but would also introduce a technical cut and increase entry barriers for new contributors.

6.2.3 Expansion Planning

A common task of energy system modeling includes expansion planning of a given energy system. This is also known as investment modeling, as the incentives of each agent to invest in the commissioning of new generation/demand capacities or grid reinforcements must be simulated.

Typically, different models like SIMONA are used for such tasks, which are generally operating on monthly or yearly timescales.

In ABM like SPARKLE, this requires the adjustment of existing agents throughout the runtime of the simulation. This is currently not possible, as the whole simulation must know about the existing agents in advance for coordination.

Of course, there are ways to integrate such through a splitting of the problem into an agent-based simulation and expansion planning. Such a hybrid approach to tackle this would be to simulate one year using the ABM tool and handing over the results to an evaluation model, which can adjust the input dataset for the next year. The next simulation year, therefore, runs as an independent simulation with an adjusted

input dataset. Such an approach to expansion planning needs careful integration of the datasets and is not part of this thesis. Recently, a similar approach to integrate expansion planning into the market simulation **AMIRIS** has been presented [249]. This has also been discussed with the authors to see which steps are needed to apply similar research to **SPARKLE**.

6.3 NEED FOR FURTHER RESEARCH

Even though this thesis covers many improvements to the availability of market simulations and configuration as well as modeling options of energy markets, many topics are still open for further improvements, analysis and inspection. The following topics can be considered as further directions in which subsequent research on this topic can be conducted on top of the presented results. They have been left out of this thesis so as not to define the scope too broadly and are generally research fields in their own and of high relevance.

6.3.1 Creation of a European Simulation Dataset

The showcases and scenarios from the evaluation in **Chapter 5** already include different scenario runs. Yet, a more sophisticated example in which all markets of Europe are simulated is of interest as a base example. This can be seen similar to the way **PyPSA-EUR**¹ provides a European simulation dataset for grid modeling. Such a dataset can be used to derive simulations with future market designs and investigate the impact on the overall energy system. The main concern of this is the correct parametrization of agent strategies and behavior. An energy system of this size is generally hard to handle and does not always provide balanced results. With the existence of scenario loaders for different input datasets, this advancement is in line with the general goal of providing validated European simulation datasets based on open data. That way, a European market simulation can be seen as a use case in which such public data can be accumulated and used for a complex market simulation as a whole.

This example would also utilize the shown feature of market coupling shown in **Section 5.3.4**, to derive the bidding strategy of one market based on the results of a previous clearing. Interrelation between results from different market zones is therefore an important field of further research. The work in this thesis provides the stepstone by advancing the tools available for this kind of multi-market coupling.

¹ <https://pypsa-eur.readthedocs.io/en/latest/>, visited on 10.07.2025

6.3.2 Investigation of Capacity Markets & Dynamic Grid Fees

Regarding the integration of further simulation scenarios, current discussions about the integration of a new German capacity market are of high interest [28]. Such a market makes it possible to bid on the availability of power generation alone throughout larger time horizons. A setting which becomes more important in renewable energy systems, where the market prices are not mainly driven by fuel costs, but investment costs.

The integration of dynamic grid fees on the other hand, incentivizes generation to be produced in less congested areas. The challenge with novel market designs, of course, is the lack of validation data.

6.3.3 Implementation of Reactive Power Markets & Storage Markets

In more local markets, different research projects focus on providing new market opportunities for specialized use cases. The concept of reactive power markets has been researched in the REMARK project and includes interesting ideas of trading reactive power, which has additional grid-related implications [26]. Similarly, a market which implements renting of batteries in a local community to utilize existing flexibility demands is a unique market concept proposed in the ongoing research project MAS4TE [155].

These scenarios can be modelled using the market abstraction to investigate the impact and changes of such markets on individual agents and on the energy system as a whole.

6.3.4 Expansion of Agent Behavior to Reinforcement Learning

Regarding the extension of bidding behavior, it would be much easier if the best bidding strategies for a given market could be directly derived from the market design provided and does not require manual adjustments. This idea is, of course, the driving force behind the implementation of reinforcement learning in agent behavior to create reinforcement learning agents.

The framework makes it possible to integrate reinforcement learning into energy market simulations. Fellow researchers from Freiburg and Karlsruhe implemented various learning strategies in that regard as shown in [93], [94] and [165] into the extended ASSUME version. These currently include LSTM and MATD₃ learning algorithms. Further advancements in the implementation and multi-market behavior of such strategies are expected from the upcoming ADAPT research project. This research field holds the potential for more agentic behavior and the exploration of new bidding strategies.

