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# Assessing the Potential of Multiple Use Cases for German Energy Communities via Integration of Machine Learning in the Energy-Economic Modeling Process

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# Abstract

Energy communities are an integral part of the energy transition. They are intended to integrate decentralized renewables into the electricity market, improve local participation, and create incentives for the provision of flexibility.

In this work, three implementation proposals are developed and analyzed in more detail. The focus is set on a labeling framework, with optimization-based allocation and three different pricing mechanisms. Their potential is assessed and the pricing mechanisms compared by means of simulation. Supervised and unsupervised machine learning is integrated into the energy-economic modeling process to accelerate it and simplify the result evaluation.

The extension of the use case method purposefully aligns the development of energy communities with the requirements of involved stakeholders. The focus is on pricing mechanisms and a labeling framework with an allocation method, which allocates generation and consumption with high temporal and spatial resolution and proves it to external third parties. The pricing mechanisms used were the supply demand ratio (SDR) and the mid-market rate (MMR) pricing. A local energy market (LEM) with a two-sided call auction and uniform price was also implemented. A qualitative analysis and two case studies show that the labeling framework meets stakeholder requirements. A specially developed simulation framework is applied to quantitatively determine whether the requirements for the price mechanisms are also met. For this purpose, the simulation framework represents German municipalities with a high level of detail. Modules for the different price mechanisms and for the allocation method are built on top. A simulation of all municipalities is not feasible due to computational cost, which is why machine learning (ML) is integrated into the modeling process.

By applying unsupervised ML, the approx. 12,000 German municipalities can be divided into 20 clusters. With the help of these clusters as well as their representatives, results for the population can be approximated, the population reduced for simulation, the level of detail can be determined individually and simulation results can be imposed to other municipalities by similarity. Using stratified sampling as the basis for supervised ML (emulation/surrogate modeling, ESM) and time series aggregation, it is possible to speed up the total simulation time by a factor of 1,874.6. At the same time, the error is relatively small with $R^2$ of 0.9291 to 0.9999. Thus, prices can be determined for all German municipalities. With this method, the reapplication, e.g., for sensitivity analysis, is up to 471 million times faster than with the simulation model. Along the modeling process, machine learning can be used at many points and, among other things, accelerate the process or facilitate the evaluation.

As a result, price mechanisms can meet almost all requirements. They guarantee better buying and selling prices than on wholesale markets, integrate energy communities into the electricity markets, and map supply and demand within the energy community. They are also clearly defined and non-discriminatory. The labeling framework makes them transparent and verifiable. However, volatile prices and the coupling to the electricity markets are in conflict with long-term price security. By means of regional direct marketing, the losses of the energy service provider can partially be covered. A prerequisite for this, however, is the reduction of administrative barriers and disproportionate costs. The potential and prerequisites in Germany are very heterogeneously distributed. Especially in rural regions with balanced supply and demand, all price mechanisms are feasible. In unbalanced communities, energy communities are only profitable on one side, but thus incentivize the further expansion and use of renewables and flexibility options.

# Zusammenfassung

Energiegemeinschaften sind ein wesentlicher Bestandteil der Energiewende. Sie sollen u. a. dezentrale erneuerbare Erzeuger in den Strommarkt integrieren, die lokale Partizipation an der Energiewende verbessern und Anreize für die Erbringung von Flexibilität schaffen.

In dieser Arbeit werden drei Implementierungsvorschläge für Energiegemeinschaften entwickelt und genauer analysiert. Der Schwerpunkt liegt auf einem „Labeling Framework“ mit optimierungsbasierter Allokation für den Nachweis der Stromherkunft und drei verschiedenen Preisbildungsmechanismen. Ihr Potenzial wird bewertet und die Preismechanismen werden anhand von Simulationen verglichen. Überwachtes und unüberwachtes maschinelles Lernen wird in den energiewirtschaftlichen Modellierungsprozess integriert, um diesen zu beschleunigen und die Ergebnisbewertung zu vereinfachen.

Die Erweiterung der Use-Case-Methode richtet die Entwicklung von Energiegemeinschaften zielgerichtet an den Anforderungen involvierter Stakeholder aus. Der Fokus liegt auf Preismechanismen und einem „Labeling Framework“ mit Allokationsmethode, über den Erzeugung und Verbrauch mit hoher zeitlicher und räumlicher Auflösung einander zugeordnet und externen Dritten nachgewiesen werden. Als Preismechanismen wurden der „supply demand ratio“ (SDR) sowie der „mid-market rate“ (MMR) Preismechanismus verwendet. Außerdem wurde ein lokaler Energiemarkt (LEM) mit zweiseitiger Call-Auktion und Einheitspreis umgesetzt. Eine qualitative Analyse und zwei Fallstudien zeigen, dass das „Labeling Framework“ die Anforderungen der Stakeholder erfüllt. Mit Hilfe eines Simulationsmodells wird quantitativ geprüft, ob die Anforderungen and die Preismechanismen ebenfalls erfüllt sind. Dafür werden deutsche Gemeinden mit hohem Detailgrad simulativ abgebildet. Module für die verschiedenen Preismechanismen bzw. für die Allokationsmethode bauen darauf auf.

Eine Simulation aller Gemeinden ist wegen der erforderlichen Rechenzeit nicht möglich, weswegen maschinelles Lernen (ML) in den Prozess integriert wird. Durch den Einsatz von unüberwachtem ML können die ca. 12,000 deutschen Gemeinden in 20 Cluster eingeteilt werden. Mit Hilfe dieser Cluster sowie deren Repräsentanten lassen sich Ergebnisse für die Grundgesamtheit abschätzen, die Grundgesamtheit reduzieren, die Detailtiefe und Genauigkeit gezielt wählen und Simulationsergebnisse durch Ähnlichkeit aufeinander übertragen. Durch eine stratifizierte Stichprobe als Grundlage für überwachtes ML (Emulation-/Surrogate-Modeling) und einer Zeitreihenaggregation ist es möglich, die gesamte Simulationszeit um den Faktor 1,874.6 zu beschleunigen. Dabei ist der Fehler mit $R^2$ von 0.9291 bis 0.9999 relativ gering. Dadurch können Preise für alle deutschen Gemeinden ermittelt werden. Mit dieser Methode wird die erneute Anwendung z. B. für Sensitivitätsanalysen um bis zu 471 Millionen Mal performanter als mit dem Simulationsmodell. Entlang des Modellierungsprozesses kann maschinelles Lernen an vielen Stellen zum Einsatz kommen und u. a. den Prozess beschleunigen bzw. die Auswertung erleichtern.

Die Preismechanismen garantieren bessere Kauf- und Verkaufspreise als an der Börse, integrieren Energiegemeinschaften in die Strommärkte und bilden gleichzeitig Angebot und Nachfrage der Gemeinschaft ab. Mittels regionaler Direktvermarktung können die Verluste des Energiedienstleisters teilweise abgefangen werden. Voraussetzung dafür ist jedoch die Senkung regulatorischer Hürden und unverhältnismäßiger Kosten. Die Potenziale und Voraussetzungen in Deutschland sind sehr heterogen verteilt. Insbesondere in ländlichen Regionen mit ausgewogenem Verhältnis aus Erzeugung und Verbrauch sind alle Preismechanismen realisierbar. In unausgeglichenen Gemeinden sind Energiegemeinschaften nur einseitig gewinnbringend, reizen damit aber den weiteren Ausbau von erneuerbaren Energien und Flexibilitätsoptionen an.

# Contents

# Abbreviations

| Abbreviation | Explanation |
|---|---|
| cCVI/sCVI | Composite Cluster Validation Index/ Single Cluster Validation-Index |
| CEC | Citizen Energy Community |
| CLC | Corine Land Cover |
| CSR | Corporate Sustainability Reporting/Report |
| CVI | Cluster Validation Index |
| DSO | Distribution System Operator |
| EC | Energy Community |
| ESM | Emulation, Surrogate (-Meta) Model |
| ESP | Energy Service Provider |
| EU | European Union |
| GDPR | General Data Protection Regulation |
| GO | Guarantees of Origin |
| GOR | Guarantee of Origin Registry |
| HDI | Hot-Deck Imputation |
| IEMD | DIRECTIVE (EU) 2019/944 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 5 June 2019 on common rules for the internal market for electricity and amending Directive 2012/27/EU (recast) [107] |
| LEM | Local Energy Markets |
| LES | Local Energy Sharing (Community) |
| LoD | Level of Detail |
| LVG/MVG/HV | Low-, Medium-, and High- Voltage Grid |
| MAE | Mean Absolute Error |
| MCDA | Multiple Criteria Decision Analysis |
| ML | Machine-Learning |
| MMR | Mid-Market Rate |
| MSE | Mean Square Error |
| nRMSE | Normalized RMSE |
| OSM | OpenStreetMap |
| P2P | Peer-to-Peer |
| PKI | Public Key Infrastructure |
| PV | Photovoltaics |
| RE | Renewable Energy |

| | |
|---|---|
| REC | Renewable Energy Sharing Community |
| RED II | DIRECTIVE (EU) 2018/2001 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 11 December 2018 on the promotion of the use of energy from renewable sources [161] |
| RED III | DIRECTIVE OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL amending Directive (EU) 2018/2001 of the European Parliament and of the Council, Regulation (EU) 2018/1999 of the European Parliament and of the Council and Directive 98/70/EC of the European Parliament and of the Council as regards the promotion of energy from renewable sources, and repealing Council Directive (EU) 2015/652 |
| RMSE | Root Mean Square Error |
| RSC | Renewables Self-Consumers |
| SDR | Supply Demand Ratio |
| SFDR | Sustainable Finance Disclosure Regulation |
| SME | Small and Medium-Sized Enterprises |
| SRS | Simple Random Sampling |
| STD | Standard Deviation |
| TSA | Time Series Aggregation |
| TSA | Time Series Aggregation |
| TSO | Transmission System Operator |
| UBA | German Environment Agency (Umweltbundesamt) |
| ZI | Zero Intelligence |
| ZKP | Zero-Knowledge-Proof |

# Figures

# Tables

# List of Publications

This dissertation is based on multiple publications of the author. The most relevant publications written by the author and cited in this work are introduced in the following. Individual citation keys [A1], [A2], etc. are assigned to the publications to differentiate them from external references. A full list of all of the author's publications can be found in section 13 "Publications of the Author" and the bibliography in section 12.

| **Publication I** | |
|---|---|
| Title | Updating renewable energy certificate markets via integration of smart meter data, improved time resolution and spatial optimization |
| Citation | Bogensperger, A.J, Zeiselmair, A. "Updating renewable energy certificate markets via integration of smart meter data, improved time resolution and spatial optimization," 2020 17th International Conference on the European Energy Market (EEM), 2020, pp. 1-5, https://doi.org/10.1109/EEM49802.2020.9221947. |
| Citation Key | [A1] |
| Abstract | This paper illustrates the processes and properties of the German guarantees of origin register (GOR) as well as its properties and European integration. Evaluations and figures about guarantees of origin show the general lack of scaling due to the increasing amount of unsubsidized renewables starting in 2020. Therefore, a new platform-based system is proposed, supplementing the trade of guarantees of origin with an ex-post optimization of certificate allocation to increase transparency, accuracy and achieve a steering effect. This optimization is formally introduced and includes spatial information as well as high time resolutions. Additional use cases are presented and their type of mathematical implementation is shown. The shift of the current register design towards a platform-based system finally leads to further added value, as shown in the paper. |
| Authors Contribution | Alexander Bogensperger conceived and designed the analysis, collected the data, performed the analysis and wrote the paper. |

| **Publication II** | |
|---|---|
| Title | A practical approach to cluster validation in the energy sector |
| Citation | Bogensperger, A.J., Fabel, Y. A practical approach to cluster validation in the energy sector. Energy Inform 4, 18 (2021).DOI: https://doi.org/10.1186/s42162-021-00177-1 |
| Citation Key | [A2] |
| Abstract | With increasing digitization, new opportunities emerge concerning the availability and use of data in the energy sector. A comprehensive literature review shows an abundance of available unsupervised clustering algorithms as well as internal, relative and external cluster validation indices (cvi) to evaluate the results. Yet, the comparison of different clustering results on the same dataset, executed with different algorithms and a specific practical goal in mind still proves scientifically challenging. A large variety of cvi are described and consolidated in commonly used composite indices (e.g. Davies-Bouldin-Index, silhouette-Index, Dunn-Index). Previous works show the challenges surrounding these composite indices since they serve a generalized cluster quality evaluation. However, this does not suit individual clustering goals in many cases. The presented paper introduces the current state of science, existing cluster validation indices and proposes a practical method to combine them to an individual composite index, using Multi Criteria Decision Analysis (MCDA). The methodology is applied on two energy-economic use cases for clustering load profiles of bidirectional electric vehicles and municipalities. |
| Authors Contribution | Alexander Bogensperger developed the concept and methodology with a focus on applications within the energy sector. He wrote the paper and the clustering in the mentioned python framework. |

| Publication III | |
|---|---|
| Title | Accelerating Energy-Economic Simulation Models via Machine Learning-Based Emulation and Time Series Aggregation |
| Citation | Bogensperger, A.J.; Fabel, Y.; Ferstl, J. Accelerating Energy-Economic Simulation Models via Machine Learning-Based Emulation and Time Series Aggregation. Energies 2022, 15, 1239. https://doi.org/10.3390/en15031239 |
| Citation Key | [A3] |
| Abstract | Energy-economic simulation models with high levels of detail, high time resolutions, or large populations (e.g., distribution networks, households, electric vehicles, energy communities) are often limited due to their computational complexity. This paper introduces a novel methodology, combining cluster-based time series aggregation and sampling methods, to efficiently emulate simulation models using machine learning and significantly reduce both simulation and training time. Machine learning-based emulation models require sufficient and high-quality data to generalize the dataset. Since simulations are computationally complex, their maximum number is limited. Sampling methods come into play when selecting the best parameters for a limited number of simulations ex ante. This paper introduces and compares multiple sampling methods on three energy-economic datasets and shows their advantage over a simple random sampling for small sample-sizes. The results show that a k-Means cluster sampling approach (based on un-supervised learning) and adaptive sampling (based on supervised learning) achieve the best results especially for small sample sizes. While a k-Means cluster sampling is simple to implement, it is challenging to increase the sample sizes if the emulation model does not achieve sufficient accuracy. The iterative adaptive sampling is more complex during implementation, but can be re-applied until a certain accuracy threshold is met. Emulation is then applied on a case study, emulating an energy-economic simulation framework for peer-to-peer pricing models in Germany. The evaluated pricing models are the "supply and demand ratio" (SDR) and "mid-market rate pricing" (MMR). A time series aggregation can reduce time series data of municipalities by 99.4% with less than 5% error for 98.2% (load) and 95.5% (generation) of all municipalities and hence decrease the simulation time needed to create sufficient training data. This paper combines time series aggregation and emulation in a novel approach and shows significant acceleration by up to 88.9% of the model's initial runtime for the simulation of the entire population of around 12,000 municipalities. The time for re-calculating the population (e.g., for different scenarios or sensitivity analysis) can be increased by a factor of 1100 while still retaining high accuracy. The analysis of the simulation time shows that time series aggregation and emulation, considered individually, only bring minor improvements in the runtime but can, however, be combined effectively. This can significantly speed up both the simulation itself and the training of the emulation model and allows for flexible use, depending on the capabilities of the models and the practitioners. The results of the peer-to-peer pricing for approximately 12,000 German municipalities show great potential for energy communities. The mechanisms offer good incentives for the addition of necessary flexibility. |
| Authors Contribution | Alexander Bogensperger did the conceptualization, developed the methodology and parts of the software, validated the results and resources, prepared the original draft, supervised the project (including project administration, funding and acquisition), performed the energy-economic analysis of the results and wrote the paper. |

| Publication IV | |
|---|---|
| Title | Comparison of Pricing Mechanisms in Peer-to-Peer Energy Communities |
| Citation | Bogensperger, A.J.; Ferstl, J; Yu, Y. Comparison of Pricing Mechanisms in Peer-to-Peer Energy Communities. In: 12. Internationale Energiewirtschaftstagung (IEWT) 2021. Wien: Technische Universität Wien, 2021. |
| Citation Key | [A4] |
| Abstract | Digitization enables new participation concepts to be designed, especially for the lower voltage levels, small-scale producers and consumers. Building on extensive regionalized data, German municipalities can be simulated in a newly developed simulation framework. The framework generates all necessary agents for a given municipality on demand and allows the simulation of multiple energy-economic use cases. One popular use case is P2P energy sharing. P2P energy sharing communities are a means of integrating small-scale producers, consumers and flexibility provider into the energy system. These communities are either in a local geographical area or driven by consumers and producers with mutual goals. Three different pricing mechanisms, i.e., supply and demand ratio (SDR), mid-market rate (MMR) and bill sharing (BS) are introduced and compared for different municipalities. The advantages and disadvantages are shown for all mechanisms using example communities. It becomes apparent that different mechanisms are better depending on the prevailing site conditions. |
| Authors Contribution | Alexander Bogensperger supervised, conceived and designed the analysis, performed the energy-economic analysis of the results and wrote a big share of the paper. |

| Publication V | |
|---|---|
| Title | Regulatory incentives for digitalization and flexibility utilization through a yardstick competition |
| Citation | Bogensperger, A.J., and Koeppl, S. "Regulatory incentives for digitalization and flexibility utilization through a yardstick competition," ETG Congress 2021, 2021, pp. 1-6. |
| Citation Key | [A5] |
| Abstract | The regulatory regime is a key-factor for a cost-effective, ecological and secure energy supply. The paper shows properties of the German revenue-cap-regulation (status quo) and compares it with a yardstick competition. Both are described and compared through a novel optimization approach. By utilizing alternative measures to cost-intensive grid expansion, identified in the project "C/sells", these regimes are compared. An analysis of efficiency-values of German grid system operators indicates a favorable basis for a yardstick regulation. The paper concludes by introducing a method to analyze the suitability of German grid system operators towards a yardstick regulation and applies it to an incomplete dataset to give first implications towards the suitability of a yardstick competition in Germany. |
| Authors Contribution | Alexander Bogensperger conceived and designed the analysis, collected the data, performed the analysis and wrote the paper. |

| Publication VI | |
|---|---|
| Title | Design choices in peer-to-peer energy markets with active network management |
| Citation | Regener, V., et al.: Design choices in peer-to-peer energy markets with active network management. IET Smart Grid. 1– 16 (2022).DOI: https://doi.org/10.1049/stg2.12067 |
| Citation Key | [A6] |
| Abstract | Due to the growing number of Distributed Energy Resources and new electrical loads at the sectoral contact points, novel organisational forms such as Local Energy Markets arise to deal with increasing complexity in the energy system. However, these markets are radically different from traditional energy markets, as they often allow individual prosumers to trade with each other via a peer-to-peer scheme. To guarantee tamper-proof settlement, an increasing number of these markets feature a distributed ledger technology. This paper analyses different design variants of peer-to-peer markets, focusing specifically on the allocation mechanism under network constraints as these mechanisms constitute the core component of a market design. We assess these designs concerning user acceptance, economic performance, practicability, and their ability to relieve grid congestion. Further key performance indicators also cover communal revenues or welfare distribution. For this purpose, we developed an agent-based simulation framework, which builds on data from three German reference municipalities derived from a novel clustering approach. Besides a consolidated presentation of the results, we highlight current implementation obstacles and identify promising concepts for further research. |
| Authors Contribution | Alexander Bogensperger supervised and supported the energy-economic analysis, validated the results and was responsible for project administration and funding acquisition. |

# 1 Introduction

The overall goal is to decarbonize the energy system to stop the ongoing global warming. To achieve a substantial reduction in greenhouse gas emissions, a large-scale extension of renewable energy resources is required. These renewables are often built by private investors in a decentralized way. To orchestrate this increasingly complex energy system, digitalization and new forms of digital interaction are needed. However, the energy transition cannot succeed on a mere technical, economic or regulatory basis alone. More participation is needed to convince people to actively participate in the energy transition. Energy communities are an important way to incorporate all these paradigms into one concept. They offer a solution for shaping the energy transition locally, by participatory elements, building on digitalization.

The relevance of energy communities is explained below in section 1.1 as the key motivation of this work. In section 1.2, the most relevant research questions are derived.

## 1.1 Motivation

Mitigating climate change is one of the greatest challenges current and future generations are facing. Since industrialization, mankind has exploited the fossil resources of planet Earth, destroyed its ecosystems and changed its climate. Although science has been pointing out for decades that steps must be taken to save the climate, progress is still insufficient. Failure to act has resulted in in global warming scenarios with a temperature increase of 4°C by the end of this century, which would cause massive climatic, environmental, and humanitarian disruptions [7].

An integral part of both problem and solution is the energy sector. In 2019 (pre Covid-19), the energy industries accounted for a total of 24.1 % of global greenhouse gas emissions by IPCC source sector [8]. To achieve zero-emissions until 2045, the energy sector needs to be decarbonized using renewable energy sources such as solar, wind and hydropower [9]. The switch to renewables involves, in particular, a strong decentralization, due to solar power. These plants are magnitudes smaller than existing large-scale power plants that have shaped the energy system to date. Digitalization is an integral part of the energy transition, to orchestrate volatile demand, supply and the grid in a renewable energy system. It is necessary for the integration of small renewables into the energy market, to offer new, accepted and sustainable business models and value-added services, down to their billing, accounting and reporting. Hence, the needed energy transition can only be achieved with sustainable, scalable, secure and economical digital transformation. Hence, upcoming smart meters enable a wide range of new interaction, participation and business models.

However, to fully utilize digitalization, todays energy-economic processes need to be adapted. In [10], Strüker et al. show necessary adaptions of today's energy system to become a "real time energy economy" including millions of renewables, electric vehicles, energy storage facilities, consumers and new ways of interaction. These systems need to be interconnected, receiving necessary information to optimize themselves, e.g., towards lower costs, emissions or grid congestions. To achieve a high market integration even of small renewables, consumers and storage facilities, the rework of roles and responsibilities especially for small market participants and a reduction of static electricity price components (i.e., taxes, levies) is required. Additionally, price components should be changed in such a way that a better consumer behavior, e.g., towards grids, markets or the energy system is achieved.

Strüker et al. highlight, among others, the importance of transparent market data, the evolution of market processes and secure and optimized data exchange. The advantages of this target system include high liquidity and more efficiency on energy markets, increased security of supply and incentives for flexibility [10].