On the other hand, learning bidding strategies generally behaves like a hard-to-interpret black box model, requiring to backtrack the decision-making process of the individual agent to get a better understanding of the learned strategies.

6.3.5 FIPA Compliant Simulation Communication

Efforts for interoperable agent communication are made through the usage of [FIPA](#) compliant messages in the agent-based simulation tool [mango-agents](#). However, a compatible implementation in a different language is not yet available. While this is technically feasible, the advantages of using [FIPA](#) compliant communication are therefore not fully exploited. In the future, the formalization of messages and their serialization should be advanced further, as some messages contain Python-specific serializations for now. Providing a reference implementation further reduces the entry barrier and improves compatibility with future requirements. Making communication with other simulations possible on a lower level. As the [FIPA ACL](#) did not receive an update in recent years, evolution towards an updated agent-based communication language are also an opportunity for further research on the coupling of agent-based systems.

6.3.6 Integration of Ontologies

Just like a standardized communication layer of how communication takes place, further standardization of which communication takes place is required. Usage of ontologies like [EMO](#) or [OEO](#) are helpful in the creation of a greater common understanding of functionalities. Even further, in [FIPA ACL](#) it is possible to announce an ontology to use for communication, making clear which responses or messages can be expected. This would further allow to define the action space of agents through a formalization. As for now, mostly energy system-related information is included in the ontologies and less so energy market specifics. Currently, ontologies are not integrated into the [FIPA](#) based communication as adjustments and clarifications are needed.

Annotations for ontologies help with the understanding of documentation as done in [AMIRIS](#) and could be used to improve the implicit information included in market models. However, this is also a tedious task which is typically required as a byproduct of other research and not the main focus. While the [National Research Data Infrastructure for Energy \(NFDI4Energy\)](#) consortium tries to tackle the adoption of updated ontologies, further research on this topic is required as well.

6.3.7 Adaptation of Intuitive User Interface

The target group of the simulation framework is currently tied to very technical affine researchers and policy makers. As the simulation framework currently does not integrate a user interface at all, scripting experience is needed to run simulations. To lower this entry barrier, an intuitive user interface should be built on top of the framework. This can bring open-source research software on par with commercial market simulation software, as there currently is a gap for user interfaces in research software. Integration of automated scenario creation based on machine-learning techniques and large language models also provides the opportunity to automatically invent new scenarios based on user input. As complex scenarios tend to be imbalanced in the grid from a modeling perspective, this becomes a challenge when generating new scenarios. Further research on this will be done in the ADAPT project, which also includes improvements to the existing reinforcement learning of ASSUME and investigation of new market scenarios.

7 | APPENDIX

7.1 AVAILABILITY OF SOURCECODE

The market abstraction itself is available as `emarketlib` at <https://github.com/maurerle/emarketlib> and can be used in conjunction with the simulation tool. The source code of `SPARKLE`, which contains the features developed and created for this thesis, is available on Github at <https://github.com/maurerle/sparkle/> while the maintained version `ASSUME` is publicly available at <https://github.com/assume-framework/assume/> as well as on Zenodo at <https://zenodo.org/doi/10.5281/zenodo.8088760>. While Github is used to further develop and organize contributions and issues, Zenodo is used to create persistent public citable versions of fixed releases.

Furthermore, easy installation of the tool is provided through PyPi at <https://pypi.org/project/assume-framework/>.

Open Source rocks!

7.2 USED SOFTWARE AND HARDWARE TOOLS

This thesis is written using the `TeX Live` LaTeX distribution with `TeXstudio` on Debian 13 trixie. The used IDEs for programming are mostly `VSCodium`, a libre fork of Visual Studio Code, and `Spyder 5` an open-source Python IDE. Profiling of Python processes was mostly done using `yappi`¹ to report times spent in functions and `tuna`² to visualize the results. For the memory usage, I used `memprof/mprof`³. Different versions of the CPython distribution were used, ranging from 3.9-3.13 in combination with the dependencies of the `assume-framework`⁴.

Major results are publicly and open-source available, such as the `emarketlib`⁵, improvements to the multi-agent simulation tool `mango-agents`⁶, the `eralchemy` tool to visualize ER diagrams from an existing database⁷ and the main part - the `ASSUME Framework`⁸ which is described in the thesis.

¹ <https://github.com/sumerc/yappi>, visited on 19.02.2025

² <https://github.com/nshloe/tuna>, visited on 19.02.2025

³ https://github.com/pythonprofilers/memory_profiler, visited on 19.02.2025

⁴ <https://assume.readthedocs.io/en/latest/installation.html#install-using-pip>

⁵ <https://pypi.org/project/emarketlib/>, visited on 19.02.2025

⁶ <https://pypi.org/project/mango-agents/>, visited on 19.02.2025

⁷ <https://pypi.org/project/eralchemy/>, visited on 19.02.2025

⁸ <https://github.com/assume-framework/assume>, visited on 19.02.2025

Most development and testing happened on an Intel Core i5-10400H, 16GB DDR4 RAM machine. Additional used machines for the simulations were various virtual machines running Debian hosted on the Proxmox hypervisor at the institutes.

The [Figure 2.2](#) used free icons from <https://www.flaticon.com/de/kostenlose-icons/>.

7.3 MQTT ROUNDTRIP PERFORMANCE BENCHMARK

The issues with MQTT described before happen to be related to the way messages are passed. [Issue 874 on MQTT-Paho](#) provides test code showing that the round trips take at least 40ms of time when waiting for the previous message. This is due to the MQTT queue waiting to aggregate messages for a short time before sending out message updates to reduce transmissions. Using `set_tcp_nodelay` in the configuration of the MQTT broker with QoS set to zero in the application removes the delay of messages. While this is negligible in distributed real-time simulations, where steps easily take longer than 40ms, this is crucial for small distributed simulations, where each timestep does not consume much time.

To mitigate this, one can either increase the number of hours cleared at once or switch to the TCP based connection in mango-agents. Using TCP instead of MQTT has the disadvantage that both sides need to be reachable from each other, while the connection to a reachable MQTT broker does not require port openings.

The code to benchmark this behavior is available at <https://github.com/maurerle/mango/blob/assume/benchmark.py>.

7.4 TWOSTAGE SIMULATION SOURCE CODE

The below source code shows the usage of the framework to simulate a twostage market. It is a complete working market simulation, showing the creation of the market design and bidding agents. For the twostage simulation, some market agents are also bidding agents on the upper market. This is accomplished using the `PayAsClearIntermediateBidder` role.

```

1 import logging
2 from datetime import datetime, timedelta
3
4 from dateutil import rrule as rr
5
6 from sparkle import World
7 from sparkle.common.fast_pandas import FastIndex
8 from sparkle.common.forecasts import NaiveForecast

```

```

9  from sparkle.common.market_objects import MarketConfig,
    MarketProduct
10 from sparkle.markets.clearing_algorithms.intermediate import
    PayAsClearIntermediateBidder
11
12 log = logging.getLogger(__name__)
13
14
15
16 def init(world, n=1, months=1):
17     start = datetime(2019, 1, 1)
18     end = datetime(2019, 1, 1) + timedelta(days=30 * months)
19
20     index = FastIndex(start, end, freq="h")
21     sim_id = "twostage_simulation"
22
23     world.setup(
24         start=start,
25         end=end,
26         save_frequency_hours=480,
27         simulation_id=sim_id,
28     )
29
30     marketdesign = [
31         MarketConfig(
32             market_id="upper",
33             opening_hours=rr.rrule(
34                 rr.HOURLY,
35                 interval=2,
36                 dtstart=start + timedelta(hours=0.5),
37                 until=end,
38                 cache=True,
39             ),
40             opening_duration=timedelta(hours=0.5),
41             market_mechanism="pay_as_clear",
42             market_products=[
43                 MarketProduct(timedelta(hours=2), 1, timedelta(hours=1.5))
44             ],
45         ),
46         MarketConfig(
47             market_id="lower1",
48             opening_hours=rr.rrule(
49                 rr.HOURLY, interval=2, dtstart=start, until=end, cache=True
50             ),
51             opening_duration=timedelta(hours=2),
52             market_mechanism="intermediate",

```

```

53     market_products=[MarketProduct(timedelta(hours=2), 1,
54         timedelta(hours=2))],
55     ),
56     MarketConfig(
57         market_id="lower2",
58         opening_hours=rr.rrule(
59             rr.HOURLY, interval=2, dtstart=start, until=end, cache=True
60         ),
61         opening_duration=timedelta(hours=2),
62         market_mechanism="intermediate",
63         market_products=[MarketProduct(timedelta(hours=2), 1,
64             timedelta(hours=2))],
65     ),
66 ]
67
68 for market_config in marketdesign:
69     mo_id = market_config.market_id + "_operator"
70
71     mo = world.add_market_operator(id=mo_id)
72     world.add_market(mo_id, market_config)
73     if "lower" in market_config.market_id:
74         mo.add_role(PayAsClearIntermediateBidder([marketdesign[0]]))
75         # gebote nach oben anlegen
76
77 world.add_unit_operator("my_demand1")
78 world.add_unit(
79     "demand1",
80     "demand",
81     "my_demand1",
82     # the unit_params have no hints
83     {
84         "min_power": 0,
85         "max_power": 1000,
86         "bidding_strategies": {"lower1": "naive_eom"},
87         "technology": "demand",
88         "price": 20,
89     },
90     NaiveForecast(index, demand=1000),
91 )
92
93 nuclear_forecast = NaiveForecast(index, availability=1,
94     fuel_price=3, co2_price=0.1)
95
96 i = 1
97 world.add_unit_operator(f"my_operator{i}")
98 world.add_unit(
99     f"nuclear{i}",