At the same time, a paradigm shift in German and EU regulation can be observed to "accelerate the deployment of renewable energy and to remove all obstacles and barriers" [9]. The energy sector, which accounts for 75 % of EU greenhouse gas emissions, is a key sector to achieve zero emissions in 2050, with a reduction of at least 55 % by 2030 [11]. In Germany, the governing parties have agreed that electricity from renewables should be used predominantly in the region where it is generated, as well as strengthening citizen energy communities and energy sharing. [9] In the "clean energy package", the EU included citizen and renewable energy communities as an instrument to include small renewables into the market, to increase participation and local value creation as well as acceptance for new renewables [12]. Both EU and Germany consider adapting and simplifying existing legislation, administrative barriers and approval periods to reach those targets. This enables citizens to participate in the energy market, e.g., by peer-to-peer (P2P) energy trading or energy sharing. Therefore, energy communities can be considered both an enabler and a critical success factor for the decentralized energy transition [13]. They give incentives to build new renewables, use available flexibility and integrate them into the energy system. Through energy communities, citizens can work together to actively shape the energy transition, e.g., by investing in renewables or by sharing or selling their own surpluses with neighbors to achieve decarbonization. Shared investments in renewables, hydrogen, electric vehicles or storage facilities, custom pricing models, sharing surplus electricity and new governance models in the local energy community are a manifestation of democratization and participation.

However, even though energy communities may provide advantages for multiple stakeholders, a common challenge among EU member states is the regulatory barriers as well as the complexity of their implementation. Regardless of the method of implementation, it must be ensured that rules are complied with, and that everything is properly accounted for and handled. Especially in cases with reduced taxes, charges and levies, a clean distinction of energy origin must be made, so, for example, it is necessary to determine whether the electricity comes from within a house, the same low-voltage grid, the community or shared asset, or from outside. While smart meters provide the infrastructure for this, the processes for the delineation of electricity quantities have not yet been established (in Germany). In the project InDEED (FKZ: 03EI6026A), a framework was developed (see [A1,14]) that is capable of bridging the gap between smart meters and any use case that requires a tamper-resistant and transparent labeling of energy supply and demand. Building on this framework, implementation proposals for energy communities are developed and described in this work. The potentials of these proposed energy communities are modeled, using a newly developed community simulator.

Parallel to these developments in the energy sector, machine learning methods have become more usable in recent years. Unsupervised learning can help recognize patterns and outliers in datasets, compress information of data, select viable samples or expand knowledge. Supervised learning can help to speed up an existing simulation model by replacing parts of the model or the model in its entirety. A secondary goal of this dissertation is therefore to incorporate machine learning into the energy-economic modeling process of energy communities and to examine where and how it can improve it.

## 1.2 Research Questions

While energy communities are already the subject of scientific research, this paper will analyze the necessity of a labeling framework in energy communities and model in which regions of Germany they are viable. To improve this modeling process, supervised and unsupervised machine learning methods are applied.

The following research questions are being answered in the course of this dissertation:

- RQ1: How can use cases of a framework for electricity labeling in the context of "Energy Communities" be developed and described ?
- RQ2: How can the potentials of the use cases be modeled and evaluated using a simulation framework?
- RQ3: How can clusters and representative regions be determined by unsupervised machine learning methods and applied in the modeling process of German "Energy Communities"?
- RQ4: How can supervised machine learning improve energy-economic modeling processes?
- RQ5: What potentials of regional direct marketing and prices are emerging in German "Energy Communities"?

An overview of the complete methodology to answer these research questions is outlined in section 2. A background on the current state of energy communities is provided in section 3. For their description, a methodology is developed, building on the use case methodology and requirements engineering process (section 3.1). These use cases include local energy sharing communities, local energy markets and regional direct marketing. They can be implemented using the labeling framework, described in [A1] and [14] (section 4). The optimization-based allocation method of this framework is then applied using a simulation framework to determine the potential of the use cases in different municipalities in Germany. To reduce computation time and cost, methods of machine learning are incorporated into this process in sections 6 and 7. Both energy-economic results and the machine-learning assisted simulation process are assessed in sections 8 and 9. The methodology, models and results are discussed in section 10. In section 11, a conclusion and outlook are provided.

# 2 Overview of the Research Methodology

In this dissertation, I use multiple methods in conjunction with each other which are summarized in this section. I developed and applied these methods to answer the research questions in section 1.2. In the respective sections, I describe the applied methods in more detail alongside literature reviews about the current state of science and technology.

Figure 2-1 depicts the structure of this work. The structure includes three parts, which are applied in a resulting model. This is followed by a result interpretation and synthesis.

The first part of this dissertation is the energy-economic analysis of a framework for the labeling of electricity in the context of energy communities. This includes energy-economic, regulatory and technical backgrounds, a method for use case development and design, implementation proposals for three **use cases**, a simulation framework and the result interpretation. The second part is a **simulation model** which simulates the proposed use cases to determine energy-economic potentials. The third part addresses the application of **machine learning** methods into the modeling process, to reduce computational costs and simplify the result evaluation. These three parts and an interpretation of the results are structured as follows:

1. **Use Cases:** in the first part (covered in sections 3 and 4), I outline the state of the science and technology of energy communities, to derive subsequent use cases with a focus on their technical implementation and processes. This includes existing systems, processes, digital infrastructure and the regulatory framework, introduced in section 3. I apply the use case methodology in conjunction with a requirements analysis, as introduced in section 3.1, to describe the used labeling framework as well as the downstream use cases from the context of energy communities in section 4. The goal of this part is to provide domain backgrounds, and depict existing challenges, regulatory requirements, existing projects and technical frameworks about energy communities. Based on this, I develop and describe energy-economic use cases for energy communities.
2. **Simulation:** the second part (outlined in section 5), is an energy-economic simulation framework to determine high-resolution results of the described use cases (i.e., resulting potentials or prices in different communities). The simulation framework builds on multiple existing datasets and includes subsequent use case modules. These use case modules are independent of each other and involve, e.g., linear programming, multi-agent models and allocation or pricing models. I investigate how the potentials and characteristics differ within Germany and provide an evaluation and interpretation of the results in section 8.
3. **Machine Learning:** the third part builds on the fact that (bottom-up) energy-economic simulations (like those in part 2) are computationally expensive and require the simulation of a large population. I integrate unsupervised (see section 6) and supervised machine learning (see section 7) methods into the modeling process, to improve the runtime performance while retaining high accuracy. The combination of simulation and machine learning methods allows to generate high-resolution results for a big population of simulation parameters in a reasonable timeframe. The applied methodology includes the sampling of simulation parameters, emulation-/surrogate-modeling (ESM) and model evaluation in section 7.

I assess the regional energy-economic potentials of the use cases in Germany in section 8, by combining simulation framework and machine learning (emulation-/surrogate-modeling). Further, I analyze the contribution of machine learning models in the applied scientific modeling process in section 9, based on the learnings of previous sections. Finally, I provide a discussion of methodology and results in section 10 and a conclusion and outlook in section 11.

I describe the methods, used in parts one, two and three, in their respective sections along with a literature review of the status quo of science and technology. Figure 2-1 provides an overview of these methods.

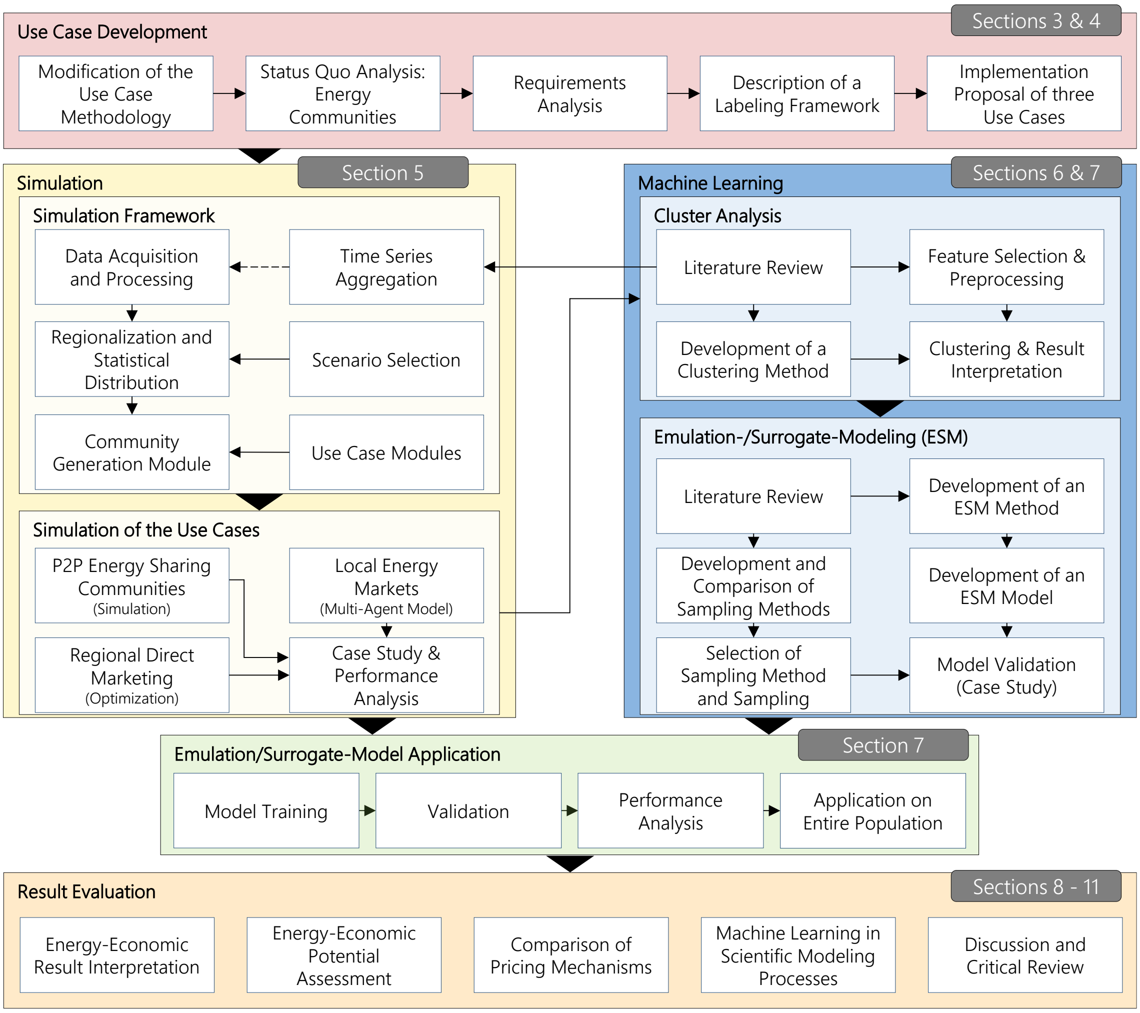


Figure 2-1: Overview of the research methodology split in three methodical parts: use cases (red), simulation framework (yellow) and machine learning (blue). Machine learning and the simulation framework are combined in the application of the Emulation-/Surrogate-Model (green). The results are evaluated and discussed (orange)

In the following, I summarize the multiple building blocks of this dissertation in more detail and give references to the corresponding sections in this work.

### 1. Use Case Development

In this block, I apply the "use case methodology" as a basis for the use case development in section 3.1, as proposed in [15] and [16]. It is used to develop and describe use cases in standardization. I modify the methodology by including aspects of requirements engineering to align the development of use cases with stakeholder requirements. A main goal of this work is the energy-economic potential assessment of selected use cases, in the context of energy communities, building on a newly developed labeling framework. I define the term "energy community" in section 3.2 and provide a comprehensive overview of the current state of science and technology in Germany and

EU member states. Sections 4.1 and 4.2 present a newly developed "labeling framework" for electricity, building on [A1] and [14]. This includes regulatory requirements, the upcoming smart meter infrastructure and stakeholder requirements in sections 3.2 and 3.3.

Based on the status quo of energy communities, the importance of the labeling framework is highlighted in section 4. It is necessary to allocate and delineate electricity towards third parties to verify claims for incentives or refunds of disproportionate costs and to provide information about the origin of electricity and resulting greenhouse gas emissions. Section 4.1 contains the description of the labeling framework and its implementation in section 4.2. I present implementation proposals for three use cases in the context of energy communities in section 4.3.

In this section, I answer **RQ 1: How can use cases of a framework for electricity labeling in the context of "Energy Communities" be developed and described?**

### 2. Simulation Framework and Simulation of the Use Cases

Based on the introduced and described use cases, I develop and describe a simulation framework in section 5. The framework allows to generate a digital model of German municipalities with a high level of detail. Input data (including data acquisition, processing and regionalization) is provided in sections 5.1 and 5.2. These processes are included into the community generation module, which is the basis for the subsequent use case modules.

Individual use case modules determine prices in local energy sharing communities (simulation), local energy markets (multi-agent model) or derive the potential of regional direct marketing (optimization). To depict future developments, I select and describe a scenario in section 5.2. Since the use cases require a high spatial and temporal resolution, which leads to high computational costs, it is only possible to simulate a small part of the approximately 12,000 municipalities. To improve the simulation time, a time-series aggregation is performed in section 7.3.

Two case studies to show the capabilities of the framework are provided in section 5.5. Respective use cases are simulated in section 8. However, the framework's high temporal and spatial resolution comes with high computational costs.

This section answers **RQ 2: How can the potentials of the use cases be modeled and evaluated using a simulation framework?**

### 3. Cluster Analysis of German Municipalities

The high computational costs conflict with the intended assessment of energy-economic potentials for all German municipalities. For this reason, I utilize various methods from supervised and unsupervised machine learning to derive the results for all municipalities.

I use unsupervised machine learning (i.e., clustering) in section 6 to identify relevant clusters for the respective use cases or to approximate energy-economic potentials by utilizing the simulation model and representative municipalities. I assess how unsupervised learning can be used in this context for pattern recognition, outlier detection, information compression, and knowledge expansion. I developed a method for cluster validation in [A2], tailoring an individual composite cluster validation index for individual clustering goals. This method and the preliminary literature are summarized in sections 6.2 and 6.3. Used datasets, data preprocessing, as well as the application of the methodology are summarized in sections 6.4 and 6.5. I evaluate and interpret resulting clusters in section 6.6 from a mathematical and energy-economic perspective.

In section 6.7, I show the capabilities of clustering in energy-economic modeling processes with large populations and propose a workflow for practitioners. Furthermore, I assess whether cluster representatives are sufficient to assess the potential of the use cases in Germany. Additionally, clustering helps interpreting simulation results and reducing the population and hence the necessary simulation runs.

In this section, I answer **RQ 3: How can clusters and representative regions be determined by unsupervised machine learning methods and applied in the modeling process of German "Energy Communities"?**

**4. Emulation-/Surrogate-Modeling (ESM)**

The clusters support a later sampling process for an emulation-, surrogate- or meta-modeling process (ESM). I summarize my preliminary works and apply time-series aggregation and emulation/surrogate-models in section 7. In ESM, the simulation model is substituted with machine learning after a training phase. A summary of the current state of science and technology is provided in section 7.1 and the methodology of ESM is depicted in section 7.4. To improve the training, a viable training set has to be sampled from the dataset (section 7.2). In [A3], I described and validated multiple sampling methods as well as time series aggregation to reduce computational costs of the simulation framework. I use a case study in section 7.5 to show the viability of the method bevor I apply it in section 7.6 on the use cases of this dissertation.

**5. Emulation-/Surrogate-Model Application**

The simulation framework and the ESM method are merged in section 7.6. The simulation is used to generate data to train and test the machine learning models. The sampling, time series aggregation as well as training and validation process, including input-data descriptions, are described. In the same section, the models runtime performance and accuracy, using multiple error metrics, is assessed.

In section 9, I provide a summary of machine learning in scientific modeling processes based on literature and the learnings in this dissertation (sections 6 and 7), answering **RQ 4: How can supervised machine learning improve energy-economic modeling processes?**

**6. Result Evaluation**

I present individual energy-economic assessments of the selected use cases in section 8, comparing the resulting prices and analyzing their synergies. The data for this assessment is generated partly by the simulation and the ESM. I interpret the energy-economic potentials and compare different pricing mechanisms. A special focus is set on regional differences in Germany. The clusters of section 6 are used to assess the potentials. In a qualitative potential assessment (see section 8.5), I discuss the requirements and value propositions from sections 3.2, 3.3 and 4.3 and align them with the simulation results, costs and practical considerations, to answer **RQ 5: What potentials of regional direct marketing and prices are emerging in German "Energy Communities"?**

Section 10 discusses the methodology as well as the results. Section 11 gives a summary and outlook.

# 3 Energy Communities

As specified in the "Renewable Energy Directive II" (RED II) and the "Internal Market for Electricity Directive 2019" (IEMD) by the EU, even small renewables and consumers should be able to participate in renewable or citizen energy communities. This section shows multiple definitions of energy communities and the necessity to include a labeling framework and pricing mechanisms. The methodology to develop and describe use cases in energy communities is provided in section 3.1.

## 3.1 Modified Use Case Methodology

In this section, I describe the methodology to develop and describe the use cases, building on the first steps of the "use case methodology", designed for and used in standardization [15, 16]. "The concept of use cases originates from software engineering and the main focus is on the description of general functionalities of systems under design and their environment. The description of use cases is independent of design specifics and allows the identification of requirements" [17].

In order to develop a use case including a viable business model from an idea or concept, various steps are necessary. This structured approach ensures that no aspect is overlooked. The standardized approach further ensures comparability and its possible transfer to standardization. The use case modeling process is based on [15, 16], was modified in [18] and tailored to the requirements of practitioners in [19]. While the use case methodology requires a vague concept as a starting point to be applied, an important part of use case development is the assessment of requirements, prior to the development of use cases. Hence, I include aspects of "requirements engineering" which aim to provide a more profound understanding and documentation of requirements and stakeholders' needs into the use case methodology, to align value propositions of the use cases. Therefore, I use elements from this method to address weaknesses of the use case methodology in this regard. The process of requirements engineering is described in [20] by the following steps, including an understanding of the domain of the application, the problem, the business context and stakeholder needs and requirements [20].

The way I combine and apply these two methodologies (requirements engineering and use case methodology) in this work is depicted in Figure 3-1. The focus of this thesis is the energy-economical assessment of the use cases. Their description, involved stakeholders, regulatory boundaries as well as basic processes are necessary to understand their functioning, value propositions and context. This section will focus on a high-level description of the use cases, as this is sufficient for the understanding of this work. An implementation requires more detailed elaboration, which, however, is not within the scope of this work.

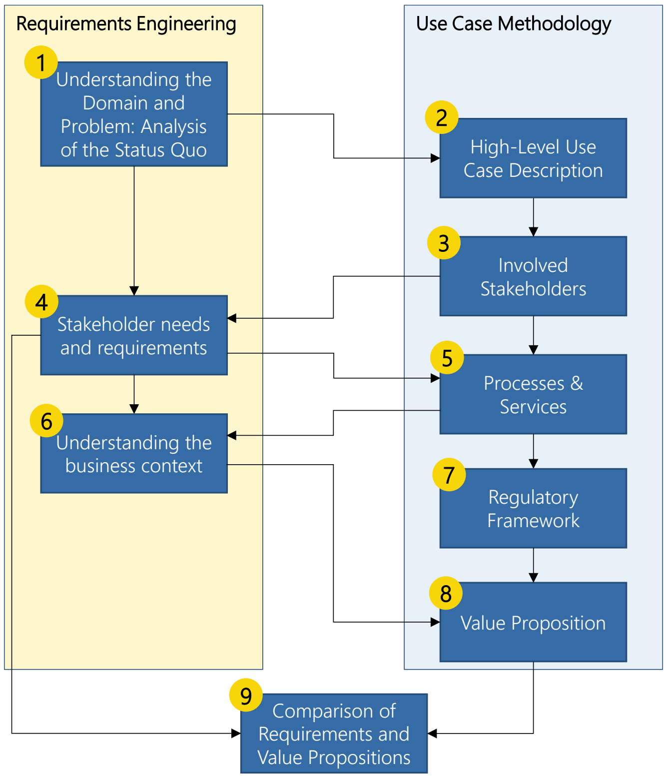


Figure 3-1: Use case development process including elements of the use case methodology (blue) and requirements engineering (yellow)

In order to develop the use cases, I conducted an analysis of the status quo **(1)** of the guarantees of origin registry in [A1], which is the basis of the labeling framework (section 4.1). In [A1], the domain, challenges as well as the involved stakeholders, as suggested by the requirements engineering, are shown. To further describe domain and problem, a definition of energy communities, current state of science, and adaptions in other EU member states are given in section 3.2 Additionally, stakeholder as well as technical and infrastructural needs and requirements are assessed in sections 3.2 and 3.3. The status quo of domain and problem are the basis for a high-level use case description **(2)** of the labeling framework in sections 4.1 and 4.2. Implementation proposals for three use cases, building on this framework, are developed and described by user stories in section 4.3. User stories are used in agile development processes (e. g. Scrum) to develop software, products or services based on a common understanding of requirements. An advantage of user stories is the integration of different stakeholder-views into the process [21]. The template for user stories includes: "As a {role}, I want {goal}, [so that {benefit}]"[22, 21].

Involved stakeholders **(3)** as well as the processes and services **(5)** are identified and formally described within each use case by the application of the Unified Modeling Language (UML) use case diagram. This method provides a deeper understanding of the use cases, the necessary services and the roles of various stakeholders as well as their interaction.

The use case methodology provides the toolkit to elaborate the processes in increasing detail, using different methods (i.e., sequence or activity diagrams). However, since the goal of this thesis is not the implementation, but the use case development and evaluation, the focus for processes and services is set on a high-level description. For an implementation (out of scope), a more detailed description of the processes and services is required.

Janzen et al. [20] suggest to not rely on identified stakeholders directly for their needs, since they often describe their needs within the existing business processes and rely on the existing system.

Additional documents, standards, laws and literature as well as existing systems are to be utilized to support the process of identifying problems and stakeholder needs and requirements **(4)** [20]. Additional information is extracted from the status quo and specific literature, as done in sections 3 and 4. These non-formalized steps outline the background and requirements of the stakeholders and their business context **(6)**, which is necessary to propose suitable new use cases and understand their implications.

Since the energy sector is highly regulated, a brief regulatory assessment **(7)** is performed to identify relevant laws and regulations for the use cases, often limiting their viability. Based on this, the value propositions are summarized per use case **(8)**. The goal of this dissertation is to evaluate whether the value propositions of each use case match the requirements of the involved stakeholders.

Due to reasons of scope, the corresponding business models will be specified and assessed in later publications. Since the requirements engineering is used to identify requirements of the stakeholders and the use case methodology provides value propositions, these two results are compared **(9)**. This last step helps to identify potential gaps on the use case side to satisfy (if possible) all stakeholder requirements.