```

```

96     "power_plant",
97     f"my_operator{i}",
98     {
99         "min_power": 200,
100        "max_power": 800,
101        "bidding_strategies": {"lower1": "naive_eom"},
102        "technology": "nuclear",
103    },
104    nuclear_forecast,
105 )
106
107 nuclear_forecast = NaiveForecast(index, availability=1,
108                                fuel_price=4, co2_price=0.1)
109
110 i = 2
111 world.add_unit_operator(f"my_operator{i}")
112 world.add_unit(
113     f"nuclear{i}",
114     "power_plant",
115     f"my_operator{i}",
116     {
117         "min_power": 200,
118         "max_power": 2000,
119         "bidding_strategies": {"lower2": "naive_eom"},
120         "technology": "nuclear",
121     },
122     nuclear_forecast,
123 )
124
125 world.add_unit_operator("my_demand2")
126 world.add_unit(
127     "demand2",
128     "demand",
129     "my_demand2",
130     # the unit_params have no hints
131     {
132         "min_power": 0,
133         "max_power": 1000,
134         "bidding_strategies": {"lower2": "naive_eom"},
135         "technology": "demand",
136         "price": 20,
137     },
138     NaiveForecast(index, demand=1000),
139 )
140
141 if __name__ == "__main__":

```

```
141 world = World()  
142 init(world, months=1)  
143 world.run()
```

Listing 7.1: Twostage simulation source code.

GLOSSARY

copperplate Typically, when only the market perspective is taken in the market clearing, it is assumed, that there is an unlimited amount of transmission capacities available, which can be imagined quite visually as a pure *copperplate* across the whole trading area. This is of course a model which does not hold up to reality, as the constraints have to be respected. Many market mechanisms which do not integrate handling of overflow situations are using this model..
37

FAIR principles to publish data for it to be Findable, Accessible, Interoperable and Reusable. 63

full activation time time a balancing provider can take until the full amount of the contracted balancing energy is provided. The required gradient of this is constrained as well. 38, 150

Message Queue Telemetry Transport Message Queue Protocol for publish-subscribe methods popular in Internet-of-Things settings. 48, 151

Natural Price The equilibrium price that emerges in a market when all participants bid truthfully and there are no distortions or strategic interventions.. 32, 35

Nomenclature of Territorial Units for Statistics spatial separation of Europe into different layers. Layer 0 is countries, layer 1 is states, layer 2 in government regions and layer 3 represents individual districts.. 120, 151

NORDPOOL Nord Pool Spot Energy Exchange; Nord Pool is a pan-European power exchange of nordic countries. 14

oracle problem The oracle problem describes that the transition of digital assets to physical assets can not be solved without a trusted party handling the transfer.
55

Remote Method Invocation Java alternative to Operation System RPC. 47, 152

strategic bidding A bidding strategy where participants intentionally deviate from their true costs or valuations to influence market outcomes in their favor.. 34, 127

truthful bidding A bidding strategy where participants submit offers that reflect their true costs or valuations, without manipulation or strategic distortion.. 34

Universal Smart Energy Framework The Universal Smart Energy Framework for Markets. [29](#), [152](#)

Variable Renewable Energy renewable energy like solar and wind turbines, which have a generation based on variable weather conditions. [30](#), [152](#)

Zenodo Public platform for archiving of individual documents, datasets or source code, to create a citable identifier. [18](#)