The requirements engineering steps are carried out in section 3. The use case methodology part is used separately for all use cases in section 4. The comparison of requirements and value propositions is done in section 4.4 and summarized in section 8.5, supplemented by the potential assessment.

In the following, I provide the definition, status quo, domain and problem of energy communities.

## 3.2 Domain and Definition of Energy Communities

The need for new ways to integrate small and medium distributed energy resources into the energy system is rising due to the energy transition, electrification, and sector coupling. Increasing digitization allows new ways of peer-to-peer (P2P) interaction. Energy communities (EC) are one way to bring the four trends of decarbonization, digitalization, democratization, and decentralization together [A3].

According to [23], a community can be defined by geographical constraints or common goals and interests. In [13] an energy community is defined as a "group of individuals (citizens, companies, public institutions) who voluntarily accept certain rules in order to act together in the energy sector to pursue a common goal." The authors further remark that their common goal within a community is not only the price but regionally produced electricity, $CO_2$ reduction, participation in the energy system or improving the quality of energy supply. A local market may be advantageous if there is sufficient demand and supply [24].

Energy communities enable energy purchasing as a group, managing of demand and supply, provision of energy-related services and of mechanisms that promote energy-related behavior change [13]. In European legislation, a further distinction is made between renewable energy communities (RECs) in RED II and citizen energy communities (CECs) in IEMD. Both aim to strengthen "active consumers'" (i.e., prosumers') participation "individually or through citizen energy communities, in all markets, either by generating, consuming, sharing or selling electricity, or by providing flexibility services through demand-response and storage" [25]. "Flexibility describes the technical capability of a plant (flexibility provider) to change the current and/or forecasted output (…)" [26].

In contrast to CECs, RECs are not only limited to electric energy, according to EU legislation. A distinction is depicted in Table 3-1.

While the directives specify possible participants, non-discriminatory participation, the use and prioritization of common assets, the lift of unjustified regulatory and administrative barriers as well as the possibility to access the markets, they do not specify any details about internal mechanisms to invest, share, trade and/or allocate energy. According to art. 15 IEMD, active customers (= prosumers) may operate an RE operation directly or through aggregation, may "provide several services simultaneously, if technically feasible" but are also responsible for their caused imbalances. RED II defines peer-to-peer (P2P) trading as the "sale of renewable energy between market participants by means of a contract with pre-determined conditions governing the automated execution and settlement of the transaction, either directly between market participants or indirectly through a certified third-party market participant, such as an aggregator."

Table 3-1: Difference of CEC and REC, according to IEMD and RED II adopted from [12]

| | CEC | REC |
|---|---|---|
| EU Directive | DIRECTIVE (EU) 2019/944 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 5 June 2019 on common rules for the internal market for electricity and amending Directive 2012/27/EU (IEMD) | DIRECTIVE (EU) 2018/2001 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 11 December 2018 on the promotion of the use of energy from renewable sources (RED II) |
| Purpose | Supply, consumption, storage, aggregation and distribution of **electricity**; other energy services | Production, consumption, storage and **selling** of **renewable energy** |
| Geographic Boundaries | - | In proximity of community renewable energy projects |
| Participation | Controlled by members or shareholders, including citizens, small and medium-sized enterprises (SME), public authorities | Controlled by autonomous local members or shareholders; exclusively citizens, small and medium-sized enterprises (SME), local authorities |
| Regulatory Framework | Elimination of unjustified costs and administrative barriers | |
| | To create a level playing field | Promote and facilitate RE development |
| Grid | The operation of the local grid by the community is optional and up to the member states. | - |
| Autonomy | Medium and large companies may not control the CEC | Community may be controlled by a SME |
| P2P Trading and Sharing | Allocation based on economic principles [13] | Sharing and automatic execution and billing of peer-to-peer transactions explicitly mentioned |

In RED II, the EU introduced another mechanism to favor renewable self-consumers (RSCs) by entitling them to "generate renewable energy, including for their own consumption, store and sell their excess production of renewable electricity, including through renewables power purchase agreements, electricity suppliers and peer-to-peer trading arrangements, without being subject (...) to discriminatory or disproportionate procedures and charges, and to network charges that are not cost-reflective". Since members of an RSC can also share an RE and use the public grid, a clear demarcation from REC or CEC is not possible in this regard without more detailed regulatory specification.

Since the EU leaves room for interpretation in the design of these three concepts, the focus of this work will be laid on "renewable energy communities", due to their geographic limitation and the possibility to include a variety of automated allocation and trading mechanisms. Their geographic limitation allows the assessment of regional discrepancies and conditions in Germany. The differences of pricing mechanisms are shown by comparison of local energy sharing communities

(LES, see section 4.3.1) and local energy markets (LEM, see section 4.3.2). The workings of the labeling framework and the subsequent allocation method is shown in the use case “regional direct marketing” (RDM, see section 4.3.3).

The terms used in this dissertation are delimited in Figure 3-2.

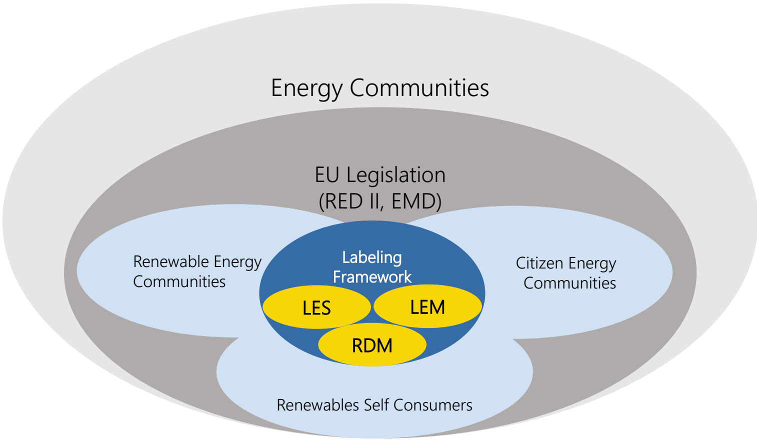


Figure 3-2: Used terms in the field of “Energy Communities”

The term “Energy Community” (EC, short: community) is used as a generic term for all concepts in this work, surrounding a group of stakeholders which “voluntarily accept certain rules in order to act together in the energy sector to pursue a common goal” [13]. The terms “Renewable Energy Community” (REC), “Citizen Energy Community” (CEC) and “Renewable Self Consumers” (RSCs) are used only when referring to EU legislation. These three concepts are the basis for the three use cases, discussed in section 4, building on the labeling framework. The use cases include “Local Energy Sharing” (LES), “Local Energy Market” (LEM) and “Regional Direct Marketing” (RDM). The stakeholder perspective on energy communities is highlighted in the next section.

### 3.2.1 Stakeholder Perspective on Energy Communities

The motives and non-functional requirements for different stakeholders towards energy communities are summarized below, based on a literature review. Non-functional requirements are a subject of debate in the field of requirements engineering. Although there is no universal consensus about the definition, they are used in the following to describe the “external constraints that the product must meet” from an energy-economic perspective and they are used to “specify criteria that can be used to judge the operation of a system” [27]. They are derived from the motivation to participate in EC.

A stakeholder is a person or an organization that has a motivation to participate in a system and (directly or indirectly) influences the requirements of the system under consideration [28]. The stakeholders involved in EC include utilities, consumers, RE operators and regulators. In addition to the regulator’s perspective, a systemic view on the system will be provided, as the task of the regulator is to ensure energy-economic compatibility and higher-level goals (e.g., the success of the energy transition and decarbonization goals). As energy communities are integrated into the energy market, many other market actors are involved in today's processes (i.e., DSO, TSO, tax and customs offices, certification authorities etc.). However, since these are only necessary for market processes due to current legislation, they are not considered below. In the use cases (section 4), they are summarized as authorities or other involved third parties.

Small and Medium-Sized Enterprises (SMEs) can participate in EC and even control REC, according to RED II. Their reasons for participating largely coincide with those of consumers. Since the focus of this work is set on private consumers, prosumers and RE plant operators, SMEs are not considered in this section.

**Regulators and Authorities**

From a regulatory and system perspective, the energy transition must be as ecological, economical and safe as possible. The motivation to establish energy communities can be summarized as follows:

- A challenge in today's energy market is the integration of decentralized, unsubsidized renewables [29]. EC help integration RE locally without the need for integration, i.e., in wholesale markets [13].
- The energy transition is slowed down by a lack of acceptance for renewables among the local population. This "not in my backyard" (nimby) effect can be overcome by a more active involvement of the local population [30, 31, 32].
- Due to their dependence on weather conditions, RE leads to large fluctuations and simultaneities in electricity generation. This causes grid congestions, resulting in high costs for grid expansion. Among other measures, flexibility is a viable method to mitigate these fluctuations [33] Therefore, (local) mechanisms are needed to incentivize flexibility [13].
- Currently, renewables are built in regions with high potentials, often far away from energy consumers. A more demand-oriented expansion of renewables leads to reduced transmission distances and a cellular energy system. This, however, requires incentives reflecting the local demand [13].
- The integration of energy communities and multiple use cases (i.e., power purchase agreements (PPA), renewable self-consumers), requires the use of the public grid infrastructure. Processes are needed to delineate and account for the monetary incentives envisioned by the EU in these use cases.
- Energy vulnerable or poor households should be alleviated by matching local production and demand, resulting in reduced electricity prices; wider and long-lasting consensus on complex multi-level investment and policy decisions related to energy strategies for a low-carbon future [34].
- The participation of citizens in the energy transition should be increased by allowing them more active engagement. [13].
- A viable business model for the continued operation of renewables after EEG subsidies needs to be created to prevent their deconstruction and incentivize repowering [13].
- Realizing dynamic electricity pricing for consumers (as per IEMD article 11), as demanded by the EU.
- Current developments, e.g., in the field of hydrogen or biological and synthetic fuels (e.g., see [35]), require proof of origin and delimitation of the type of generation across sectors. In the heat sector (i.e., power-to-heat), a proof of origin is also required to verify green products for heating or cooling.

According to RED II, local authorities can be shareholders or members (including municipalities) of EC. Local authorities strive:

- to reach their own climate targets [13, 36]. To achieve this, an increased acceptance of the local population is needed [13],
- for local value creation and employment opportunities [37, 34],
- to improve regional attractiveness for businesses, i.e., by a low carbon footprint and low energy costs, [38, 39],
- to increase social acceptance and dialogue between specialists and non- specialists [34],
- to create trust in local representatives and municipal governments [40, 13],
- for energy independence and self-sufficiency [41, 13].

From these motivations of regulators and (local) authorities to establish EC, the following non-functional requirements are derived:

- a secure, safe and scalable implementation (i.e., by fulfilling "General Data Protection Regulation" (GDPR) requirements) building on the secure smart meter infrastructure,
- compliance with legal and other requirements,
- integration of sector coupling,
- reduced electricity prices to alleviate vulnerable or poor households,
- clearly defined, transparent, non-discriminatory and verifiable rules within energy communities (IEMD, article 5),
- since energy consumption related data is sensitive and personal information, it is covered by the GDPR. Hence, any implementation needs to be compliant with the GDPR.

**Utilities and Energy Service Providers**

Utilities are service providers in the context of energy communities. Instead of selling a commodity product to passive consumers, they may operate the EC, manage energy-economic responsibilities and handle residual loads. Unlike for the other stakeholders, who profit from ECs, they result in higher operational expenses and lower sales of electricity for the utilities (or ESP). The main goal of utilities to establish and coordinate ECs include:

- the development of new business models in the context of energy communities,
- marketing advantage to sell locally produced RE production,
- long-term customer loyalty.

From these motivations, the following non-functional requirements are derived:

- a recognized and easily verifiable method to prove the origin of electricity and to allocate electricity within an EC.
- high and stable long-term revenues,
- monetary incentives or reduced costs,
- a framework to provide high temporal and spatial information about the origin of electricity to provide the information to their customers,
- integration of energy communities in the wholesale markets,
- tamper-resistant verifiability of compliancy to set rules towards third parties (e.g., authorities, regulators and grid system operators).

**Distribution System Operators**

Due to unbundling, DSOs are not directly involved in energy communities. However, as Austria shows (see section 3.2.3), the DSO may be in charge for the allocation, settlement, or billing of electricity within different use cases of an EC, including:

- reduced peak loads, increasing network efficiency, improving system reliability [42]
- incentives for the use and the addition of flexibility (e.g., via dynamic pricing),
- transparent and simple allocation of electricity i.e., for reduced network charges or other financial benefits within energy communities.

From these motivations, the following non-functional requirements are derived:

- the reflection of demand and supply in the price to incentivize flexibility and demand-oriented expansion of renewables [A5],
- smart meter integration,
- clearly defined, transparent, non-discriminatory and verifiable rules within energy communities,
- delineation of different use cases and claims regarding monetary incentives within energy communities,
- consideration of distribution grid constraints.

**RE Plant Operators and Investor**

RE operators and investors are a key part of EC. They invest their (private) money into building RE and provide electricity to the community. Their value requirements to participate in EC include:

- the mobilization of private capital [34] for investments and mobilizing additional, local investors [36],
- more stable and better prices than on wholesale markets, [43],
- additional revenues,
- local support for building new and repowering old RE [36],
- increased environmental benefits and technical, institutional values to the entire community (instead of only individual benefits) [A4],
- a business model for the (continued) operation of renewables.

From these motivations, the following non-functional requirements are derived:

- a pricing mechanism providing additional revenues and better prices than on wholesale markets,
- incentives for the demand-oriented expansion of renewables.

However, since administrative barriers are still high, requirements include simple processes and low administrative barriers to participate in EC.

**Private Consumers and Prosumers**

The role of private consumers changes within energy communities. They can actively take part as volunteers, participants, or investors to fund new or existing projects. Local investors tend to support

RE projects run by social enterprises and cooperatives more often than if run by large investors, as these projects tend to be smaller and focused on environmental goals [42].

Based on a survey in [42] among 115 participants of existing energy communities mostly from Portugal, Spain and Belgium, the most important motivations include the contribution to funding and revenues, collective procurement and the trust and support of local investors.

The goals of private (active) customers to participate in energy communities are summarized below:

- maximization of own consumption within the energy community, [13],
- local value creation and energy exchange, more efficient use of resources and improved economic efficiency [13],
- trust, confidence, social connection with the community or special institution, strong connection and identification [42],
- increased environmental benefits and technical, institutional values to the entire community (instead of only individual benefits), [A4],
- reducing the $CO_2$ emissions in the community and decreasing the dependency on imported energy [A4],
- additional income through flexibility services or sales of energy, local economic growth and contribution to local prosperity, [34],
- economic benefits for individuals or the entire community; fair market design [A4].

From these motivations, the following non-functional requirements are derived:

- reduced costs of consumed electricity, long-term price security [A4],
- a pricing mechanism to reflect local supply and demand within the community,
- clean energy with known origin, [A4]
- an indicator to optimize towards reduced $CO_2$ emissions in the community and increased own consumption.

**Excursus: Corporate Sustainability and the Labeling Framework**

The importance of sustainability is gaining an increased momentum for businesses, e.g., due to the "2030 Agenda for Sustainable Development" [44], including 17 sustainable development goals, the "Paris Agreement" [45] and the "European Green Deal" [46] with its "Sustainable Finance Strategy" [47].

Since 2017, the EU mandates companies, financial institutes and insurance companies to report non-financial aspects of their business [48]. With the "Corporate Sustainability Reporting Directive" (CSRD) [49], the "Sustainable Finance Disclosure Regulation"(SFDR) [50] and the "EU taxonomy for sustainable activities" [51], the regulatory framework is provided for companies to include sustainability into strategy, management and reporting. In 2021, the "Corporate Sustainability Reporting Directive" suggested an extension to smaller companies with 250, instead of 500 employees. Additionally, these sustainability reports are supposed to be audited by a certified public accountant, starting in 2023.

To evaluate and report the greenhouse gas (GHG) emissions of a company, standards are provided e.g., by the "Greenhouse Gas Protocol". These standards include three scopes which can be summarized as follows:

- Scope 1: direct emissions from company-owned sources,
- Scope 2: upstream emissions from consumed (e.g., electrical, thermal) energy,
- Scope 3: emissions resulting from downstream or upstream activities of the companies (e.g., travelling, waste management)

Metrics such as scope 2 GHG emissions are mandatory in sustainability reporting requirements CSRD [52] and SFDR [53]. To determine these emissions, companies need reliable and tamper-resistant data of consumed energy as well as the resulting emissions. This data is needed for monitoring, reporting and audit purposes, benchmarking or to track and proof the progress of reducing emissions. In [54] and [55], it is stated that the consumed electricity from the power grid is to be modeled as precise as possible including "supplier-specific data". Similar specifications are also made in ISO14067:2018 [56]. In addition to regulatory specifications, demand from companies and consumers for products with low greenhouse gas emissions is increasing constantly and getting more and more media attention, including in advertisements. In order to prove that the products were actually produced sustainably (as claimed), appropriate proof and documentation is required to foster customer relations.

This section shows a number of benefits of ECs for different stakeholders. In the following, the current state of science and technology will be evaluated to see if ECs are already possible in Germany.

**Conclusion of Stakeholder Perspectives**

The stakeholder perspectives show very different motives and non-functional requirements to participate in and profit from energy communities. Despite all the environmental, social and technical reasons for participation, economic benefits are an important aspect of participation. Pricing mechanisms are hence a key factor for success of energy communities.

It is clear that both producers and consumers want to be on an equal or better footing than in the status quo. However, if none of these two main contributors are willing to pay extra for this system, either additional revenues have to be generated or another involved stakeholder (e.g., the utility) loses revenues. An additional generation of revenues could for example be achieved by the aggregation and marketing of flexibility, but it is questionable whether these incentives alone are sufficient to achieve widespread participation. Therefore, further incentives and/or the reduction of disproportionate costs have to be implemented to increase the attractiveness of energy communities to all sides. The EU proposed, among others, reduced grid fees, taxes and levies as well as regulatory barriers, reducing the cost to establish ECs. Therefore, a shared interest of all stakeholders is the simplification of processes and lowered regulatory barriers to increase the economic feasibility.

In the following, the implementation status of ECs in Germany is summarized.

### 3.2.2 State of Science and Technology in Germany

Many studies cover different aspects of energy communities. In this section, an overview of selected works in the context of energy communities is provided.

[13] gives a comprehensive description of energy communities in Germany. The authors define the word "energy community" (as introduced in section 3.2) and highlight their roles in the energy system. Additionally, they show which technologies are necessary to establish them. A focus is set on the resulting business models. Since other countries have already realized energy communities and have a more suitable digital infrastructure and regulatory framework they are compared to Germany. The study closes with the recommendations to reduce barriers to harvest the full potential of energy communities.

In [57], a concept for energy sharing is provided, trying to implement it into the current regulatory framework. The authors suggest DSO balancing areas as spatial limits for an EC, since this fits today's processes well. Even though zip-code areas, counties or voltage-levels of the distribution grid are more advantageous, the authors point out the complexity of balancing and accounting since they resemble no energy-economic dimension. Additionally, recommendations concerning balancing, determination of load profiles as well as the reduction of taxes, charges and levies are made. The authors suggest a capacity charge for the EC to incentivize grid-friendly behavior.

[58] studies the potentials of energy sharing in Germany, based on the description of energy sharing in [57]. All wind and PV plants > 100 kWp are considered. The scenario is 2030 and considers newly built and old RE, after the end of the EEG-subsidy. The considered scenario is based on the goals of EEG 2023 with 115 GW onshore wind and 215 GW PV. To determine future suitable areas for additional wind and PV, a method is proposed building on local site conditions and population. Consumer data (number of inhabitants, share of population < 18 years, average household size and average living space) is generated by Census data in conjunction with annual consumption data from [59]. The spatial resolution of the data is 1 km x 1 km. The temporal resolution is one year. The proximity of consumers to producers is limited to 25 km. The authors assume that the annual generation and consumption must be balanced in any community. In an iterative approach they assess whether a combination of RE (existing or newly build according to the scenario) and consumers can meet this assumption. Based on these assumptions and model, a total of 75,300 energy communities are identified, covering 35 % of the current RE targets in the scenario. In a next step, own consumption and impact on the local grid in these communities are approximated.

In Kett et al [60], a technical implementation of a CEC is provided, based on a platform solution building on smart meter and the blockchain-technology. Their platform is used to gather, manage and provide relevant data to stakeholders, via the blockchain-technology and smart meters. It optimizes plant operation within the community (i.e., to reduce residual loads), handles market communication with involved market participants (e.g., DSO, TSO) and visualizes the results of an allocation mechanism. The authors remark that GOs with high temporal and spatial resolution are an integral part of CECs. They highlight the importance of a transparent allocation method (they implemented an iterative first-come-first-serve mechanism) as well as digital and tamper-resistant guarantees of origin without double spending. Therefore, the platform stores and matches supply and demand on the blockchain and processes them via smart contracts. Yet, sensitive data (including supply and demand from private households [61]) on a blockchain violates the GDPR. Although the technology brings many advantages in this use case, its productive usage is therefore questionable [60].

All in all, many aspects of ECs have already been covered in various studies. Regulatory and technical hurdles in particular have been highlighted many times. Some implementation proposals can also be found in the literature. Since the EU legislation leaves a lot of room for interpretation, many questions are still open, especially in the field of technical implementation, allocation methods and price mechanisms.

**Implementation status in Germany**

RED II was passed in 2018. According to EU law [62], member states have two years to implement directives into national legislation. The deadline for implementation for IEMD was the end of 2020 and RED II mid-2021. As of 2022, RED II and IEMD were not integrated into national law in Germany regarding energy communities [13, 63, 64].

Most taxes and levies are eliminated on own consumption within a building [63]. Own consumption, requiring the public grid (as specified in Art. 21 (6) in RED II), is only exempt from electricity tax under restrictive conditions, as specified in § 9 (3a) StromStG. Renewables with a capacity of ≤ 2 MW can get an electricity tax return, if they supply their electricity within 4.5 km to consumers. However, administrative barriers are still very high, as described in section 4.3, lowering economic benefits. Moreover, this regulation has been in place for some time and was not created specifically for EC.

Already in 2016/2017, CECs were favored in Germany to participate in RE tenders more easily (§ 36g EEG). A CEC requires at least ten citizens, and a single participant may not hold more than 10 % of voting rights. A CEC may not exceed eight wind turbines with a maximum of 18 MW. Local municipalities must be given the opportunity to invest up to 10 %. This reduces administrative barriers for CECs to obtain wind power plants.

In a draft to accelerate the extension of renewable energies [65], renewable investments by CECs and RECs are supposed to be excluded from tenders. Additionally, an adaption of the RE funding and support system is made possible, i.e., to include "Contracts for Difference". In the future, there will no longer be any levies on own consumption and direct supply behind of the grid interconnection point [65]. This increases economic benefits of use cases in this field (e.g., tenant electricity) and reduces administrative barriers. Thus, it almost equalizes the shared self-supply to the individual self-supply behind the grid interconnection point. Administrative barriers of the KWKG levy and the offshore-grid levy are reduced. Remaining benefits and levies are to be standardized and streamlined. Additionally, the information about a coupling of supply and guarantees of origin is included into the current GOR [65].

All in all, it can be stated that first parts of RED II and IEMD in the context of energy communities are already or soon to be implemented into German law. The focus of German lawmakers is the reduction of administrative barriers and cost for use cases behind grid interconnection points. However, the role of prosumers, the simplification for P2P trading or sharing as well as reduced barriers and costs to establish energy communities or renewable self-consumption, while still using the public grid, is not included into the draft. Since multiple components of RED II and IEMD have to be transferred into German legislation, this leaves certain design choices for implementation. In the following, a brief overview of the design of REC, CEC and RSC implementations in EU member states, which already adapted the directive, is given. The focus is set on those use cases, including the use of public grid infrastructure.

### 3.2.3 Adaptations in EU Member States

A directive, contrary to regulations, only provides boundaries for member states to achieve certain regulatory goals, generally within two years [62]. Since RED II was passed in 2018, many EU member states have already implemented energy communities into their regulatory system [13]. Austria and France had an implementation before the clean energy package was passed.

A summary of selected implementations is given in [63] and shown below:

- In Poland, RECs were implemented 2019, allowing communities to operate renewables up to a total of 10 $MW_{el}$ and 30 $MW_{th}$. Without any spatial constraints, 70 % of the members' consumed electricity must come from these renewables. RECs do not have to pay for billing, grid fees or subsidies for renewables. Surplus electricity is fed into the grid without compensation, leading to high incentives for own consumption. 60 % of electricity, consumed from the grid is exempt from taxes and levies [63].
- In Portugal, RECs must be located around their RE. The radius is a case-by-case decision in this respect and not regulated by law. Smart meters are a requirement for this use case. RECs only have to pay for the grid levels they require, incentivizing high spatial

concentration. Surplus electricity can be fed into the grid for free or sold to a service provider for a fixed price [63].

- Spain implemented boundaries for RSCs in "Real Decreto 244/2019". Own consumption is restricted to 500 m around RE with a cumulative power of ≤ 100 kW. The public grid may be used without charge but only within one voltage level. For electricity provided by the RE, owned by the consumers, there are no electricity costs. According to [63], the definition of REC in RED II was adopted literally in "Real Decreto 23/2020" without further specifying them, leading to no practical application yet.
- In Italy both for RECs and RSCs, 50 % on the VAT and 10 €/MWh reduction on electricity tax is granted for private customers in the low voltage grid. Furthermore, own consumption is "compensated" with 10 ct/kWh (REC) or 11 ct/kWh (RSC). Surplus electricity is sold for current market prices [63].
- Austria already implemented RSCs in 2017. The public grid can be used for residual loads. For electricity provided by the RSC, no grid fees or levies are charged. Exemptions are also made on electricity tax (1.5 ct/kWh) and VAT. For realization, a smart meter is mandatory. In 2021, the regulatory framework for RECs was passed. Participants must be located within a low voltage grid and the allocation is conducted by the DSO [63]. To do so, smart meter data with a resolution of 15 minutes is required. The energy is allocated either in a static or dynamic way. The result is provided via a standardized interface to community members as well as the community operator (responsible for the residual load). Based on the allocation result as well as generation and consumption data, the billing is conducted by the community operator [66].

  Austria provided a roadmap for the integration of ECs in [66]. The authors defined multiple levels of energy communities, starting with a single RE and multiple consumers within one grid either local (step 1) or regional (step 2). Since "local" is defined by the grid topology and reduced grid fees are to be posed, depending on grid use, consumers within the same low voltage grid are to be prioritized. In a third step, multiple REs can be used in a local or regional way. In step 3, the goal is a mixed generation with multiple participants, and DSOs. A free choice of switching from own consumption, the community, trading on energy markets or ancillary services, as requested in [13], is not possible with this system.

The examples show great differences in how this directive was implemented and interpreted in different EU member states. The example of ECs in Spain shows that a pure adoption of the EU requirements does not lead to success [63]. Implementations in other EU member states show differences in the design of ECs. It also becomes apparent that RSCs and RECs cannot be separated clearly.

The designs include different monetary incentives or reduction of disproportionate costs. These include no costs for billing (Poland), electricity tax (Italy), grid fees (Poland, Austria, Spain), levies (Austria) or subsidies for renewables (Poland). Monetary incentives are given to RSCs (10 ct/kWh) and REC (11 ct/kWh) in Italy. Boundaries for a right to claim these may include, e.g., close proximity of generation and consumption (Portugal, Spain, Germany) or the use of the same voltage level (Spain, Austria). In any case, it must be verified how much electricity may be billed for these cases and residual quantities be clearly distinguished. In Austria, the reduction of grid fees, taxes and levies reduces electricity costs for consumers by 20 %. In Portugal collective self-consumers (i.e., RSC) pay 33 % less for electricity of their own RE plant. In Italy, only 4 % price reduction is granted on grid fees [67].

Based on the implementations in other EU countries, technical and infrastructural requirements are derived in the following.

## 3.3 Technical and Infrastructural Requirements

The EU directives specifies basic regulatory requirements as well as the foundation for the energy-economic realization. They do not provide any technical background. Yet, implementations and learnings from existing literature, projects and other countries make it possible to derive basic technical requirements for an implementation. These are deduced in the following:

- The basis for both all use cases (REC, CEC and RSC) is the **acquisition of data via smart meter**. Austria shows that a 15 min interval of data is necessary to conduct billing and proof simultaneity of consumption and generation. This corresponds to the usual time interval in the energy sector.
- Energy communities are not completely self-sufficient. Residual quantities need to be **imported or exported** from **wholesale markets** to cover shortfall and surplus.
- Since the EU required member states to introduce some form of **monetary incentives** for ECs, it is necessary to delineate those quantities that apply for the incentives (e.g., self-consumption within a community) and those quantities that don’t (i.e., residual loads). This must be proven to **external third** parties (e.g., DSO, TSO, authorities), which are in charge of executing the resulting payments.
- Since the monetary incentives are to the advantage of community members and disadvantage of, e.g., the state (e.g., through reduced electricity tax or VAT) or the grid operators (reduced grid charges), the allocation must be done transparently and be tamper-resistant. To **prove** simultaneity of generation and consumption as well as residual supply both on community and individual level, processes must be developed.
- An integral part of any energy community is a **pricing** mechanism to achieve behavioral change and incentives for local flexibility to increase self-consumption and reduce peaks. Based on supply and demand, allocation method as well as import and export prices, a price within the community is determined. Monetary incentives and prices are **billed** and paid by community members.
- All member states, especially Poland, provide strong incentives for own consumption within the community. This requires a) either a **community operator** who is capable of balancing local demand and supply or b) sufficient data (including forecasts) for participants to optimize their consumption themselves.
- There can be more granular incentives within communities. For example, if electricity is produced and consumed within the same low voltage grid, no medium-voltage fees need to be paid (see Austria). If consumers collectively invest in a RE, they don’t have to pay for the electricity. If consumption is in close proximity to generation, no electricity tax has to be paid (§ 9 StromStG in Germany). To delineate those quantities and provide community members with a proof of origin, it is necessary to **allocate** generation and consumption within the community.

Based on the analysis of technical and infrastructural requirements, Figure 3-3 depicts a schematic representation of the required services within an energy community. The community services are provided by the service provider.

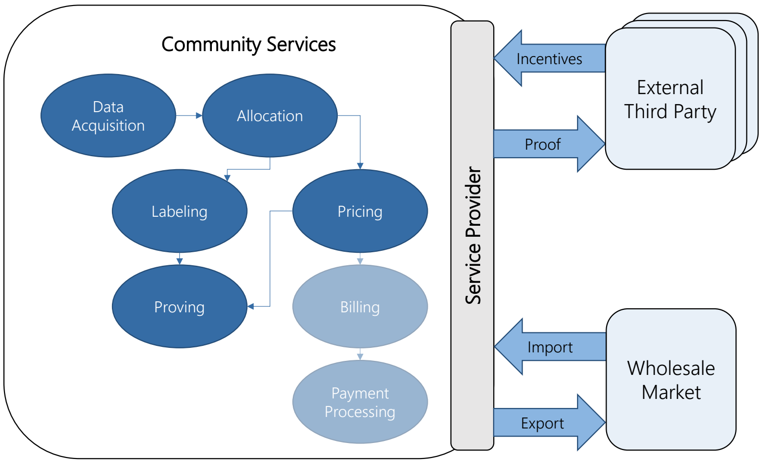


Figure 3-3: Schematic depiction of a single energy community

In this work, the labeling and proving is done with a **labeling framework**, described in section 4.1. The allocation within a community is done via an optimization, introduced in section 4.2 or via a local energy market, described in section 4.3.2, as part of this framework. Different **pricing mechanisms** are introduced in section 4.3. Billing and payment processing are omitted in this work, due to reasons of scope.

In the following, the current state of the smart meter infrastructure in Germany is provided, which is the basis for the data acquisition in energy communities.

### Smart Meter Infrastructure in Germany

Based on EU [68] and German legislation [69], smart meter infrastructure is to be rolled out until 2032 for 95 % of consumers (> 6,000 kWh/a), flexible consumers (see § 14a EnWG) and renewables > 7 kWp (§ 29 MsBG). The official rollout was started in 2020 after certification by the German Federal Office for Information Security (BSI) [70]. Depending on annual consumption or production, regulated price-caps ensure fixed annual costs. For consumers and producers under the defined thresholds, an optional rollout is possible if smart meters are technically and economically feasible.

A detailed description of the smart metering infrastructure, added value, and use cases is provided in [71]. The standardized functionality (TAF) of smart meters includes different forms of pricing such as data-saving-, time-of-use-, load-, consumption- or event-based tariffs (TAF 16). Additionally, current sum of consumption and/or generation can be read out if required or by a certain time (TAF 6, 7). Maximum and minimum power as well as current generation (TAF 8, 9) and information about the grid (e.g., voltage) can be among possible readouts. TAF 11 allows to remotely control flexible devices. With TAF 13, consumption and generation can be visualized to the consumer via the wide area network interface. Generation one Smart Meters are only capable of TAF 1,2,6 and 7 [71].

The following use cases are intended to build on the full functionality. Although the smart meter rollout in Germany is behind schedule and the rollout was temporarily stopped in 2022 [72], this work assumes that everyone has the opportunity to receive a smart meter for the defined price-caps, including all functionalities necessary.

These sections provide an overview of the domain, technical and infrastructural requirements and available technology. According to the methodology in section 3.1, stakeholder requirements are shown in the following.

## 3.4 Preliminary Summary

In this section, a methodology to develop and describe digital use cases was introduced. The methodology builds on both requirements engineering and the use case methodology, developed and used in standardization [15, 16]. This combination aims at integrating stakeholder requirements as well as domain understanding and the business context into the process of use case development. The domain of the application, the problem, the business context, and stakeholder needs and requirements were presented in this section.

The **domain** understanding is provided in section 3.2 by introducing definitions for renewable energy community (REC) and citizen energy communities (CECs) as well as renewables self-consumers (RSC), based on current EU legislation. A community builds on peers sharing or selling their surplus energy to improve economic and environmental benefits, and add technical and institutional values to the entire community [A4]. EU legislation requires member states to lower administrative barriers alongside taxes, charges and levies for energy communities (= monetary incentives), providing a **business context**.

Section 3.2.1 gives insight into the motives of stakeholders to participate in energy communities. These include better integration of renewables into the energy system, reduced GHG emissions, regional value creation, utilization of (monetary) incentives to consume and produce electricity locally, variable prices, integration in wholesale markets and incentives for flexibility. The **problems** within this domain are primarily of a regulatory and technical nature. A literature review in section 3.2.2 shows that the implementation of the EU requirements has not yet been sufficiently carried out in Germany. Requirements include the reduction of regulatory barriers and the creation of monetary incentives, or the reduction of disproportionate costs for ECs. As shown in section 3.2.3, many other EU members are further advanced in this respect, so that ECs have already been used successfully for years. However, the interpretation of EU legislation in the member states is very different. This leaves room for interpretation on how energy communities can be designed in Germany and how regulatory requirements will be designed.

The technical and infrastructural **requirements** are derived in section 3.2.3, showing the necessity for digitalization, which is currently behind schedule in Germany. Additionally, possible reduced taxes, charges and levies within energy communities need to be distinguished e.g., from residual electricity. Simultaneity of generation and consumption of residual and local supply both on community and individual level needs to be verified in a tamper-resistant, transparent and efficient way. Further to a method allocating electricity within a community, a pricing model needs to be established that accounts for locally produced as well as externally procured electricity. Any technical solution needs to fulfill GDPR requirements.

Hence, two key technical components in the context of energy communities are identified in sections 3.2 and 3.3. These two components need to delineate electricity produced and consumed inside and outside the community via a **labeling framework** and need to include a **pricing mechanism**. A labeling framework is required to prove the origin of electricity and resulting GHG emissions within the community and to allocate electricity in such a way as to make the best possible use of the available monetary incentives or refunds of disproportionate costs. The result must be proven to external third parties (e.g., grid system operators or authorities) to rightfully claim applicable incentives or cost refunds. The latter may include the refund of disproportionate costs, such as electricity taxes or grid fees or the claim of monetary incentives (as provided in Italy). The pricing mechanism needs to integrate local supply and demand of the community into wholesale markets and establish long term incentives to participate in the community.

In Table 3-2, the needs and requirements of different stakeholders referred to in section 3.2.1 towards the two components of energy communities (labeling and pricing) are summarized. In the development stage, a product's value proposition needs to be designed in such a way that it satisfies all requirements. This thesis will compare the technical, infrastructural and non-functional requirements of this section with the value propositions of the labeling framework and implementation proposals of different pricing mechanisms to validate its viability.

Table 3-2: Consolidated requirements

| **Labeling Framework** |
|---|
| guaranteeing scalability and security (i.e., by fulfilling GDPR requirements) building on the smart meter infrastructure |
| guaranteeing compliance with legal requirements (i.e., double spending) and existing processes |
| providing clearly defined, transparent, non-discriminatory and verifiable rules within energy communities |
| verifying the origin and correct allocation of electricity within the EC |
| providing an indicator about past and future $CO_2$ emissions and own consumption in the community |
| integrating multiple sectors (e.g., via power-to-heat/gas) |
| proving high resolution temporal and spatial information about the origin of electricity |
| delineating different use cases and claims regarding monetary incentives within energy communities |
| consideration of distribution grid constraints |
| **Pricing Mechanisms** |
| guaranteeing high and stable long-term revenues and providing better (sell) prices than on wholesale markets |
| reducing electricity costs, guaranteeing long-term price security to alleviate vulnerable or poor households |
| integrating energy communities into wholesale markets |
| reflecting demand and supply in the price to incentivize flexibility and demand-oriented expansion of renewables |
| Providing a clearly defined, transparent, non-discriminatory and verifiable pricing mechanism |

Since prices should reflect the fluctuations of supply and demand, static pricing models (e.g., bill sharing, as used in [A3]) are not considered in this dissertation. The requirements for pricing mechanisms cannot all be evaluated, based on an implementation proposal alone. Especially additional costs and revenues as well as economic benefits need to be evaluated based on quantitative data. This requires extensive simulations.

In the following, two use case implementation proposals for pricing mechanisms are developed and evaluated. One is based on passive sharing and one on an active trading scheme. Additionally, the only monetary incentive already existing in Germany for local consumption and generation is presented and further investigated as a third use case. All three use cases rely on a labeling framework and are part of energy communities.

# 4 Use Case Specifications

In the following section, a new way of labeling electricity is presented. This allows tracking of the balance sheet flows of electricity (not considering the physical flow) with a high temporal and spatial resolution. This system bridges the gap between smart meters and energy communities, involving small scale renewables and prosumers, which is a necessary requirement to establish, process, verify and bill energy communities. Building on the labeling framework, two pricing mechanisms in energy communities are described. Since the EU wants taxes, levies and grid fees lowered for ECs, a third use case is presented that already makes it possible in Germany to avoid the electricity tax (see §9 StromStG). It applies the allocation method of the labeling framework. The use cases are then described with the methodology introduced in section 3.1. The definition and the basics for the potential assessment in this work is laid out in section 4.5. The goal of this is not a detailed description but to build a foundation for the simulation of use cases as well as the discussion of the simulation results.

## 4.1 Framework for Electricity Labeling

As presented in section 3, the rollout of smart meters is not sufficient to map and allocate electricity within an EC and verify the result to external third parties (e.g., authorities) in a transparent, tamper-resistant and efficient way, according to defined rules. Therefore, the concept of a "labeling framework" for electricity from an energy-economic perspective was introduced in [A1] which was implemented, based on [14] in the joint project InDEED. The definition of labeling is provided in the following.

**Definition of Labeling**

In this work, "labeling" is defined as the unambiguous, transparent, and tamper-resistant digital mapping and allocation of electrical supply and demand as well as their temporal and spatial linkage, taking into account simple contractual and physical constraints.

**User Story**

Private and corporate consumers of electricity (demand) want to receive information with high spatial and temporal resolution about the origin of their consumed electricity to adjust their consumption behavior and get $CO_2$ certificates. All consumers, prosumers and RE generators want to allocate their supply to maximize and claim available monetary incentives or get refunds on disproportionate costs (e.g., electricity tax refunds) on locally consumed and produced electricity.

Authorities and involved third parties (e.g., DSO) want a simple, secure, GDPR-compliant and economic tamper-resistant process to verify claims of multiple stakeholders to receive incentives or the refund of disproportionate costs, and to oversee the compliance with regulations (e.g., no double spending).

**Reference System**

The only way to allocate the origin of electricity today in Germany is the Federal Environment Agency's (UBA's) guarantees of origin registry (GOR) which only includes the origin of electricity per generation type (e.g., hydropower, wind or PV) but neither temporal nor spatial linkage nor the verification of the adherence of physical constraints. In [A1], it was highlighted that this system is not suited to allocating supply and demand, fulfilling these requirements. Additionally, the system's processes need to be revised for better scalability, to include small-scale RE. In [13], the authors came to the same conclusion in 2022 that a key technology for the realization of EC is a functioning labeling system (according to [60], on the blockchain) in conjunction with smart meters.

Based on the assessment in [A1], a labeling framework was developed in the project InDEED. The technical use case specification is summarized in the following. This use case specification led to the technical integration, outlined in [14]. Building on this functionality, EC can be implemented more easily, as shown in section 4.3.

## 4.2 Implementation of the Labeling Framework

As described in [A1], the framework is intended to complement the GOR as a first step. This is illustrated below. Building on this (see [A1]), further use cases such as energy communities can be realized with this system in a next step, as shown in section 4.3.

### 4.2.1 Energy-Economical Processes and Services

New ways of interaction, like CECs, RECs, RSCs, local energy markets (LEMs), tenant electricity models, asset sharing, regional direct marketing etc. [73] require common basic functionalities. They can be summarized as "basic labeling requirements":

1. supplied electricity needs to be allocated from one or more RE to one or more consumers,
2. supplied electricity needs to be allocated among consumers, considering (contractually determined) rules such as ownership structure, prohibition of double spending, equilibrium of demand and supply, proximity etc.
3. supplied electricity must be differentiated between electricity from within the use case (e.g., a commonly owned plant or generation from the community) and residual load,
4. the result of the allocation must be provided, and proper execution must be proven to third parties, to ensure legal compliance of the processing.

In the following, these requirements are addressed from a technical perspective by the labeling framework.

**Technical Processes and Services**

Labeling includes the "proof of origin" for any given quantity of electricity within a discrete time step, by mapping and allocating available supply and demand. For this purpose, at least the following information is needed: the location of the energy resource as well as the type of the power plant, generation, and consumer load data. This data is then allocated according to defined rules. This can be done by allocating the supply equally among all consumers (status quo), individual assignment (e.g., based on proximity or prioritization) or other allocation methods, e.g., a market model in local energy markets. A goal of this framework is to provide participants or external parties (e.g., regulators) with information about the origin of their consumed electricity in a transparent, tamper-resistant way, while avoiding double spending and following defined rules [14]. Since electricity is allocated according to contractual or legal constraints, it is referred to the provided information within the labeling framework as "guarantee of origin" (GO). Backgrounds about the guarantees of origin registry (GOR) are provided in [A1].

Figure 4-1 shows the UML use case diagram of the labeling framework. It depicts involved stakeholders as well as their interactions, processes, and services.

As depicted in Figure 4-1, labeling requires a supply or direct marketing contract among participants, which includes the registration of consumers and RE generators, plant data and geolocation. For an allocation of generation and consumption, corresponding data must be provided via smart meters and TAF6/7 for any given allocation cycle (e.g., 15 minutes).

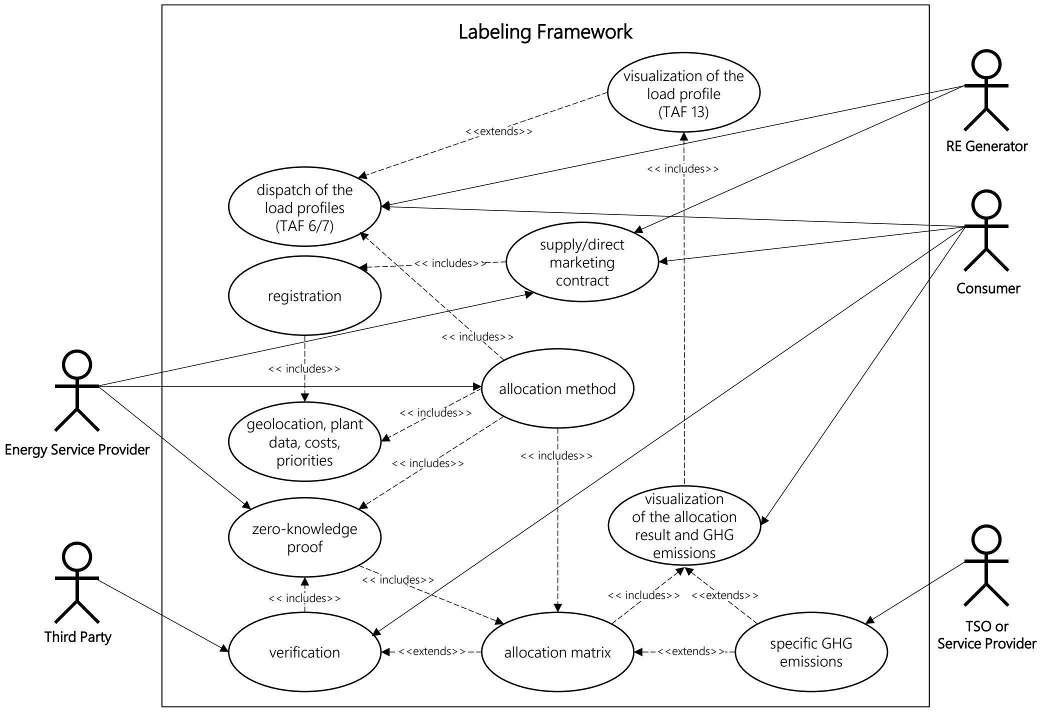


Figure 4-1: UML use case diagram of the labeling framework

In the status quo, GOs are allocated equally among all consumers obtaining a (green) electricity product. The matching cycle usually is one year, and consumption is still provided by manual readouts. The allocation in Figure 4-1 allows equal allocation (status quo) or individual allocation, matching generators with (multiple) consumers, depending on costs, proximity, priorities and/or the use case.