ACRONYMS

- ABM** Agent-based Modeling. 19, 44–46, 49, 50, 67, 86, 134, 136
- AC** Altering Current. 24, 26
- ACER** Agency for the Cooperation of Energy Regulators. 28, 40
- ACL** Agent-Communication Language. 46–49, 69, 90, 92, 139
- ADAPT** Adaptive AI-supported Simulation Toolbox for Energy Markets Design. 91, 138
- aFRR** automatic Frequency Restoration Reserve. 38, 39
- AMES** Agent-Based Modeling of Electricity Systems. 58
- AMIRIS** Agentenbasiertes Modell zur Integration Regenerativer in den Strommarkt. 18, 56, 82, 89, 92, 116, 118, 124, 125, 133, 137, 139, 157
- API** application programming interface. 60
- ARCOL** ARTIMIS COmmunication Language. 46
- ASAM** Ancillary Services Acquisition Model. 56, 80
- ASSUME** Agent-based Simulation for Studying and Understanding energy Market Evolution and bidding behavior. 91, 118, 124, 125, 138, 141
- CfD** Contract for Differences. 12, 43, 44, 96, 132
- CHPP** Combined heat and power plant. 55
- CLI** Command Line Interface. 48
- CPU** Central Processing Unit. 49, 83
- CSV** Comma Separated Values. 89, 93, 107, 118
- DAG** directed acyclic graph. 85
- DAM** Day-Ahead-Market. 38, 135
- DBMS** Database management system. 107
- DC** Direct Current. 24, 26
- DC-OPF** Direct Current – Optimal Power Flow. 25
- DHI** direct normal irradiation. 122
- DLR** Deutsches Zentrum für Luft- und Raumfahrt. 48, 57
- DNI** direct normal irradiation. 122
- DRL** Deep Reinforcement Learning. 91
- DSO** Distribution System Operator. 30, 57
- DTLR** Dynamic Thermal Line Rating. 24
- ECMWF** European Centre for Medium-Range Weather Forecasts. 62, 63, 122
- EDF** Électricité de France. 33
- EEG** Renewable energy Law. 57

- EEM** International Conference on European Energy Markets. 18
- EEX** European Energy Exchange. 14
- emarketlib** energy market library for Python. 91, 111, 112, 116, 155
- EMO** Energy Market Ontology. 70–72, 139
- ENTSO-E** European Network of Transmission System Operators for Electricity. 14, 28, 40, 63, 124, 126, 133, 156
- ENTSO-G** European Network of Transmission System Operators for Gas. 28, 63
- EOM** Energy only market. 98, 111, 113, 114, 129, 155
- EPEX** European Power Exchange. 14, 64, 72, 123
- ERCOT** Electric Reliability Council of Texas. 58
- ESM** Energy System Modeling. 61–63
- ETS** Emission Trading System. 28
- EU** European Union. 11, 14, 28, 29, 40, 43
- EV** Electric Vehicle. 29, 55, 59
- FAME** Framework for distributed Agent-based Modeling of Energy systems. 49, 57
- FAT** full activation time. 38, *Glossary: full activation time*
- FBMC** Flow-Based Market Coupling. 41, 59
- FCR** Frequency Containment Reserve. 38
- FIFO** First-In First-Out. 86
- FIPA** Foundation for Intelligent Physical Agents. 46, 47, 49, 69, 90, 92, 139
- FIT** Feed in tariff. 43, 44, 96, 132
- FNCS** Framework for Network Co-Simulation. 57, 58
- GAMS** General Algebraic Modeling System. 52, 60, 61
- GHI** global horizontal irradiance. 122
- GIL** Global Interpreter Lock. 83, 88, 136
- GIS** Geographic Information System. 61
- GPU** Graphical Processing Unit. 83
- GSY-e** Gridsingularity Exchange. 54
- GUI** Graphical User Interface. 49
- HPC** High Performance Computing. 49
- HTTP** Hypertext Transfer Protocol. 47–49
- I/O** Input Output. 49, 83
- IAEW** Institut für Elektrische Anlagen und Netze, Digitalisierung und Energiewirtschaft. 59
- ID3** Intraday 3-hour pre delivery average benchmark. 43
- ISO** Integrated System Operator. 17, 26, 32, 59
- JADE** Java Agent DEvelopment Framework. 47
- KPI** Key Performance Indicator. 13, 15, 20, 68, 92, 107, 108, 128, 129, 131, 134