To provide both the allocation result and individual electricity consumption, relevant information (such as composition of the consumed electricity, plant location and type) is visualized for the consumer via a digital interface. To prove the correctness of the allocation towards third parties (e.g., authorities, DSO), consumers and producers, the energy service provider (ESP) provides a "zero-knowledge-proof" (e.g., via a Blockchain).

Excursus: Blockchain-Based Integration and Zero-Knowledge-Proofs

Blockchain-technology is based on a distributed ledger. Nodes in the network process transactions, ensure tamper-resistance and prevent double spending by a consensus mechanism. [74] provides detailed information about the technical functionality, advantages and limitations of this technology. Among others, it provides disintermediation, P2P transactions, automation (via smart contracts) and hence more independence. In [75] multiple projects using the blockchain-technology are assessed. As shown in [61, 73, 75, 76], a key legal hurdle for most blockchain implementations is the GDPR, because energy data from private households (especially with a spatial component) is sensitive information. Since data cannot be changed once on the blockchain, and is transparently available to all nodes, this fundamentally conflicts with the GDPR. In [76] verifiable computation techniques in blockchain systems are analyzed and compared. They include trusted oracles, ZKP and multi-party computation in terms of security, performance and practicality. Additionally, a simplex algorithm as a non-interactive ZKP (zkSNARK) was implemented. A ZKP "must convince the verifier that the prover" knows certain information or data. It "may not be forged by a malicious prover without knowledge" of this data and "may not allow the verifier to obtain" it [76]. A detailed analysis on ZKP and alternative technologies is provided in [76].

Technically, a blockchain is not necessary for using ZKPs as they are independently created by the ESP and could be verified by producers and consumers individually. However, in the context of the Labeling Framework, a ZKP can only ensure the correct processing of data if all necessary information is provided to it that defines "correctness". Correctness is defined in this work as follows:

1. only signed data from smart meters is used,
2. only data from the same time step (i.e., 15 minutes) is used,
3. supply and demand in any time step are balanced (residual quantities are reported),
4. no double spending,
5. any ESP uses only data to which it is entitled, and not used by other ESP,
6. any ESP uses all the data from the provided smart meters

While 1 to 4 above are ensured by the ZKP with data available to the ESP, 5 and 6 require a higher-level data reconciliation between all ESPs. This ensures that smart meters are only assigned to exactly one ESP in each time step. Otherwise, double spending can be prevented by the ZKP within each ESP, but the smart meter data can appear in the ZKP of different ESPs. In order to prevent the ESP from disregarding data, it must be ensured that all the data it has received has been used.

The use of blockchain is aimed at these two last aspects. Smart meters are assigned on the blockchain to a single ESP as long as there is a contract between the two. The ESP accesses this information and includes it in the ZKP to prove it only used the producers and consumers to which it is entitled. Additionally, Merkle trees (hashes) of the used generation and consumption are included on the blockchain to check if all data was considered [14]. Furthermore, the blockchain serves as verifier for the ZKP, so the ZKP does not need to be attached to each individual labeling proof. The ESP sends the ZKP to a smart contract, which verifies its correctness and provides this information to all relevant stakeholders.

**Allocation**

The allocation method is the central point of the labeling framework, as depicted in Figure 4-1. It assigns supply and demand based on a cost function and defined rules (e.g., boundary conditions). This solution allows for different use cases, which have an influence on the allocation during the optimization. It requires data from smart meters of consumers and producers, as well as additional data for certain use cases (e.g., proximity, costs, boundaries) [A1].

The allocation can be done by (linear) optimization in order to optimally consider all temporal, spatial or use case-induced constraints. The goal of the linear optimization is to allocate GOs with regard to spatial information, costs, smart meter data and high time resolution. Thus, generated renewable electricity certificates are allocated to the most preferred consumers every time step. In the basic case, as formulated in Equation (4-1), the GOs are allocated to minimize the distance between generation and consumption (i.e., based on proximity). Furthermore, it serves as foundation for many other use cases, as shown in section 4.3 [A1].

<table>
<tr><td colspan="2">$$\min_{z \in \mathbb{R}^{(n+1)\times(m+1)}} \sum_{\substack{i \in I \setminus \{n+1\},\\ j \in J \{m+1\}}} \tilde{c}_{ij} z_{ij} \ s.t.$$
$$\sum_{i \in I} s_i z_{ij} = d_j \ , \ \forall j \in J$$
$$\sum_{j \in J} z_{ij} = 1, \ \forall i \in I$$
$$z \geq 0$$</td><td>(4-1)</td></tr>
<tr><td>$C_{ij}$</td><td colspan="2">representing the "costs" between supply ($s_i \in \mathbb{R}^n$) and demand ($d_j \in \mathbb{R}^m$) while $I = [n]$ and $J = [m]$ with $n, m \in \mathbb{N}$. Costs can be a monetary value in ct/kWh or the distance in meter between $s_i$ and $d_j$</td></tr>
<tr><td>$\tilde{c}_{ij}$</td><td colspan="2">weighed costs with $\tilde{c}_{ij} = s_i C_{ij}$</td></tr>
<tr><td>$z$</td><td colspan="2">individual shares of GO in a given time step</td></tr>
<tr><td>Source</td><td colspan="2">[A1]</td></tr>
</table>

Equation (4-1) minimizes the sum of the weighed distances ($\tilde{c}_{ij}$) multiplied by the individual GO-shares ($z$) of each consumer in any given time step (e. g. seconds to years). The weighed distance ($\tilde{c}_{ij} = s_i C_{ij}$) represents the generated GO in each time step multiplied with the costs ($C_{i,j}$), between supply ($s \in \mathbb{R}^n$) and demand ($d \in \mathbb{R}^m$) while $I = [n]$ and $J = [m]$ with $n, m \in \mathbb{N}$ [A1]. Instead of costs, $C_{i,j}$ can also be the distance between demand supply.

The first constraint takes into account that the shares of each consumer ($z$) in the generated GO must not exceed the consumption in the same time step. The prerequisite for this is that sufficient GOs are always available. This is achieved by adding a virtual source of grey electricity certificates with a total generation/consumption of the residual load. This solution ensures that every consumer is provided with information on the origin of electricity at every time step and for every kilowatt-hour. In order to implement electricity of non-renewable sources and ensure balance neutrality, grey electricity counts as a virtual supply unit with relatively high virtual costs. The second and third constraint ensure that the sum of shares for any consumer and producer is always one and that none of the shares can be negative (non-negativity condition) [A1].

The result of the formula is an allocation table for each time step showing the origin of each consumer's electricity in terms of percentages of all available generation. The optimization formula is implemented in the simulation framework (details see section 5) and allows the implementation of different use cases solely by altering the costs or adding additional constraints as shown in section 0 [A1]. The simultaneity of generation and consumption is taken into account with a high temporal resolution. Boundary conditions may include, for example, grid constraints or ensuring the physical feasibility of the allocation result. However, this is not pursued further in this dissertation.

**Regulatory Assessment**

[77] gives a comprehensive analysis of the marketing of green electricity products with digital and real-time GOs, based on the use cases described in section 4. Art. 19 of the RED II defines that only renewable electricity labeled by GOs may be sold as such to consumers [77]. Additionally, GOs can be traded within EU member states and are not bound to physical boundaries. In Germany, according to § 79 EEG, the UBA is responsible for the GOR.

Current legislation and design of the GOR do not support the implementation of real-time proofs with high spatial or temporal solution, as proposed in [A1] and [14]. [77] contemplates multiple scenarios on how the current GO and the introduced labeling framework can be intertwined. It is concluded that it is possible to provide digital GOs in real-time (on a separate platform). However, as long as nothing is changed in the current regulation, official certificates must be acquired additionally for all quantities sold as green electricity product, even if they are already labeled in real time.

A ZKP can be validated by a smart contract on a blockchain. The blockchain-technology is also used to store and track generation and consumption data used in the allocation by the application of hashing algorithms and Merkle proofs [14]. No GDPR-relevant data is stored on the blockchain. In addition, the blockchain can ensure that different suppliers do not use the same RE in their allocation (double spending), in that there is an assignment of RE to supplier.

A primary advantage of this system is its capability to provide high-resolution data to consumers about the origin of their consumed electricity. This allows the determination of individual greenhouse gas (GHG) footprints [A1]. To provide sufficient information about the expected as well as the actual GHG emissions in the energy mix, a free GHG tool for ex-post data and the following day was developed in [78]. The forecast is based on supervised machine learning and data on generation, consumption and prices provided by the ENTOS-E [79]. GHG emissions are determined by data from [80]. This allows a more granular tracking of GHG emissions which fits increasing requirements, i.e., in the context of corporate sustainability reporting and $CO_2$ pricing, as assessed by Strüker et al. in [81]

The advantages of the proposed and implemented system lie in the combination of transparency regarding data and processes, tamper-resistance and the prevention of double spending. While these properties can be provided by a blockchain implementation (i.e., see [60]), existing projects show a lack of compliance with GDPR, as shown in [75]. The proposed implementation by [14] overcomes this barrier while preserving the required properties (compliancy with rules, transparency and tamper-resistance of data and processes).

**Use Case Integration**

The previously described requirements and implementation remain the same for different use cases. The main difference is the allocation method. Based on possible use cases described in [82], the different implementations only require alternative allocation methods:

- In the status quo, utilities allocate guarantees of origin equally among all consumers within a green electricity product [83],
- as proposed in [A1], the allocation can be done by an optimized approach, preferring to allocate generation and consumption based on proximity,
- in local energy or flexibility markets (e.g., [A6]), the allocation can be done by different auction or trading mechanisms or by optimization,
- in the context of sharing renewables (e.g., see [84]) the ownership structure may not only affect the revenue streams but also the shares in annual electricity generation. Hence, the shares of energy provided to the investors should match the ownership-structure, which can be achieved by optimization.

**Value Proposition**

The proposed system offers scalability and compatibility with smart meters. The allocation method allows to implement multiple use cases, as proposed in [A1], by altering the cost function of the optimization. It offers consumers high spatial and temporal information about their consumed electricity as well as corresponding GHG emissions while complying with the GDPR. Based on this, GHG emissions can be calculated on individual and community level. Since electricity is allocated between generators and consumers, the result of the allocation can be used to verify the origin of electricity to external third parties to claim monetary incentives or to get a refund on disproportionate costs. An advantage of this system is its flexibility to optimize costs with multiple different incentives or regulatory boundaries. Therefore, it may simultaneously include proximity-based (i.e., regional direct marketing), grid topology based (i.e., reduced grid fees within the same low voltage grid) or other use cases (e.g., monetary incentives for own consumption within an EC), which require a clear match between generation and consumption with a high spatial and temporal resolution. In section 4.4, requirements and value propositions of the labeling framework are summarized and compared. In section 5.5, multiple use cases are used at the same time in a case study to show the advantages of the labeling framework in allocating electricity accordingly.

Service providers are able to offer this labeling framework to their customers, integrating different use cases with their own front end (details see section 4.3). A great advantage of this solution is that many service providers can offer it without the need for governmental oversight. The verification that all rules (e.g., no double spending, consideration of proximity) have been followed by all these service providers is difficult to manage today, but a basic requirement to avoid fraud. ZKP provide all stakeholders, including third parties (e.g., authorities or grid system operators), with the possibility to verify the correctness of the used data and the compliance with defined rules without the necessity to access underlying (sensitive) data.

### 4.2.2 Applications of the Labeling Framework

The labeling framework's main advantage is its capability to delineate energy quantities with high spatial and temporal resolution. Based on [A1] and the implementations in other EU member states (see section 3.2.3), the following use cases can be depicted by the framework:

- Guarantees of Origin (generic use case): the framework is capable of providing GOs with high spatial and temporal resolution to all involved stakeholders.
    - regional electricity: the allocation (= optimization) of the framework can minimize the distance to supply electricity to the closest consumers.
    - prioritization of origin: the allocation of the framework can reflect the preferences of customers regarding the origin of electricity.
    - power-to-x labeling: if the necessary digital infrastructure is available in downstream sectors, the origin of the electricity can be provided e.g., to hydrogen, synthetic fuels or district heating.
    - storage labeling: a challenge today is the labeling of energy in storage systems. The labeling framework is capable of tracking inputs- and outputs and hence keeping track of the composition in the storage.
- Proof of Claims (generic use case): if a set of measurable rules entitle one or more stakeholders to cost refunds or monetary incentives, the framework is capable of proving rightful claims to the granting third parties.
    - consideration of proximity: some EU member states offer incentives for electricity consumed within proximity of the generation. In Germany, this is called regional direct marketing.
    - consideration of grid topology: some EU member states offer reduced grid fees for electricity consumed within the same low or medium voltage grid.
    - renewables self-consumer/asset sharing: the labeling framework can be used to allocate electricity among shareholders of renewables and distribute the resulting electricity according to their shares.

- tenant electricity: within a multifamily house, electricity from a PV system can be allocated to participating tenants.
- power purchase agreements (PPA): are long-term contracts between RE and one or more consumers. The labeling framework can consider allocation rules within these PPA and provide the information to involved stakeholders.

- $CO_2$ certificates: the framework provides a composition of the consumed electricity for every consumer. If information about specific $CO_2$ or GHG emissions of the different electricity sources is added, every consumer can receive real-time information or certificates about their $CO_2$ or GHG emissions.

These applications are compatible with each other and can be realized at the same time. The following two applications are also compatible to the ones above but not to each other. They are alternative means to determine a price within energy communities:

- Local energy markets (LEMs): in local energy communities, a market can be established to determine (uniform) prices. The involved stakeholders need to actively place orders on the market to buy and sell electricity. A uniform price ensures the compatibility with the use cases above. If individual prices (e.g., via pay-as-bid) are used, the allocation of supply and demand is determined on the market at the same time as the price (instead of using the optimization-based allocation of the labeling framework).

- Local energy sharing community (LES): in local energy communities, available supply and demand is used to determine a price to share electricity. An energy service provider is in charge to calculate the price, procure and sell residual loads, and optimize the community towards common goals that may exceed individual benefits.

In the following, selected use cases in the context of energy communities are outlined, based on this foundation. They include the consideration of proximity via the use case "regional direct marketing" which is already applicable in Germany, the LEM and the LES.

## 4.3 Implementation Proposal: Components of Energy Communities

In the following, implementation proposals for three use cases in the context of energy communities are provided. Two of them are pricing mechanisms, and one is the delineation of electricity, applicable for electricity tax exemption. They are developed and described according to the methodology in section 3.1. The allocation method, as an integral part of the labeling framework, is capable of labeling electricity and providing the information to the involved stakeholders. It is compatible with any uniform pricing mechanism. Pricing mechanisms without a uniform price (pay-as-bid) already bring their own allocation and are not compatible with the optimized allocation in section 4.2.1.

### 4.3.1 Use Case: Local Energy Sharing Communities

As described in section 3.2, a pricing mechanism is a key element within energy communities. It links consumed, generated and externally purchased energy within the community.

Contrary to local energy markets (LEMs, see section 4.3.2), sharing communities pursue broader goals than just the maximization of the individual economic benefit. In [A4], it was shown that energy sharing communities are not yet precisely defined in Germany. It was defined as "peers sharing their surplus energy with other energy customers to improve economic, environmental benefits and add technical, institutional values to the entire community", in accordance with EU legislation [A4]. It was also pointed out that despite this diversity of goals a price mechanism still plays a central role in these communities, and introduced three possible pricing mechanisms for this purpose [A3].

Since the sharing communities in this work involve a close proximity of the participants, the term "local energy sharing" (community) (LES) is used for this use case. The implementation of pricing mechanisms into an LES, based on the introduced labeling framework, is presented in the following.

**User Story**

Participants of LES communities want to share their produced electricity for a fair and transparent price and avoid disproportionate costs, as well as to achieve common goals defined by a set of rules to gain economic and environmental benefits and add technical and institutional values to the entire community.

**Use Case Processes and Services**

Figure 4-2 shows the LES use case. Contrary to "local energy markets", no contracts between consumer and generator are required in this concept. Instead, generators and the community operator (i.e., the energy service provider, ESP) have a direct marketing contract. The ESP offers an electricity product to the consumer in which it is guaranteed to set a local price depending on demand, supply, retail price and exchange price. Within the community, generation and consumption are allocated according to Figure 4-1.

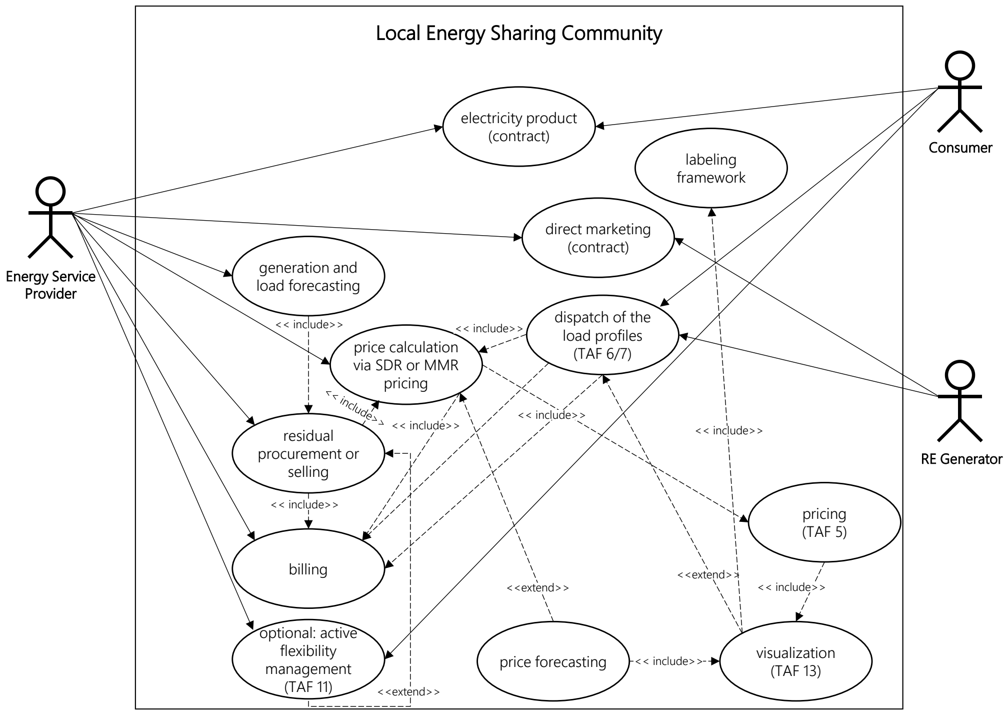


Figure 4-2: UML use case diagram of LES

To calculate a price, the ESP must forecast generation and load within the community and procure or sell residual electricity in advance. From these calculations and trades, a price is derived with a pricing model (for details see section 5.4.2). The expected price is visualized both for generators and consumers in order to enable behavioral change.

Pricing in energy communities can be done by electricity tariff-based incentives. This can be achieved by local grid fees, rolling cost models, ex-post remuneration or dynamic tariffs [67]. The focus in this work will be set on dynamic tariffs, including local supply and demand. However, a combination of tariff-based incentives is possible and shown in section 5.5.

After the period for which the price was forecasted (e.g., 15 min or 1 hour), the actual price is calculated based on transmitted load profiles of supply and demand. Additional costs, such as balancing energy, are included in the actual price. Depending on the actual price and the load profiles, billing is initiated. An optional step in this use case is active flexibility management (TAF 11) if flexibility providers are available within the community and access is granted to the CO.

Based on the actual generation and consumption, electricity is labeled within the community as introduced in section 4.1. The results of the forecasting, billing, labeling etc. are visualized along with the load profiles.

#### Regulatory Assessment

In article 22 of RED II, the EU imposes "that final customers, in particular household customers, are entitled to participate in a renewable energy community while maintaining their rights or obligations as final customers, and without being subject to unjustified or discriminatory conditions or procedures that would prevent their participation in a renewable energy community, provided that for private undertakings, their participation does not constitute their primary commercial or professional activity."

It is further clarified in article 22, what energy communities are entitled to. REC should be able to "produce, consume, store and sell renewable energy, including through renewables power purchase agreements", " share, within the REC, renewable energy that is produced by the production units owned by that renewable energy community", and " access all suitable energy markets both directly or through aggregation in a non-discriminatory manner". Besides, member states are required to assess existing barriers for REC and provide a "framework to promote and facilitate the development of renewable energy communities". This includes the reduction of unjustified regulatory and administrative barriers, coordination with the local DSO, and "fair, proportionate and transparent procedures" (i.e., registration and licensing, charges, levies and taxes).

With this directive, the EU has laid the foundation for the implementation of REC. This directive has not yet been implemented in Germany. Hence, no monetary incentives or cost refunds can be claimed yet. Nevertheless, it is possible to implement the use case, as presented above, in Germany. However, this system does not go beyond the status of a more innovative electricity product. Cost and revenue of the participating consumers and producers is determined, documented, and billed by the ESP, who functions as an intermediary. As long as the contracts allow it, the ESP can even optimize existing flexibility e.g., to increase own consumption within the community, reduce GHG emissions, or reduce grid load.

#### Value Proposition

The proposed use case includes a pricing mechanism on top of the allocation method. The pricing mechanism is based on demand, supply and exchange prices, allowing to determine predefined distribution of cost and revenue within the community. The price forecast allows participants to adjust their individual behavior to save costs or increase the self-consumption within the community. If available flexibility is actively used, this effect is increased. Additionally, common goals (e.g., lower GHG emissions in the community) can be achieved by utilizing available flexibility.