- KQML** Knowledge Query and Manipulation Language. 46
- LEM** Local Energy Market. 29, 51, 53, 66
- lemlab** Local-Energy-Market Lab. 55, 135
- LMP** Locational Marginal Pricing. 14, 41, 50, 112
- LODF** Line Outage Distribution Factor. 26
- LP** Linear Problem. 59, 61, 76, 112
- LSTM** Long short-term memory. 138
- LTM** Long-Term-Market. 113
- mango** modular python agent framework. 48, 91, 106, 155
- MARI** Manually Activated Reserves Initiative. 39
- MASCEM** Multi-Agent Simulator of Competitive Electricity Market. 60, 70
- MaStR** market master data records. 63
- MATD3** Multi-Agent Twin-Delayed Deep Deterministic Policy Gradient. 138
- MC** marginal costs. 94
- MESA** Multi Agent-based simulation in Python. 56, 80
- mFRR** manual Frequency Restoration Reserve. 38, 39
- MIBEL** Iberian Electricity Market. 60
- MPI** Message Passing Interface. 48, 49, 82
- MQ** Message Queue. 57
- MQTT** Message Queue Telemetry Transport. 48, 49, 88, 90, 106, 134, 136, 142, *Glossary:*
Message Queue Telemetry Transport
- NFDI4Energy** National Research Data Infrastructure for Energy. 63, 139
- NTC** Net Transfer Capacities. 41, 42, 59, 153
- NUTS** Nomenclature of Territorial Units for Statistics. 120, 122–124, 156, *Glossary:*
Nomenclature of Territorial Units for Statistics
- OCI** Open Container Interface. 106, 107
- OEDS** Open Energy Data Server. 9, 118, 122, 134
- OEO** Open Energy Ontology. 70, 139
- OEP** Open Energy Platform. 53
- OPEC** Organization of the Petroleum Exporting Countries. 21
- OTC** Over-The-Counter. 15, 42–44, 73, 157
- OWL** Web Ontology Language. 70, 71
- P2P** Peer-To-Peer. 14, 39, 42, 131
- PICASSO** Platform for the International Coordination of Automated Frequency Restoration and Stable System Operation. 39
- PPA** Power Purchase Agreement. 12, 43, 44, 57, 96, 132
- PSST** PowerSystem Simulation Toolbox. 58
- PV** photovoltaic. 13, 55

- PyPSA** Python for Power System Analysis. 56, 89, 92, 111, 112, 116, 118
- QoS** Quality of service. 142
- RDF** Resource Description Framework. 70
- REMIT** Regulation on Wholesale Energy Market Integrity and Transparency. 40
- RePAST** RePAST agent-based simulation toolkit. 82
- REST** Representational State Transfer. 46, 60
- RMI** Remote Method Invocation. 47, 49, *Glossary: Remote Method Invocation*
- RPC** Remote Procedure Call. 82, 147
- SCED** security-constrained economic dispatch. 58
- SCUC** security-constrained unit commitment. 58
- SDAC** Single Day-Ahead Coupling. 40
- SOAP** formerly Simple Object Access Protocol. 47, 49
- SPARKLE** Simulation Platform for Agent-based Research on energy marKet dynamics for Lower Emissions. 17, 18, 84, 91–93, 98, 105–108, 115–118, 131–137, 141, 154
- TCP** Transmission Control Protocol. 87, 88, 90, 142
- TERRE** Trans European Replacement Reserves Exchange. 39
- TSO** Transmission System Operator. 23, 26, 30, 42
- USEF** Universal Smart Energy Framework. 29, 31, 32, 57, 58, 153, *Glossary: Universal Smart Energy Framework*
- VCG** Vickrey-Clark-Groves. 12, 36, 132
- VCS** Version Control System. 18
- VPP** Virtual power plant. 31, 40
- VRE** Variable Renewable Energy. 30, 60, *Glossary: Variable Renewable Energy*
- WS** Websockets. 48, 49
- XML** eXtensible Markup Language. 47
- YAML** Yet Another Markup Language. 71, 89

LIST OF FIGURES

Figure 1.1	Overview of a comparison framework of different market designs. On the left is input data of a comparison scenario, in the middle are different market designs and on the right are performance indicators for the evaluation of a market design.	13
Figure 1.2	Visualization of a design science process after Peffers [182].	16
Figure 2.1	Energy policy triangle showing the three targets of environmental compatibility, economic efficiency, and safety of supply [253].	22
Figure 2.2	Market liberalization allowed to break up monopolies. In the regulated market small generation is traded flexibly. Therefore, decentralization enables integration of new players and opportunities [54].	28
Figure 2.3	Overview of balancing energy types in European energy market inspired by Next Kraftwerke [172].	39
Figure 2.4	Focus of ACER market rules containing different generalized timeframes of trading [1].	41
Figure 2.5	Flow-Based Market Coupling constraints in comparison to NTC flow domain from Zone A to B and C. Constraints of FBMC model the interplay of transferring capacity between the zones. Inspired by [235]	42
Figure 2.6	Top-down simulations (left) focus on macroscopic results which are upsampled for individuals, while bottom-up simulations (right) model individuals themselves and draw general conclusions for the whole system. Agent-based simulations generally tend to the bottom-up approach.	45
Figure 2.7	Interaction of an agent with its environment. Agents contain state and behavior and can interact with the simulation environment or other agents. Inspired by [148]	47
Figure 2.8	Visualization of obligations (top) and message handlers (bottom) of a sample market agent modeled with mango agents.	48
Figure 2.9	Visualization of possible energy market configuration in the Gridsingularity Exchange [88].	54
Figure 2.10	Architecture of the ASAM simulation framework from [82].	56
Figure 2.11	Architecture of the USEF market framework from [233].	58
Figure 2.12	Description of the PowerACE model from [125].	60

Figure 2.13	Visualization of the interplay of components from the Open Energy Data Server [157].	63
Figure 3.1	Visualization of Open Energy Ontology OWL definition from [30]. Interacting with the definitions and interconnections of an ontology are possible through web-based viewers.	71
Figure 3.2	Visualized class diagram of the simulation framework – taken from the framework documentation	78
Figure 3.3	Visualization of acyclic depending code layers of the market simulation tool	78
Figure 3.4	Flow of the basic simulation loop. For each step, a fixed order of hard-coded agents is executed.	80
Figure 3.5	Flow diagram of the generic simulation loop. Each step executes each agent in a randomized or set order – independent of the number and action of each agent.	81
Figure 3.6	Flow of an event-based simulation. Each agent is queried for the next action they want to act upon. Only the time steps in which any of the agents act are simulated.	82
Figure 3.7	Memory usage using "fork" as a multiprocessing method for new processes – on a simulation of they year 2019 with 31 processes and 263 bidding agents in total.	83
Figure 3.8	Memory usage using "spawn" as a multiprocessing method for new processes. The fork method references the same memory mappings, while spawn copies the simulation space into each process, as memory access is split per process.	84
Figure 3.9	Visualization of vector clocks – the timestamps of other processes are tracked through individual process counters, creating a partial ordering.	86
Figure 3.10	Sequence diagrams of agent communication without synchronization call and with additional readiness check.	87
Figure 3.11	Duration graph for various counts of roundtrips for TCP and MQTT using a direct roundtrip vs synchronization with a clock in the timestamp scenario. TCP connection includes lower overhead, while MQTT has more flexibility in the connection handling.	88
Figure 4.1	Overview of configurable elements of the simulation SPARKLE. Moving parts of a market simulation can be adjusted as required.	93
Figure 4.2	Schedule of multi-market dispatch using the simulation tool. Offset between bidding intervals and delivery are important when evaluating strategies for multi-market simulations.	97

Figure 4.3	Complex bidding behavior for block bids of power plant. The black blocks can only be accepted by the market if the red blocks are accepted as well. This accommodates ramping constraints of power plants.	98
Figure 4.4	Complex Bidding behavior of for exclusive bids of storages. Only one color of the provided blocks can be accepted by the market. The bids differ in the charge time, as well as the maximum power that can be charged or discharged.	102
Figure 4.5	Interplay of the distributed clock in a <code>mango</code> simulation. Mango containers require some kind of synchronization, as each has a separate clock. Instead of an external signal, these clocks are synchronized through updated timestamps from the manager.	106
Figure 4.6	Calculation of economic parameters for example 01a of a selected power plant. Besides the aggregated values, an inspection of when which cost or profit occurred is shown.	108
Figure 5.1	Market result for two-node nodal clearing example of a single clearing using <code>emarketlib</code> . Demand (red) is lower on the left side, so there is more generation (blue) available to be transferred to the right side. The line capacity between the two nodes is 400 MW. It is fully utilized, transferring 400 MW from node 0 to node 1 to reduce the price at node 1 to 40€/MW.	111
Figure 5.2	Validation of optimal clearing of the implemented pay-as-clear market mechanism in edge cases of typical clearing behavior in pay-as-clear. The market minimizes the total cost while maximizing the possible dispatch.	113
Figure 5.3	Schedule of the two market designs under comparison. One includes the <code>EOM</code> with pay-as-clear only, which is compared to the addition of a contract market with 7d products with pay-as-bid. Also published in prior work [159].	114
Figure 5.4	Results from market comparison of the laid out design. Total dispatch costs vary, as more energy is sold for the bid price, instead of the clearing price. The average price of the <code>EOM</code> is decreased as well. Also published in prior work [159].	114
Figure 5.5	Number of cores visualized to the reduction of the runtime of a simulation with 16 market participants.	116
Figure 5.6	Visualization of simulation grid from a given PyPSA input dataset. Utilization of grid lines is visualized from power flow calculation in market results (green – low utilization; yellow – medium utilization; red – high utilization).	119