Since the ESP determines a price, no active participation of the community members is necessary. Current smart meter capabilities are sufficient for this use case. Since the ESP is the central coordinator of the community, the community can be optimized towards a common goal. Available flexibility of the community can be used to reduce costs, GHG emissions or to gain additional revenues via other markets (i.e., via secondary or tertiary frequency control).

Without regulatory changes as required by the EU, this use case only provides a different pricing mechanism, yet only limited economic benefits. Since it reflects local supply and demand and is coupled with the wholesale markets, the broader goals (such as more self-sufficiency, less GHG emission etc.) are however represented in the prices. The economic incentive to participate increases when electricity that is generated within the community and consumed at the same time is subject to reduced taxes, levies and charges. These financial benefits can then be reflected in the price or billing. The labeling framework ensures that these quantities are accounted for to the relevant parties.

In the next use case, the introduced passive pricing mechanism is changed for a more active trading scheme.

### 4.3.2 Use Case: Local Energy Markets

Local Energy Markets (LEMs) or P2P electricity trading are the subject of many studies and projects. In [85], the authors remark on the steady increase of LEMs as the "awareness of the shared economy has grown and the microgrid has spread". The increasing penetration of smart grid technologies (including smart meters, batteries, smart heat pumps, inverters etc.) as well as increasing digitalization, connectivity and interoperability offers the basis for new and more complex ways of interaction, such as LEMs. In [86], these markets are defined as "a tool to decentralize the coordination of participants in a grid, by unifying participants behind a common denominator – local electricity market prices. These market prices aim to facilitate local trade, or in other words, prioritize the exchange of energy resources in smaller spatial distances over larger distances". The authors of [87] name three key components for P2P trading: "an adequate pricing mechanism to incentivize supply and demand; a digital transaction loop to reduce transaction costs to the point when transactions become economically viable; and a delivery loop to implement trading decisions contracted among peers and verify such transactions".

The distinction from LES is not always clear but can be made on the basis of the "common denominator". While in LES, a pricing model is usually an integral part of the system, the goals are more general and - contrary to LEMs - include, e.g., environmental benefits and add technical, institutional values to the entire community" [A4]. In this dissertation, the distinction is made that LEMs operate purely through a market price, requiring active involvement of market participants. LES, on the other hand, pursues other goals that can go beyond economic interests and do not require active involvement of participants in the pricing mechanism. LEMs often aim to substitute a utility by utilizing blockchain technology. LES on the other hand usually requires an ESP who coordinates and optimizes the community towards a common goal. Hence, LEMs require more active participation such as active bidding on the local market as well as the fulfillment of obligations in the energy market.

The advantages of LEMs include the activation of small actors, new business models, lower costs and more steady revenues [88], better economic feasibility of e.g., home storage systems (HSS), [85] and market access for small- and medium-size RE [89, 90]. Additionally, the fluctuating prices in the LEMs serve as an incentive for flexibility, stabilizing the electricity grid and reducing the need for long-distance transmission while strengthening the local economy [89].

**Market Model**

The core feature of a LEM is its market model. Possible allocation methods are summarized in [A6] and include double-sided auctions [91, 92, 93], call auctions [93, 94, 95] with simple order books (correlating or inverse order), optimization approaches [96, 97], continuous trading by directly matching supply and demand [98, 99, 100, 101], and multi-bilateral trading without a central coordinator or marketplace [102, 103]. Pricing mechanisms are closely related to the allocation method. They include uniform pricing with the last [92, 95] or average [104] bid determining the market price, or discriminatory pricing [94, 100, 105] where the price is derived as the mean of the respective buyer's and sellers' price bid for any pair. Other markets include differentiation, e.g., due to the origin of electricity [102, 103].

[A6] analyzed multiple different allocation mechanisms for LEM in three case studies (i.e., municipalities). The analyzed combinations of allocation and pricing mechanisms included double-sided call auction with uniform market-clearing price (UN), double-sided call auction with discriminatory pricing scheme; reverse order book arrangement (DR), continuous trading with closed order book (CC), continuous trading with open order book allowing agents to adjust their prices based on previous transactions (CO), double-sided call auction with discriminatory pricing scheme; correlating order book arrangement (DC), central optimization routine matching bids and asks to maximize P2P revenue (OP) [A6]. The results of the case study showed a higher average social welfare for UN and DR, compared to the considered alternatives. The gross profit increase in the communities however was lower than in compared mechanisms, while the equality index, used to measure the equality of the revenue distribution, depended heavily on the considered municipality. Additionally, in [A6], the relatively simple market design of UN as well as good privacy protection by design were highlighted. Even though UN fell short in terms of communal gross profit, it performed well for overall welfare. Additionally, since UN has been tested in multiple projects in practice, it meets regulatory requirements better than other market designs.

Based on these findings, its compatibility to the optimized allocation method and preliminary work in [A6], a double-sided call auction with a uniform pricing is considered and implemented in this dissertation. In the following, the use case processes and services including this market model are described.

**User Story**

Participants of LEMs want to actively trade their produced electricity on a local market for a fair and transparent price which resembles supply and demand and the wholesale price, to avoid disproportionate costs, reduce their electricity bill (consumption) and gain additional revenues (supply).

**Use Case Processes and Services**

There are multiple ways to design a LEM. To satisfy current regulatory requirements, the direct supply between a generator and a consumer requires the generator to formally become a supplier. The resulting bureaucratic effort has a negative impact on the economic feasibility.

Figure 4-3 depicts the UML use case diagram of local energy markets, as considered in this dissertation. The aim of this market is the practicability under the current legal framework. A prerequisite of this is that the generator/producer has already formally become a supplier (details see Figure 14-1 in the appendix).

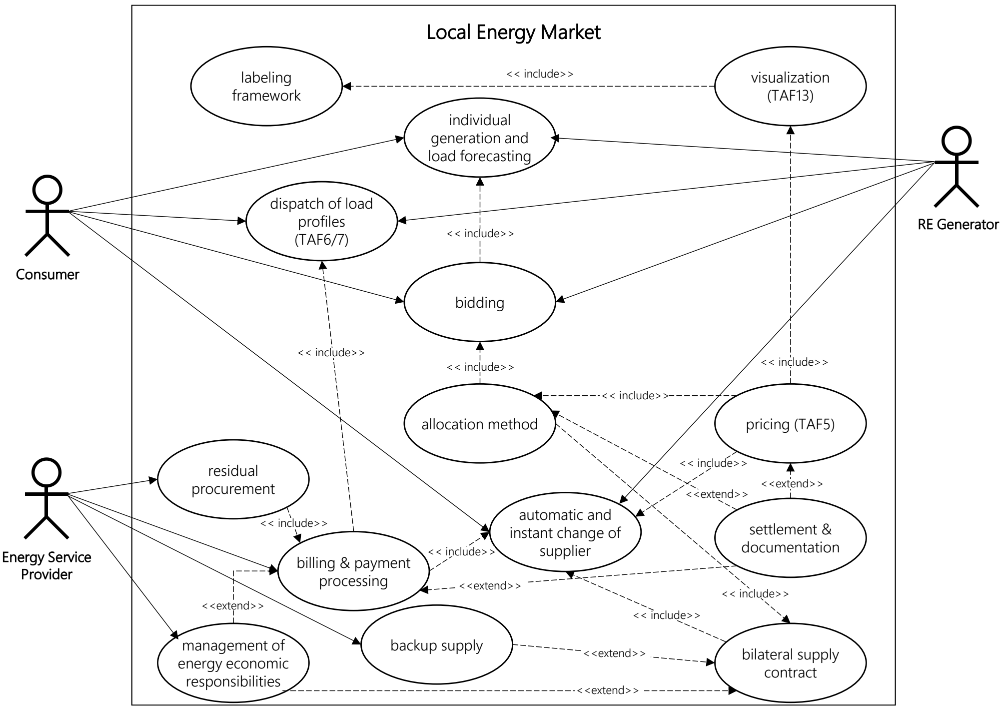


Figure 4-3: UML use case diagram of local energy markets

The process starts by the forecasting of the individual generation and load by the involved stakeholders. Based in these forecasts, bids are placed, including individual preferences. To reduce the constant involvement of stakeholders, this process can be performed automatically by agents. Depending on the chosen allocation method of the market, a matching is performed, and pairs of supply and demand are matched. The chosen pricing mechanism determines whether individual prices based on the bids (pay-as-bid), or a uniform price is set for all market participants.

The matched pairs of supply and demand (automatically) enter into a supply contract which includes the price, duration and quantity of the delivery. Additionally, a third party is included to provide both backup supply and aid with energy-economic processes and responsibilities necessary to fulfil the contract. Additionally, an automatic change of supplier is initiated, so that a supply agreement can officially begin. While all other parts of the process can be performed on the LEM directly, this process involves multiple external stakeholders (e.g., the DSO) and may take up to three weeks as of today [106]. However, this process is limited by manual interactions as well as regulatory specifications and outdated protocols. It is technically possible to map it in almost real time [106].

After the change of supplier, the pricing is done using smart meters (TAF 5). After the contractual period of supply, the respective load profiles are used to process billing and payment. Forecasting errors are met by the backup supplier. Service fees as well as the cost for residual procurement or balancing energy are included in the bill.

An alternative but less decentralized way of implementing these markets can be realized without the switch of supplier and the necessity for such an involved bureaucracy. After the matching process, a uniform price is set for all market participants. Matching information (i.e., resulting pairs) is provided to all participants and the resulting price set by the ESP. Instead of bilateral contracts, both generators and consumers hold a contract with a common ESP. This process is similar to Figure 4-2 with a more active involvement of prosumers in the market.

The labeling framework is subsequently used to provide information about the origin of electricity to all participants. If a bilateral supply contract is established, the pair (consumer and producer) is prioritized in the labeling framework. If the market is realized with a uniform price, the electricity is allocated, as introduced in section 4.2.

**Regulatory Assessment**

So far, the role of "prosumers" is not specified in German legislation. The EU, however, defined the word "active customer" (prosumer) legally as "final customer, or a group of jointly acting final customers, who consume[s] or store[s] electricity generated within its premises located within confined boundaries or, where permitted by a Member State, within other premises, or who sell[s] self-generated electricity or participate[s] in flexibility or energy efficiency schemes, provided that those activities do not constitute its primary commercial or professional activity" [107]

Due to the lack of legal definition of the role in Germany, the introduced use cases come with administrative and regulatory barriers, lowering economic benefits. In [108], Fietze et al. analyzed the main challenges for P2P trading in a comprehensive way. They showed that the realization of active and bilateral trading between prosumers (as required in LEM and RDM) is legal, but requires prosumers to meet the same obligations and processes as (corporate) utilities. In order to sell electricity to their peers, they have to legally become a "supplier". This requires many obligations and processes, which are shown for the German market in Figure 14-1 in the appendix. Prosumers are among other things required to legally establish a business, conduct a supplier disclosure at the BNetzA, acquire an EIC-Code (for 130 €/a), find a contractor to handle their balancing obligations (e.g., forecasts, reports, settlements), and be able to communicate with the other market participants (e.g., grid system operators) via common standards (EDIFACT). Suitable software, digital certificates or service providers are prerequisites for this.

An EU directive stipulates that every end customer should have access to flexible electricity prices as long as the necessary digital infrastructure is available. This gives the opportunity to include all consumers into the market in order to adapt their consumption depending on market prices to save costs [107]. Additionally, the EU demanded in RED II to lower administrative and regulatory barriers.

In order to supply electricity between two prosumers, current legislation requires not only bilateral supply contracts but also an official switching of suppliers. After a contract initiation (e.g., via a LEM) and closure, defined GPKE processes need to be followed [109]. These complex processes involve the old supplier, metering operator, local DSO and TSO. Per § 20a EnWG, this process may take up to three weeks. Starting on 1 January 2026, this process must be conducted within 24 hours.

In the LEM use case , this means that a trading period between prosumers should not be less than one day. In [106], Hinterstocker et al. analyzed current processes. Today's process requires eight steps, manual checking of consistency and validation of the transmitted data, slowing down the process. The authors show that a more efficient and digitalized process can be established using automation and blockchain-technology.

Based on the assessment of [106], it is assumed in this work that a change of supplier is possible in smaller time steps (i.e., hourly).

**Value Proposition**

Value propositions and business models of LEMs, as assessed in [A6], both have benefits for the consumers and producers. This includes lower electricity prices than the retail price with higher revenues for RE than feed-in tariffs. This business model is only viable if the marginal costs of supply are lower than the existing electricity rates. The results showed strong differences in how and why LEMs were implemented, e.g., hardware manufacturers offering added value services such as a LEM to improve the economic feasibility of their hardware (e.g., batteries or inverters) for their customers.

The service is hence limited to their customers who are prosumers. Aggregators and energy service providers on the other hand aim to directly market renewable energy from independent producers to consumers.

The value propositions include more independence from energy suppliers and corporations, lower prices for local electricity (i.e., through monetary benefits for locally produced electricity) and higher revenues for RE. The resulting variable prices are incentives for the use of flexibility and the addition of further RE. The use of flexibility may lead to lower costs for grid expansion. A LEM transforms electricity from a commodity to a product with a link between producer and consumer, origin, quality and value. Since prosumers are actively involved in the market, the system builds trust and increased acceptance for new renewables. A main advantage is that through this use case, the local, citizen-driven energy transition can proceed more efficiently. The flexible price on the market serves as a natural incentive, e.g., for peak shaving.

Instead of selling a low effort commodity product, utilities become energy service providers that help to procure and sell residual electricity, overcome remaining administrative barriers, and manage energy-economic responsibilities. However, due to the high regulatory and administrative barriers that exist today, the business model is still relatively difficult to implement. This changes if barriers are lowered, and monetary incentives are created for EC.

### 4.3.3 Use Case: Regional Direct Marketing/ Renewables Self-Consumers

Based on § 9 StromStG, electricity which is consumed and produced simultaneously within a radius of 4.5 km is exempted from the 2.05 ct/kWh electricity tax. This rule applies only to renewables with an installed capacity of up to 2 MW and only if there is a direct supply contract between the involved stakeholders. In RED II, the EU requires the creation of incentives for RSC that use the public grid. Even though § 9 StromStG has existed for some time, this can be seen as an incentive for EC. Furthermore, it fulfills the use case "consideration of proximity" in section 4.2.2.

**User Story**

Local RE owners want a simple and transparent way to claim reduced electricity tax on their own consumption or regional direct marketing towards the customs office to generate additional revenues or a competitive advantage over non-regional RE.

**Use Case Processes and Services**

To qualify for this electricity tax exemption, the producer and consumer must enter into a supply contract. As already shown in section 4.3.2, this requires generators to undergo an extensive process to become a supplier. This process, as well as all other processes necessary to fulfil a supply contract, are omitted for reasons of simplicity in Figure 4-4.

In order to ensure the secure supply of electricity, an energy service provider or a utility company is usually integrated into the contract. After a time period (e.g., one year), the supplier can request a tax exemption by submitting several forms, provided by the customs office. These forms are based on § 12c StromStV (i.e., forms 1470, 1422a, 1422az [110]). They can be filled out digitally (via XML). The forms require basic information about the plant (i.e., in 1422a: type, capacity, grid connectivity, subsidies etc.) as well as more detailed information such as serial numbers, a description, address and site plan in 1422az. Additionally, a site plan including the location of consumers within 4.5 km has to be provided. The information within these forms is usually static and does not need to be changed regularly. Form 1470 is the formal application for the tax exemption, which also includes proof or a calculation of simultaneity[1]. This requires the data of generation and consumption with a granularity of 15 minutes. The provided information as well as the forms are audited by the customs office and (if applicable) a tax exemption granted. A tax refund is then provided to the supplier.

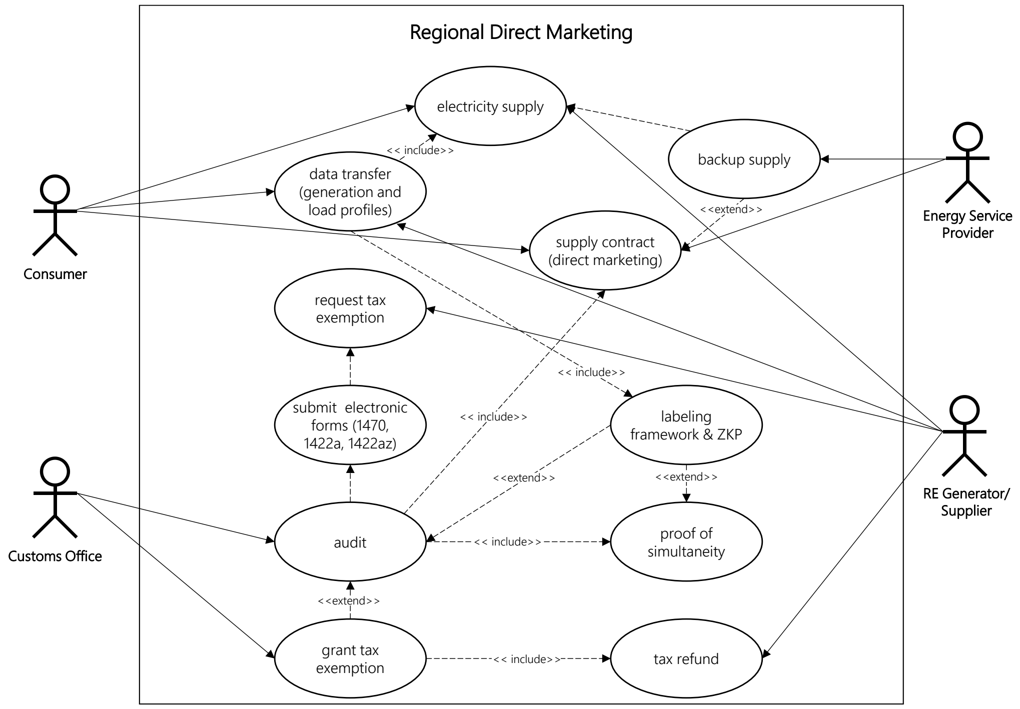


Figure 4-4: UML use case diagram of regional direct marketing

**Regulatory Assessment**

German law and authorities provide the basis as well as the necessary forms in § 9 StromStG and § 12c StromStV. Renewables up to 2 MW can make use of the tax exemptions of regional direct marketing as long as they are suppliers and have a bilateral supply contract with their customers or own the plant and supply themselves (using the public grid). Demand and supply for these two cases must be in close proximity to each other (i.e., within 4.5 km). This process requires extensive efforts and costs which are described in Figure 14-1, in the appendix. The regulatory challenges are hence the same as in section 4.3.2.

As long as the supply and demand have a bilateral contract and are within 4.5 km, this use case is complementary. LEMs are hence compatible, due to their requirement of a bilateral contract (contrary to LES).

In article 21, RED II, the EU laid the foundation to further promote RSC by lowering grid fees, taxes and levies in a cost-reflective way, as well as reducing administrative and regulatory barriers. In this thesis, it is assumed that the existing regulation § 9 StromStG serves as a basis for the implementation of Article 21 RED II. It can further be assumed RSC will receive higher benefits in order to comply with RED II. Additionally, § 9 StromStG resembles the "consideration of proximity" use case in section 4.2.2 which is one way to incentivize energy communities (as done in Portugal and Spain). Thus, it is possible to save electricity tax in LEM as long as the proximity requirement is met.

[1] When asked, the authorities stated that the information must be printed and sent in completely signed, by mail. This makes it very difficult to check the values provided.

As of today, the data provision as well as the check by the customs office is based on paper. A digital interface, e.g., to smart meter data is not yet implemented. However, a digital proof of simultaneity can be submitted.

**Value Proposition**

The value proposition of this use case is the reduced electricity tax of 2.05 ct/kWh for locally produced electricity. This creates an incentive to increase the amount of electricity generated and consumed locally. Due to current regulatory and administrative barriers, this is only viable for larger unsubsidized RE. In case of reduced administrative barriers, this use case may become relevant even for small renewables.

This use case can be seen as reference model for RSC in Germany, since EU legislation requires the reduction of taxes, levies and charges even if using the public grid. The use case may compensate for higher costs of LEM, since these concepts are compatible.

## 4.4 Comparison Requirements and Value Propositions

As introduced in the modified use case methodology (see section 3.1), a key step of use case development is the alignment and comparison of stakeholder requirements with value propositions of the use cases. This ensures that both aspects fit together and nothing is forgotten.

The requirements, summarized in Table 3-2, are compared with the value propositions of the proposed labeling framework and pricing use cases (sections 4.3.1 and 4.3.2).

Whether the requirements are fulfilled by the implementation of the labeling framework can be evaluated in a qualitative way. It is already capable of fulfilling most of the requirements. Most value propositions of the pricing mechanisms, however, need to be assessed in a quantitative way. While an integration of energy communities in wholesale markets is given by all three pricing mechanisms, and local demand and supply reflected in the prices, neither price stability, cost, revenues nor incentives for flexibility can be assessed without a quantitative assessment.

In section 8, a qualitative analysis is performed based on the simulation to determine whether the requirements are met. In addition, the simulation results are used to evaluate and compare the different regional potential of the use cases. A special focus is set on the prices, resulting costs and revenues for different stakeholders, which are compared to the status quo. The price spreads give an indication of how well the pricing mechanisms provide incentives for new RE and exiting flexibility.

Table 4-1: Comparison of requirements and value propositions of the labeling framework

| Requirements | Value Proposition of the Labeling Framework |
|---|---|
| Guaranteeing scalability and security (i.e., by fulfilling GDPR requirements) building on the smart meter infrastructure | The security (especially GDPR compliancy) of the proposed system is very high if implemented correctly, since it is implemented into existing systems of critical infrastructure providers (i.e., the ESP). |
| Guaranteeing compliancy with legal requirements (i.e., double spending) and existing processes | The use of ZKP in the labeling framework verifies compliance with predefined legal and other requirements to involved stakeholders (i.e., to avoid double spending). ZKP only works if the involved stakeholders agree on a set of (verifiable) rules (e.g., a non-discriminatory pricing and/or allocation mechanism)<br>The ZKP provides transparency about the processes without revealing sensitive information |
| Providing tamper-resistant verifiability of compliance to set rules for third parties (e.g., authorities, regulators and grid system operators) | |
| Verifying the origin and correct allocation of electricity within the EC | |
| Providing an indicator about past and future $CO_2$ emissions and own consumption in the community | The labeling framework allocates supply and demand and provides consumers with high resolution data about the origin of their electricity. Based on this origin, certificates about the resulting GHG emissions can be issued. Based on a forecast (see [111]), future GHG emissions will help to optimize the carbon emissions. |
| Integrating multiple sectors (e.g., via power-to-heat/gas) | The labeling framework provides high resolution temporal and spatial information about the origin of electricity and is not limited to electricity. Its use across sectors has to be evaluated and tested in future projects |
| Proving high resolution temporal and spatial information about the origin of electricity | |
| Delineating different use cases and claims regarding monetary incentives within energy communities. | The allocation method is capable of considering multiple boundary conditions, prices or proximity, depending on the use cases implemented. This is shown in section 5 |
| Consideration of distribution grid constraints | The allocation method can be used to include grid constraints as boundary condition in the allocation method. |

## 4.5 Definition of Energy-Economic Potential Assessment

Since this dissertation aims to derive the potentials of the introduced use cases with a focus on regional differences, the word "potential" needs to be defined. It can be defined as "all available resources, possibilities, abilities, energies" [112]. In [113, 114, 115, 116] it is defined using various terms that build on each other:

- The theoretical potential describes the maximum available main resource of a use case (e.g., tradeable electricity, participants or turnover) without considering existing restrictions. The theoretical potential hence describes an upper boundary of a use case's potential [114].
- The technical potential includes the theoretical potential, considering technical, economic and infrastructure-related boundaries. In this study, this includes all technically available resources (i.e., prosumers, electric cars, renewables) under the consideration of temporal and spatial restrictions [114]. Additionally, the use cases are designed to include the technical capabilities of smart meters.
- The economic potential is comprised of the share of the technical potential that can be exploited economically. This includes certain costs, e.g., for soft- and hardware [114]. The economic potential is assessed from multiple stakeholder perspectives.
- The practical potential includes regulatory and practical restrictions [114].