Figure 5.7	Heatmap of yearly energy demand per NUTS ₃ area for Germany, publicly available from OpenEgo project, based on synthetic data generated with OpenStreetMap.	120
Figure 5.8	Comparison of best linear combination from BDEW profiles to the actual power demand of Germany in 2015. Actual values deviate from the best linear combination, highlighting the requirement for updated standard profiles.	121
Figure 5.9	Merit order visualization of the market result of a given hour from the simulation dashboard of Germany 2023 NUTS ₁ . Results for other NUTS aggregation vary only slightly.	123
Figure 5.10	Summary of correlation coefficient with historical benchmark dataset of ENTSO-E between market simulation with different NUTS aggregations. One can see that the focus on correct price modeling and bidding behavior has a higher influence on the results than the aggregation, while all simulations provide good out-of-the-box results.	124
Figure 5.11	Comparative electricity price simulation for the German Market (2019).	125
Figure 5.12	Scatter plot of the price simulation from ASSUME and AMIRIS on the y-axis, with benchmark prices from ENTSO-E on the x-axis. One can see that a high correlation between the two exists. Published in [160].	126
Figure 5.13	Price duration curve for AMIRIS, ASSUME and the historical data from the 2019 Germany dataset. Despite the good overall fit, the simulations do not fit negative prices well. Published in [160].	126
Figure 5.14	Schedule of two-stage market dispatch. The lower markets have a longer duration, as they are waiting for the result from the upper market auction and reintegrate this into the lower market clearings.	127
Figure 5.15	Results from Grafana dashboard showing different markets of the twostage simulation. Prices for lower1 are higher, while the leftover volume is traded from the lower2 market to lower1 through the upper market.	128
Figure 5.16	Visualization of hourly market dispatch and actual feasible dispatch using clearing mechanism and bidding strategies described in Section 4.3.1 for the fuel market scenario. The tooltip shows a deviation due to a ramping constraint, which the market did not respect, leading to a reduced dispatch.	130

LIST OF TABLES

Table 1.1	Overview of contributions to related open-source projects throughout the thesis.	19
Table 2.1	Overview of different energy market support policies. While all calculate the payout from the actual dispatch of the unit, not all require the additional market price. Such support policies are either contracted outside the market as OTC or auctioned by a support entity, e.g. the government.	44
Table 2.2	Overview of the features of different agent-based simulation tools. Mango suffices the simulation requirements.	49
Table 2.3	Overview of existing energy market simulation tools - comparison of different market designs is not covered in existing tools.	53
Table 3.1	Adjusted table from Table 2.3 which also contains the proposed model covering the required features.	66
Table 3.2	Description of the parameters used to configure a single trading option/market extended from [3, 204]. The configuration of multiple market products allows for extensive configuration of trading options. Taken from [159].	73
Table 3.3	Exemplary bid showing mandatory fields used in all markets. The volume is positive for generation while it is negative for demand bids. The sender id contains a unique id of the bidding agent.	74
Table 3.4	Link bid requiring the first bid, with base id 0 to be accepted by the market to be able to activate the other two bids as well. . .	75
Table 4.1	Overview of market configurations to simulate the European energy market. Selected markets are Day-Ahead (DA), the two Intra-Day (ID) markets and the Futures market.	96
Table 5.1	Overview of simulations with increasing liquidity as the number of agents increases. The average prices decrease with increasing liquidity, analogous to the total cost. As the demand is similar between the simulations, the total volume stays the same. . . .	117
Table 5.2	Quantitative Performance Metrics from the Comparison of the created simulation model towards AMIRIS.	125
Table 6.1	Overview of challenges limiting runtime of the simulations and the found solution	136

LIST OF LISTINGS

Listing 3.1	Definition of eligible obligations lambda method for German feed-in tariff.	73
Listing 3.2	Sample portfolio strategy without ramping.	76
Listing 3.3	Scenario creation and adjustment through loader.	79
Listing 4.1	Configuration of custom market mechanisms and bidding strategies in the world. Once added to the world - units and markets using the strategies can be added.	93
Listing 4.2	Getter function of a RandomForecaster with randomized noise applied to the forecast data.	95
Listing 5.1	Addition of an agent to the simulation world through the object-oriented interface.	110
Listing 5.2	Deployment and monitoring of the docker swarm to a cluster using the generated compose.yml.	117
Listing 5.3	Definition of additional KPI query for a given simulation in the construction of the simulation world.	129
Listing 7.1	Twostage simulation source code.	142

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