In this study, the term "potential" is used, depending on the considered use case. All use cases are simulated with the same simulation framework and based on the same data. The following restrictions and assumptions impacting the potential are considered:

- It is assumed that all households, regardless of size and location are participating in the use cases.
- A temporal resolution of one hour is considered to adequately depict simultaneity of consumption and generation and as a compromise between accuracy and computing time.
- A spatial resolution of 100x100 m is considered due to the availability of data and as a compromise between accuracy and computing time.
- Single households are modeled to accurately include own consumption of prosumers and available flexibility (i.e., battery storages).
- Renewables are modeled up to 2 MW, since this is the defined upper bound by § 9 StromStG for regional direct marketing. This ensures that all considered plants are capable of exhausting their RDM potential. RE with bigger capacities are neglected in this work.
- There is no distinction between subsidized and unsubsidized renewables. All available renewables are taking part in the market. § 80 EEG is neglected in this work.
- Further model assumptions are provided and explained in section 5.5.2.

The simulation framework is designed to determine the technical potential, considering technical capabilities of smart meters (see section 4) as well as temporal and spatial restrictions. In the case of LES and LEMs this includes all households and renewables ≤ 2 MW. In these use cases, individual prices are determined for every hour of the year. These prices are the basis to assess the economic potential for different stakeholders in section 8. For RDM, the electricity which can be utilized for this use case is determined. Even though it is not the focus of this work and hence not included in the simulation model, indications about the practical potential are given in this section (section 4) with brief regulatory assessments of the use cases.

The main goal of the simulation is to determine the regional differences of prices with different pricing mechanisms both for 2019 and 2035. Additionally, possible savings within these municipalities are determined by the RDM potential.

**Qualitative Potential Analysis**

The introduced labeling framework and subsequent use cases are described in section 4, along with their value proposition. The technical, infrastructural, and non-functional stakeholder requirements are described in sections 3.2 and 3.3. Based on these requirements and value propositions, a qualitative potential analysis is conducted in section 8.5. The goal is to summarize the met requirements by the value propositions and discuss the results. This should give an indication if requirements have been met by the entire framework and where improvements are still needed. The identified and quantified technical potentials from the previous section forms the basis to this. It further discusses economic and practical potentials on a qualitative level.

## 4.6 Preliminary Summary

In this section, the technical labeling framework, conceptualized in [A1], and partly implemented by [14], was introduced. The framework is a solution to delineate different use cases within a community and claim the corresponding monetary incentives. This labeling framework, as summarized in section 4.1 and 4.2, is the foundation to implement multiple use cases from the field of energy communities. It utilizes smart meter data in conjunction with cryptographic methods to ensure transparency and tamper-resistance both of data and allocation method while still achieving GDPR compliancy. This is achieved by zero-knowledge proofs (ZKP) and the use of the blockchain-technology. The framework allows, e.g., energy service providers (ESP) to handle the processes within a community, based on smart meter data and a defined set of rules. They can proof the correctness towards internal or external stakeholders, without revealing sensitive information in a data-saving way. This allows authorities to trust the results without the need to check underlying processes and data in detail. The approach allows thousands of ECs to be implemented without the necessity for detailed monitoring by authorities or the need for intermediaries for the allocation, as done by the DSO in Austria. The proof of how much network charges, taxes or levies have been saved within a community can thus be provided to any involved party by the community operator.

The framework allows the implementation of multiple use cases in the context of ECs, as described in section 4.3.

- "Local Energy Sharing Communities" have a focus on sharing electricity within the community, using different pricing models. They require an energy service provider to set a price and handle the necessary digital and contractual processes. This model can already be implemented today as an "innovative electricity product", but offers little added value due to a lack of regulatory incentives. It will become interesting when additional financial incentives for communities are realized.
- "Local Energy Markets" are a more market-based and decentralized approach, building on P2P trading. Community members are required to participate in a local energy market which sets a price. Multiple allocation methods and pricing mechanisms are available to realize these markets. This approach does not require an ESP but responsibilities must be handled by individual prosumers, leading to major administrative efforts by the individuals, reducing feasibility.
- "Regional Direct Marketing" provides an exemption of 2.05 ct/kWh electricity tax for electricity produced and consumed within 4.5 km by RE ≤ 2MW. Like LEMs, it requires a bilateral supply contract leading to the same administrative efforts. However, it can be considered the only existing reduction of a tax for ECs in German law, as of today. This use case is compatible with both prior use cases, if regulatory barriers are reduced.

In section 4.5, a definition of "potential" within this work as well as necessary assumptions are provided. The potential assessment is a "technical potential", including households and all renewables up to 2 MW regardless of whether subsidized or unsubsidized, with a temporal resolution of one hour and a spatial resolution of 100 x 100 m.

# 5 Community Simulation Framework

A goal of this dissertation is the evaluation of potentials of the described use cases. Since the use cases aim at private households, these must be simulated individually in order to determine, e.g., the economic potential at the individual household level. A model that considers households in detail and maps them individually as well as in the context of its surrounding renewables such as battery storages, electric vehicles and other relevant technologies, leads to high computational cost, but also provides high-resolution and high-quality results. Since the model depicts components and interconnections and "does not take into account the connections between the energy system and the macro-economic sectors" [117], it is a bottom-up model.

The municipality or district level would be optimal from a simulation perspective. Yet, datasets for energy-economic data usually have a much lower resolution as shown in [118] and even on a municipal level, the computational complexity of the simulation is high. Counties and independent cities are too computationally expensive to calculate since the population is much higher. For these reasons, the simulation at the municipal level is chosen in the following to evaluate the potentials of the selected use cases with the simulation framework. Results apply not only to an entire municipality but also to a representative subset from that municipality. This is based on the assumption that an energy community in a municipality is proportionally composed like the municipality itself.

The simulation framework consists of the following main parts:

- Input data from numerous different sources, including energy, economic and spatial information as well as geographical and population data. A special focus is set on time series data for generation and consumption of every agent within the framework individually.
- A community generation module to generate a "digital twin" consisting of python objects, representing relevant consumers, producers etc. as well as their location and properties.
- Use case modules to derive potentials (e.g., prices) for different use cases independently, building on the python objects generated in the community generation module.

These components of the simulation framework are already described in [A3] and [A4], and are summarized below.

## 5.1 Input Data

The data is mainly from the FfE regionalized energy system modelling tool (FREM). The data was downloaded, regionalized or derived in preliminary works of the FfE. Detailed backgrounds are available in [118]. The data includes census data on population, buildings or administrative data, renewables from the MaStR and geodata e.g., from OpenStreetMap. In order to depict future scenarios concerning additional renewables, electric vehicles, heat pumps or other developments, existing scenario data includes regionalization at the municipality level.

A challenge of modeling consumption of trade, commerce and services as well as the industry sector is the lack of consumption data. The focus of the simulation is hence put on private households and renewables. The resulting potentials in section 8 hence only apply to private households.

The community generation module queries the data from FREM and processes it to derive the necessary information. The data as well as its origin is introduced in the next section.

## 5.2 Community Generation Module

The community generation module is capable of filtering only relevant data on the selected administrative level as well as for selected temporal parameters. These include start time, end time and temporal resolution of the simulation (e.g., a week in summer, in hourly resolution). The temporal resolution is variable and can be as low as one minute. The community generation module either queries data from the FREM, (if available) or derives data based on available information. These steps are summarized in the following.

### 5.2.1 Status Quo 2019: Buildings and Households

The necessary information is taken from census data, as provided in [119] and [120]. The census grid includes information on residential buildings by type and building age as well as number of households and household sizes on a 100 m x 100 m grid. Due to privacy protection, the combination of these attributes at household level is not provided. In order to generate individual households from this information, the distribution of those feature combinations, provided in [121] at the administrative level (e.g., municipality) is utilized to combine them to individual households. As described in [A2], "households are allocated to individual buildings per cell iteratively by (1) determining the building type of a household and (2) randomly assigning it to a building of this type. Step (1) is done by a weighted sampling of the building type from the distribution of population by building type for the area of interest".

The result is a dataset, which includes information about each building and household, including the building type (e.g., one-, two-family houses and apartment buildings), building age and household size as well as a location with a resolution of 100x100 m.

This information is the basis to derive individual thermal (i.e., room and water heating) and electrical load- as well as driving-profiles at the building level. Instead of utilizing the standardized load profiles (SLP), which do not account for the fluctuation of individual households, data from an agent-based model introduced in [122], was utilized, to determine individual load profiles. In this model, individual load profiles are generated using a Markov-Chain and individual behavior. The input for this model includes the household size, building type, building age as well as local weather data from [123]. To reduce the computational complexity, 7,366 buildings with 42,899 residential units were precomputed, including all building age classes and building types. Thus, simulation time is decreased while still providing high variance.

Electricity demand by battery electric vehicles (BEVs) can also be extracted from [122], using mobility profiles for each household. The data includes the number of vehicles, time of departure, return and distance driven as well as energy consumption. The battery capacity is determined, as specified in [122] by the size of the electric vehicle. The battery sizes of the BEV range are either small (20 kWh), medium (40 kWh) or large (60 kWh). Charging power is assumed to be 11 kW during the charging process and is independent of the size of the BEV [124]. The vehicles immediately charge when returning home until the battery is charged or the vehicle is used for another trip. The number of electric vehicles per district are disaggregated at the municipal level by population [125, 126]. Electric vehicles are assigned to one- and two-family houses with a PV system randomly before other buildings until the target number is reached. By default, the target number corresponds to the current BEV stock (status quo). For scenarios this value may be altered by providing the desired number of EVs.

Buildings can also include residential PV systems as well as battery storages. The total capacity of an installed residential PV system is known for any municipality and assigned to individual houses within the municipality. This is done randomly but one- and two-family houses have a three times higher chance than apartment buildings to be selected. This is based on the estimate of the market segmentation of residential PV systems from [127], which shows a share of 71 % for one- and two-family houses and 26 % for apartment buildings. This ratio is confirmed in [128] with 70 % and 25 %.

The capacity and location of the residential PV systems for the status quo are known. For these PV systems, the orientation is determined in the form of the (roof) inclination (tilt) and the azimuth (horizontal direction). Since this information is only available for 10% in the MaStR, it is determined depending on a statistical distribution, which results from the existing data for Germany as of 2019. All combinations of tilt (30°, 45°) and azimuth (0°=south, 45°=south-west, 90°=west, 270°=east, 315°=south-east) are considered possible orientations. The installed capacity as well as orientation are used to determine generation profiles by using the local solar radiation. Details are provided in section 5.2.2

In addition to PV, some households own battery storage systems. These home storage systems (HSS) are queried using the municipality key from the MaStR as of 2019. Only data records from the low voltage grid level are used, which include values for the usable storage capacity and net nominal power. Furthermore, only HSS with a usable storage capacity of 10 kWh or less are considered. According to [129], the average capacity of registered lithium-ion solar power storage systems in 2017 was 7.8 kWh and only about 12 % of the studied storage systems had a capacity of 11 kWh or more. The distribution of the capacities in [129] shows a clear drop-off between 10 kWh and 11 kWh, which makes this assumption on the maximum storage capacity reasonable.

Data for most HSS, installed and still in use in 2019, are known by capacity and power for any municipality [130]. Yet, there is no exact geolocation or assignment to PV system available. For any possible pairing of PV and HSS, the ratio of installed power of the residential PV system and capacity of all available HSS is known. The HSS is assigned to PV in order to meet the distribution of ratio of installed PV power and HSS capacity from [129]. The HSS are currently modeled in a simplified way, which charges the battery in timesteps with a surplus and discharges it in cases with higher consumption than generation, depending on the residual load of the household, which includes all consumers (i.e., electric vehicles). The efficiency of the batteries is static (94 %) [131] and available power symmetric.

The different components within buildings, as included in the simulation framework, are depicted in Figure 5-1. While every building must include the basic information as well as a thermal and electrical load, the other technologies are optional and depend on the status quo or applied scenarios.

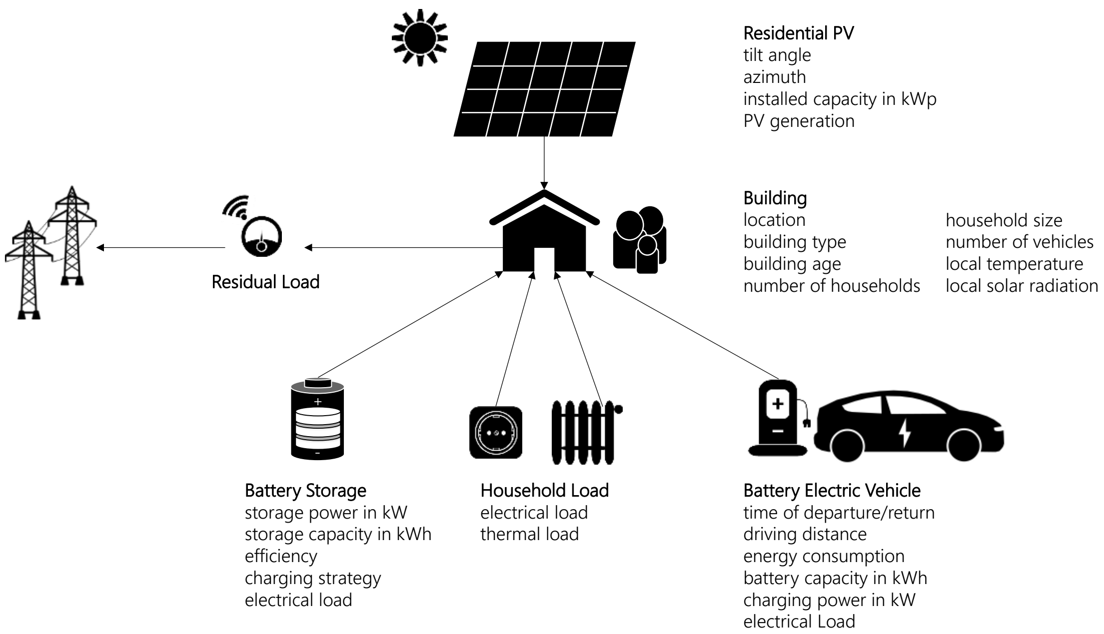


Figure 5-1: Schematic representation of households in the simulation framework.

### 5.2.2 Status Quo 2019: Renewable Generation

Power, location and type of commercially operated renewable generation (i.e., biomass, wind, ground mounted PV), which is not affected by the GDPR, is published in [132]. They are assigned to municipalities by their known location. Additional data including onshore wind is taken from [133].

**Photovoltaics**

For ground-mounted and commercial PV, a minimal capacity of 20 kWp is defined. They are all directed south with a tilt of 30°, which resembles the ideal parameters of installation [134]. For weather-dependent renewables such as wind and PV, the yield is modeled using the weather data of 2019.

The grid-based weather data for PV generation has a resolution of 0.2°, which resembles a grid size of roughly 22 km x 15 km (north-south x east-west) per cell and is based on the Copernicus Atmosphere Monitoring Service (CAMS). Based on the location, direction and tilt, a normalized PV generation profile is generated, according to [135]. Additional data, i.e. temperature [136] and albedo [136], are included as well. In [135], "generation profiles for different inclinations and orientations of the panels" were calculated and included in the simulation framework. These normalized generation profiles are multiplied with the installed capacity of installed residential and ground mounted PV in order to generate an individual time series data for PV generation.

Existing wind turbines are provided by the MaStR with additional data about the wind turbines from [137] (e.g., turbine stocks on per NUTS-3 level, power, hub heights, commissioning dates) and information about the sites etc. from [138]. Based on installed wind turbines and additional information, "time series of generation are calculated with the wind speed in hub height and turbine-specific power curves" [139] The time series data for wind power plants are based on a classification of the counties according to wind frequency. According to [140], these are assigned to five categories from weak to very strong using data from the COSMO-EU model [123], according to the average full load hours from 2011 to 2013. For each category, a generation profile with hourly resolution is calculated using the power curve of a reference plant (according to [140]) and wind speeds for the year 2019 according to [141]. The reference plant is necessary, since individual information about hub height etc. is not provided in most cases. To obtain the generation curves of the individual wind turbines in the model, the reference curve of the region to be mapped is normalized and then scaled with the individual power of every plant.

**Biomass and Hydropower**

The hourly resolved generation curves for hydropower and electricity generation from biomass are based on [142]. While the normalized generation from biomass is available regionalized on county level, there is no regionalization for hydropower, so that the generation depends exclusively on the installed capacity. A time series for hydropower is generated by normalizing a generation profile for German hydropower according to [142] and multiplying it with individual installed capacities from MaStR. The time series for electricity generation from biomass is calculated using the regionalized and normalized generation profile of the respective county as well as the installed capacity.

### 5.2.3 Scenario 2035

An important part of simulating energy-economic use cases is the modeling of future developments. This work does not develop scenarios that depict future development, but instead utilizes an existing scenario. This scenario as well as the methods to determine the impact on municipality-level are described in the following.

**Used Scenario**

The simulation framework allows to apply arbitrary scenarios. The scenarios must be defined as detailed as possible and include total installed capacities. For electric vehicles, rooftop PV, heat pumps and HSS either a total amount, power (PV) or penetration must be provided. The community generation module is capable of converting these inputs into individual components and assigning them to buildings.

The scenario (NEP B 2035 (2021)) used in this work was developed in [143] and [144]. According to [144], "all scenarios are based on the currently applicable legal framework and on additional energy and climate policy targets formulated in line with the current political consensus". This includes the achievement of $CO_2$-targets as set in [145] in all scenarios. The scenarios do not yet include political developments surrounding the war in Ukraine from 2022, which changed political premises in Germany and Europe (e.g., dependence on and substitution of Russian natural gas, increased demand for residential PV, HSS and heat pumps). The data for the scenarios from [144] is depicted in Table 14-2 in the appendix.

In this work, NEP Scenario B 2035 was used since it includes the regionalization of onshore wind and "takes into account not only the area potential but also the political targets of the federal states. Compared to NEP Scenario A, this results in a broader geographic distribution of the plants across Germany." In NEP Scenario B 2035, coal phase-out is assumed to be completed by 2035 [144]. The FfE provided the regionalization in the scenario in [146] and hence data on rooftop mounted PV, ground mounted PV as well as onshore wind power plants readily available at the municipality level.

**Rooftop PV and HSS**

The capacity of new PV is determined by the distribution, provided in [132].Hence, the capacity-distribution of PV systems is the same in all municipalities. From the scenario, the total installed PV capacity as well as the number of HSS are known per municipality. New PV is drawn according to the distribution in [132] and assigned to a suitable building (prioritizing detached houses and semidetached houses. This process is repeated until the desired total capacity, defined by the scenario, is reached. The generation profile is generated, as described in section 5.2.2

In a scenario, the overall share or absolute number of PV with HSS can be determined. To assign suitable HSS, PVs are chosen randomly and assigned with a reasonably sized HSS, based on the distribution of PV capacity to storage capacity from [129] until a desired share or number is reached.

**Electric Vehicles**

Electric vehicles are distributed randomly on available buildings. Load profiles are generated, based on driving behavior of the underlying household from [122]. Buildings with a PV system are prioritized.

**Onshore Wind**

The potentials of onshore wind energy depend on local site conditions as well as protected areas, settlements, traffic routes, and buffer areas around each of the aforementioned [139]. In [135], a method was developed, applying GIS models to determine wind potential areas as well as suitable wind turbines, depending on local site conditions. In 100x100 m cells, protected areas (e.g., nature reserves) as well as data on land cover (Corine Land Cover, CLC) and slopes in conjunction with buffer zones (100 – 5.000 m) were applied to determine the remaining areas suitable for wind energy [139]. Additionally, every potential site for onshore wind was classified, depending on restrictions (weak, strong, taboo). The resulting classification can be seen in [146].

To determine the site-typical wind power plant, local full load hours (as an indicator for long-term average wind speeds), technical data of the existing turbines and the future development of the wind turbines were considered in [139].

As a result of this preliminary work, not only wind areas based on site conditions (including classified restrictions) are provided, but also individual wind power plants, based on [147] and [148]. These power plants reflect the typical wind turbine, power and hub height as well as spacing between the plants to optimize the local yield. The community generation module hence must only pick individual wind power plants from this dataset until the power threshold by the scenario is met. The model starts with picking the wind area with the lowest restrictions, building individual wind turbines until either the scenario threshold or the maximum potential of the area is met. It proceeds until either all wind potential areas are exploited, or the scenario threshold is met.

Based on this preliminary work, suitable areas are provided including a measure of spatial suitability and solar radiation. Contrary to onshore wind, optimal power of individual ground mounted PV plants is not yet provided in the dataset. Based on area and solar radiation, a PV potential is calculated with 1 MWp/ha [149].

To determine individual ground mounted PV plants within the municipality, the distribution of today's installed ground mounted PV capacity is analyzed to determine the power of future installations. This is based on the assumption that the installed capacity of ground mounted PV plants will remain the same in the future as it is today. From this distribution, single plants are drawn at random until the limit, set by the scenario, is reached. If a threshold of 500 kW is undercut, the remaining power is put into one plant.

For any so determined plant, all potential areas that provide sufficient space to build the planned capacity are selected. Areas with spatial resistance are preferred for PV installations, and areas with the least resistance preferred over those with a higher resistance. To avoid PV in the same location as wind installations, onshore wind is built prior to ground mounted PV. Afterwards, areas with an initially low spatial resistance but now installed wind capacities are categorized with the highest spatial resistance. When a ground mounted PV plant is positioned on an area, the still remaining area is calculated in order to install additional plants in the future. This prevents areas from being built on only once and thus better exploits its full potential. Areas which are already used for onshore wind are used only if there are no other areas remaining.

## 5.3 Resulting Model

In this section, the resulting model is presented. The model is a digital representation of a municipality with python objects. The objects within a municipality all include at least a type, a location, and a load profile. This is the basis for any subsequent use case module, presented in the next section.

### Model Plausibility Check

A goal of the model is the correct representation of private consumers. Figure 5-2 depicts a comparison of load duration curves of 16 representative municipalities[2] (excluding big cities).

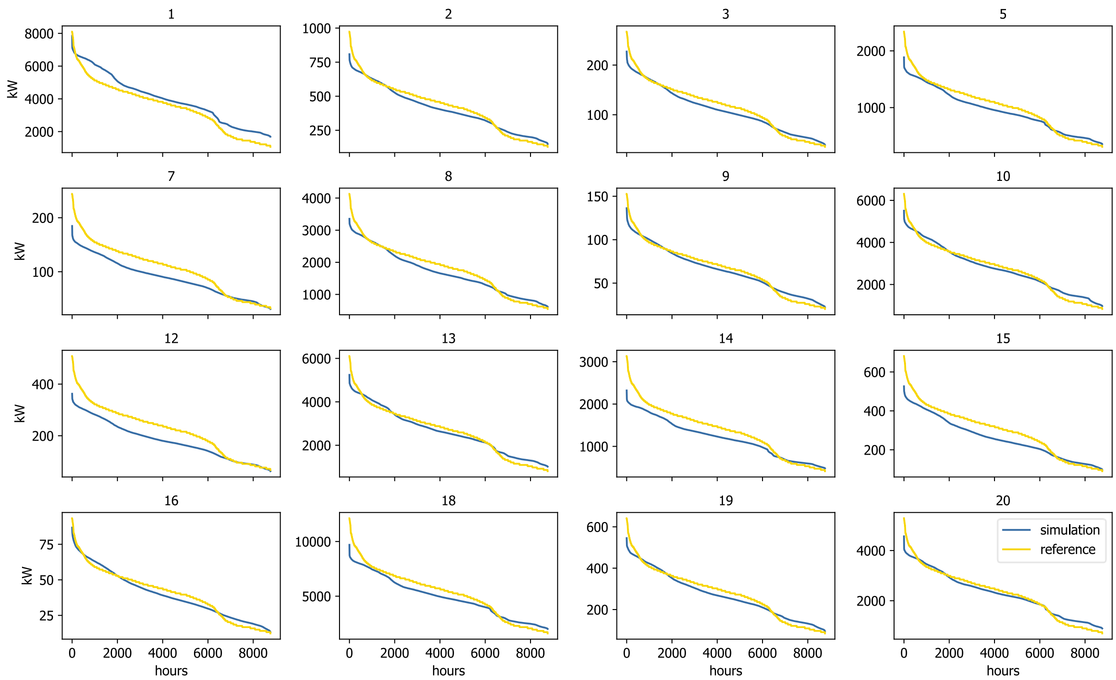


Figure 5-2: Load duration curve of representative municipalities of 16 clusters with H0 profiles and aggregated load profiles of the simulation framework

The results show a good representation in all municipalities. Overall, the load profiles of the simulation (blue) are slightly lower than the H0 profiles (yellow). Especially the morning peak is not hit optimally by the data from [122]. The accuracy of the total annual household consumption within all representative municipalities, however, is 94.9 % and hence good.

Figure 5-3 depicts the accuracy of 16 representative municipalities for seven different simulation parameters. The accuracy indicates how well the model depicts the reference values. A value of 100 % implies a perfect depiction of the specified reference data. Deviations up or down from 100% indicate whether and how much the model exceeds or falls short of the reference value.

[2] The model validation is done with representative municipalities. The method to identify them as well as their description can be found in section 6.

The number of households (96.2%), buildings (98.9 %), inhabitants (97.0 %), and the annual household consumption (94.9 %) are simulated very closely to the corresponding reference data. These values are the same in 2019 and 2035, since household data is not included in the scenarios and does not change much over time. To avoid redundancies, only 2035 is depicted in Figure 5-3.

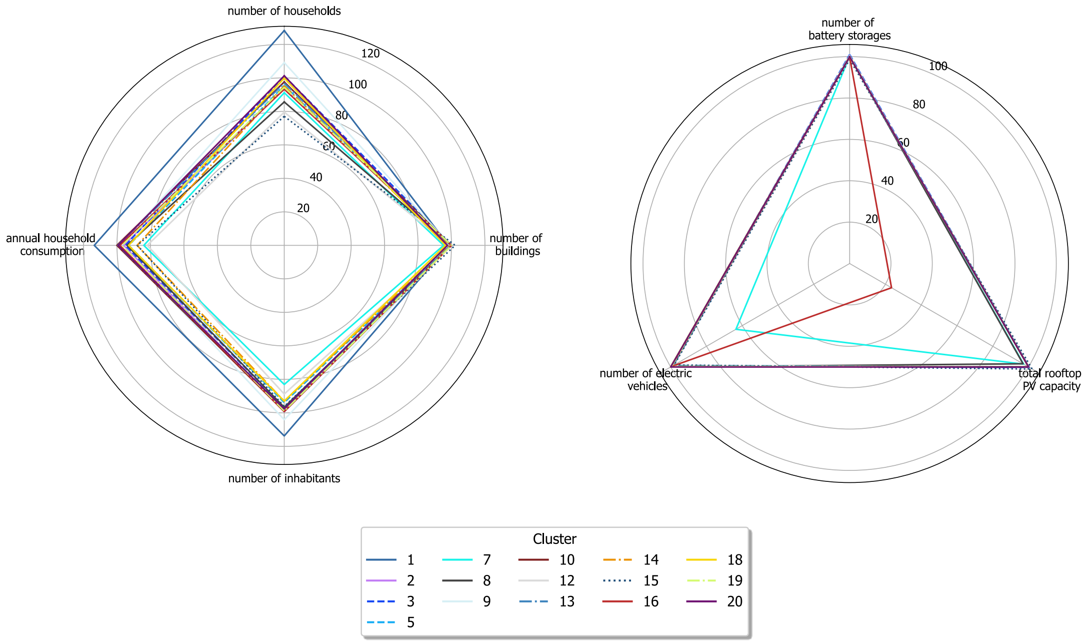


Figure 5-3: Accuracy of the simulation framework to reference data in percentage for inhabitants, households, buildings and consumption (2019 & 2035 left), battery storages, rooftop PV and electric vehicles (2035, right).

The number of batteries (100 %), total installed rooftop PV capacity (96.0 %) and number of battery electric vehicles (97.7 %) are also modeled very accurately, with some outliers in cluster 16 (rooftop PV) and 7 (electric vehicles). This is due to the very low installed capacities of PV (cluster 16) and electric vehicles (cluster 7) in these municipalities. If only a few units are missing, a large percentage error occurs. One challenge is correct mapping of the status quo of home storage systems. This is done, based on MaStR. Especially HSS data includes many missing and incorrect entries. However, since only a few HSS are installed, this is almost irrelevant for the total load profile of the municipalities in 2019. While the reference data is undershot by the model in most clusters, cluster 1 is overshot, leading to a slightly higher annual household consumption than given by the reference data. All in all, however, the results can be considered very accurate, as the deviations are in the small, single-digit percentage range.

Figure 5-4 depicts five days of the load profiles of a randomly chosen four-person prosumer household with a home storage system (battery) and 7 kWp rooftop PV. The HSS acts as intended and charges when the residual load becomes negative. The HSS hence shifts morning surpluses into the evening hours. Since the battery is not optimized, it has almost no impact on PV peaks since it is already fully charged around noon.

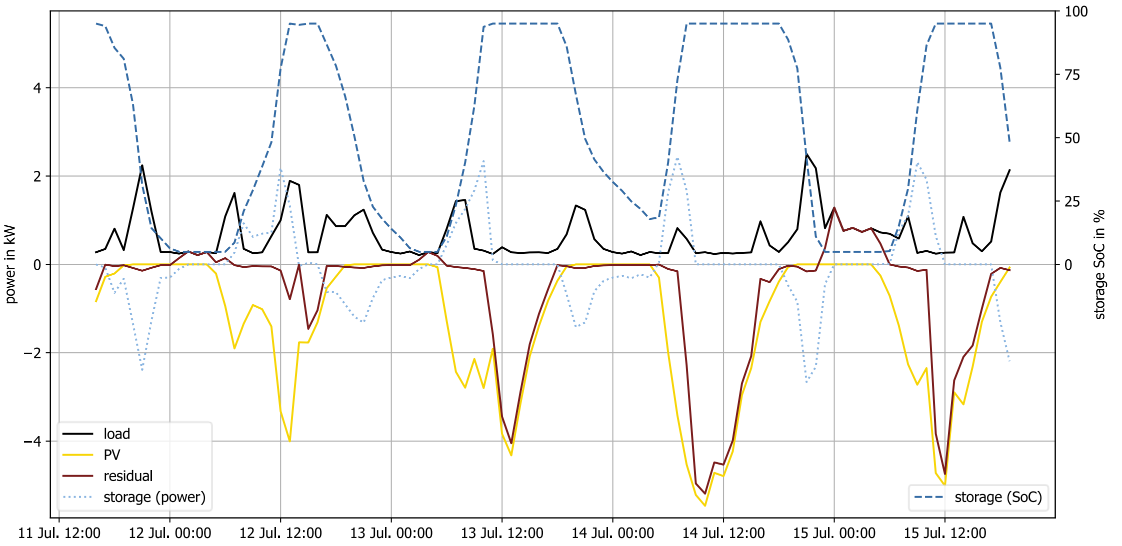


Figure 5-4: Data of a randomly chosen building with one household, 4 inhabitants with a 3.3 kW/7 kWh storage and 7 kWp PV (2019)

All in all, the bottom-up model reflects top-down reference data very well. A discussion of model weaknesses and possible improvements is provided in section 10. In the following, the spatial depiction of the households and renewables is examined.

### Spatial Plausibility Check

Figure 5-5 shows the status quo on the left. Buildings are visualized in 100 x 100 m grids and represent existing settlement structures.

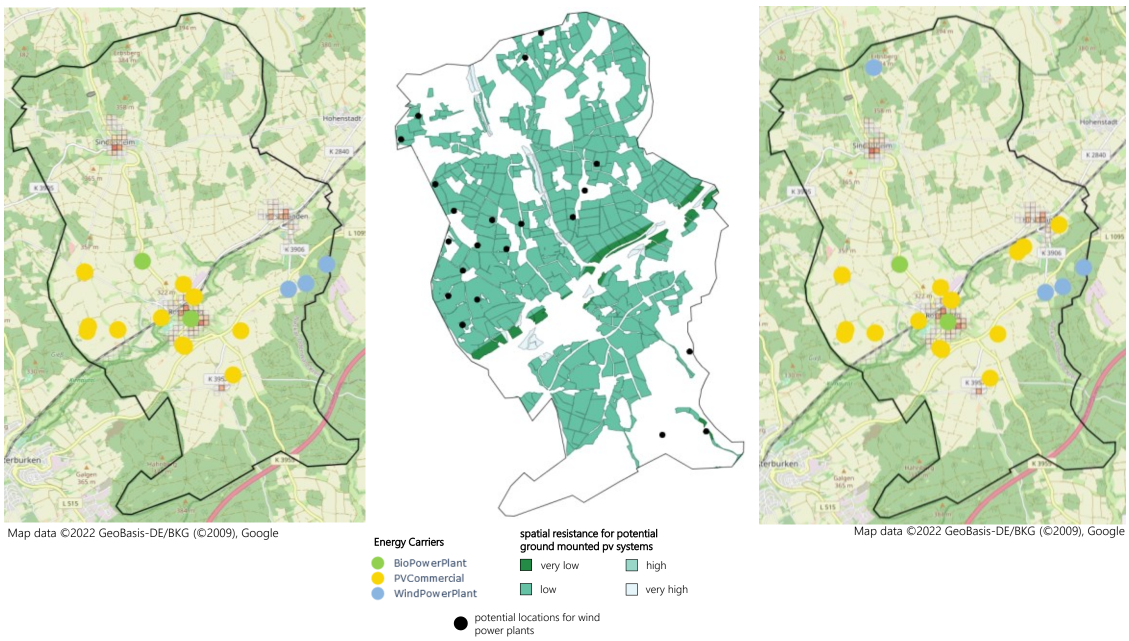


Figure 5-5: Visualization of a randomly chosen municipality (Rosenberg), generated by the simulation framework. The status quo (2019) is depicted on the left, areas available for PV and wind in the middle and the resulting scenario for 2035 on the right.

PV plants (yellow), biomass (green) and wind installations (blue). The middle figure shows the viability of certain areas for ground mounted PV (green) and sites for additional wind turbines (grey). The figure does not include a visual representation of rooftop PV. Additional ground mounted PV is best located around the train tracks, passing through the municipality. In this area, three additional PV installations are added in 2035 (right). An additional wind turbine is installed in the north.

## 5.4 Use Case Modules

The community generation module generates the necessary data to simulate the introduced use cases. The community generation module only needs to be executed once per parameter-setting and municipality. The use case modules use the data of the pre-generated municipalities to execute their individual calculations. In the following, these use case modules are introduced.

### 5.4.1 Allocation in Regional Direct Marketing

Regional direct marketing incentivizes simultaneous generation and consumption within a range of 4.5 km by freeing it of the electricity tax. The goal of Equation (4-1) is to minimize the distances between generation and consumption. Accordingly, a certain tendency with regard to regional direct marketing is already inherent. To optimize the yields within 4.5 km, the cost $\tilde{c}_{ij}$ is set to the proximity between supply and demand and weighted by an additional factor $w_{ij}$, increasing the costs in the optimization for distances > 4.5 km. This weighting-factor is calculated as follows

$$\tilde{c}_{ij} = w_{ij}\, s_i\, C_{ij}$$
$$w_{ij} = \begin{cases} w_{ij} = 1 & 0 < C_{ij} \leq 4.5 \\ w_{ij} = 1000 & C_{ij} > 4.5 \end{cases} \quad (5\text{-}1)$$

By these weights, the minimization in Equation (4-1) prefers to pair supply and demand within a distance ≤ 4.5 km. Surplus electricity is still provided to the next available consumers outside this range but does not count as regional direct marketing. Only electricity that can be consumed within 4.5 km is added up to determine the overall potential of this use case per timestep.

### 5.4.2 Pricing in Local Energy Sharing Communities

A P2P price within a community is calculated for each time step, based on the following main parameters extracted from the community generation module of the simulation:

- Residual loads of each prosumer household, dynamically calculated for each household. If a household produces more electricity than it consumes, the residual load is added to supply. If a household produces less electricity than needed, it is added to the demand within a community.
- The load of all consumer households within a time step are added to the demand of a community
- Generated electricity from RE is added to the supply within the community

Additionally, the exchange price for any time step as well as the static retail price are used.

As introduced in section 4.3.1, two different pricing mechanisms are to be assessed, based on this data. The implementation of the SDR and MMR pricing, as implemented in the simulation framework, are described in the following. Both mechanisms have been assessed in [A4] and [A3].

**Supply and Demand Ratio Pricing (SDR)**

SDR pricing was proposed in Liu et al. [150] and calculates the "relation between price" and supply demand ratio as the "inverse-proportional". With rising supply, the $SDR_t$ increases and hence the product price decreases. With high demand and low supply, the $SDR_t$ decreases and hence the product price increases [A3]. This mechanism can be applied to LES and be simplified to the following formula according to [151]:

| | |
|---|---|
| $$p_t^{sell} = f(SDR) = \begin{cases} \dfrac{p_t^{wholesale} \cdot p_t^{retail}}{\left(p_t^{retail} - p_t^{wholesale}\right) \cdot SDR_t + p_t^{wholesale}} & 0 \leq SDR_t \leq 1 \\ p_t^{wholesale} & SDR_t > 1 \end{cases}$$ $$p_t^{buy} = \begin{cases} p_t^{sell} \cdot SDR_t + p_t^{retail} \cdot (1 - SDR_t) & 0 \leq SDR_t \leq 1 \\ p_t^{wholesale} & SDR_t > 1 \end{cases}$$ | (5-2) |
| $p_t^{wholesale}$ | exchange price for selling oversupply or buying undersupply |
| $p_t^{retail}$ | retail price, paid by consumers for electricity that is not supplied by the community |
| $p_t^{sell}$ | selling price for electricity that is to be sold by prosumers within the community after their own consumption has been subtracted |
| $p_t^{buy}$ | resulting buying price, paid for consumed electricity generated within the community |
| $SDR_t$ | Supply Demand Ratio with $SDR_t = \frac{supply_t}{demand_t}$ |
| Source | [A3] |

Key findings in [A4] included that the SDR pricing mechanism offers high price volatility and hence good incentives for the construction of additional renewables or flexible assets such as batteries, electric vehicles, or heat pumps. Since the price fluctuates between retail price and the electricity exchange price, a high $SDR_t$ leads to buy prices at exchange rates $p_t^{wholesale}$. In these cases, the advantages of participating in a community are low for suppliers but high for consumers. For low $SDR_t$, this is reversed. Due to its mathematical formulation, the SDR pricing mechanism is not robust against outliers, e.g., negative prices or outliers of $p_t^{wholesale}$ [A3]. To overcome this lack of robustness, a modification is introduced. Analogous to $SDR_t > 0$, the $p_t^{sell}$ and $p_t^{buy}$ are set to $p_t^{wholesale}$ if $p_t^{wholesale} < 0$. While this increases the profitability of the community it does not necessarily support the reduction of GHG emissions if the negative prices are induced by fossil generation.

Since $p_t^{buy}$ and $p_t^{sell}$ and the $SDR_t$ are rarely balanced, a financial delta arises from these prices within the community. On the one hand, this is needed to buy or sell the residual quantities at the exchange for $p_t^{wholesale}$. What remains are the revenues of the ESP. A detailed analysis of these revenues in all pricing mechanisms covered in this work is conducted in section 8.4.

### Mid-Market Rate Pricing (MMR)

In the MMR pricing mechanism, as proposed in [152], a P2P price is set mid-way between selling and buying prices, when the energy supply and demand within the community are balanced. In this mechanism, three different cases are distinguished, based on the $SDR_t$ [A3]. The mathematical formulations according to [151] are as follows:

| | | |
|---|---|---|
| $SDR = 1{:}\ p_t^{buy} = p_t^{sell} = p_t^{mid} = \frac{p_t^{retail} + p_t^{wholesale}}{2}$ <br> $SDR < 1{:} \begin{cases} p_t^{sell} = p_t^{mid} \\ p_t^{buy} = \frac{p_t^{mid} \cdot \sum_{i=1}^{peers} P_t^{supply} + P_t^{shortage} \cdot p_t^{retail}}{\sum_{i=1}^{peers} P_t^{demand}} \end{cases}$ <br> $SDR > 1{:} \begin{cases} p_t^{sell} = \frac{p_t^{mid} \cdot \sum_{i=1}^{peers} P_t^{demand} + P_t^{surplus} \cdot p_t^{wholesale}}{\sum_{i=1}^{peers} P_t^{supply}} \\ p_t^{buy} = p_t^{mid} \end{cases}$ | | (5-3) |
| $P_t^{shortage}$ | residual load with $P_t^{shortage} = P_t^{demand} - P_t^{supply}$ | |
| $P_t^{surplus}$ | residual load with $P_t^{surplus} = P_t^{supply} - P_t^{demand}$ | |
| Source | [A3] | |

As analyzed in [A4], this leads to a lower price volatility as is the case with the SDR-mechanism. For both sides (supply and demand), the revenues are more evenly distributed. While this leads to more price stability and better long-term security, it offers fewer incentives for additional supply or flexibility.

The calculation of the pricing mechanisms is computationally inexpensive.

### 5.4.3 Pricing in Local Energy Markets

As introduced in section 4.3.2, this use case is a double-sided call auction with a uniform pricing. The input data used from the simulation framework is the same as in section 5.4.2. Contrary to the pricing mechanisms in LES, the price within local energy markets is set by asks and bids by the agents in the market. In the following, the two assessed market models as well as the applied bidding strategies are described. The use case module was already described in [A6].

**Bidding Strategies**

The complexity of bidding strategies in agent based market models can range from simple to very complex. Traders can transact randomly (zero-intelligence), on the value of the traded asset or based on historical information [153].

In [A6], it was decided to implement “zero intelligence (ZI) traders” in a first step to ensure simplicity and transparency. This is a common method found in the literature (e.g., see [154, 155, A6]), often outperforming or achieving equal results compared to more complex (i.e., adaptive strategy- or AI-based) trading strategies [156, 155]. Since the goal of this dissertation is not to compare different agent-based pricing strategies but to apply the model in all German municipalities to determine market prices, this approach is suitable. In future works, more complex bidding strategies can be implemented to evaluate their impact on individual revenues as well as market price.

The bids $\lambda_b$ and asks $\lambda_s$ of ZI traders, hence “follow a normal distribution $\mathcal{N}$ between the borders of the trading corridor, with the respective $\mu$ values lying exactly between retail and wholesale tariffs and $\sigma$ covering the entire interval.” [A6] Only in markets with an open order book, traders might adjust their transactions based on previous transactions [95].

The bidding strategy is depicted in the following:

| $\Lambda_b, \Lambda_s = \mathcal{N}(0.5; 0.5) \cdot (p^{retail} - p^{wholesale})$ | (5-4) |
|---|---|
| $\lambda_b$ | single bid $\in \Lambda_b$ (all bids) |
| $\lambda_s$ | single ask $\in \Lambda_s$ (all asks) |
| $\mathcal{N}$ | normal distribution |
| Source | [A6, 95] |

The use case module was realized with the Mesa agent-based modelling framework [157].

## 5.5 Case Studies

Two case studies show how the various use cases can be implemented in an integrated manner using the optimized allocation (see Equation (4-1)) of the labeling framework. Mapping different use cases at the same time ensures that, depending on the allocation method, economic efficiency is increased for all parties involved.

### 5.5.1 Energy Community

The simulated energy community is depicted in Figure 5-6. The energy community (blue rectangle) is comprised of two low voltage grids (north and south), connected via a medium voltage grid. The EC includes three prosumers (1, 7, 10), a small hydropower plant (13), a ground mounted PV plant (14), private consumers (2-6, 8,9) and a small enterprise (11).

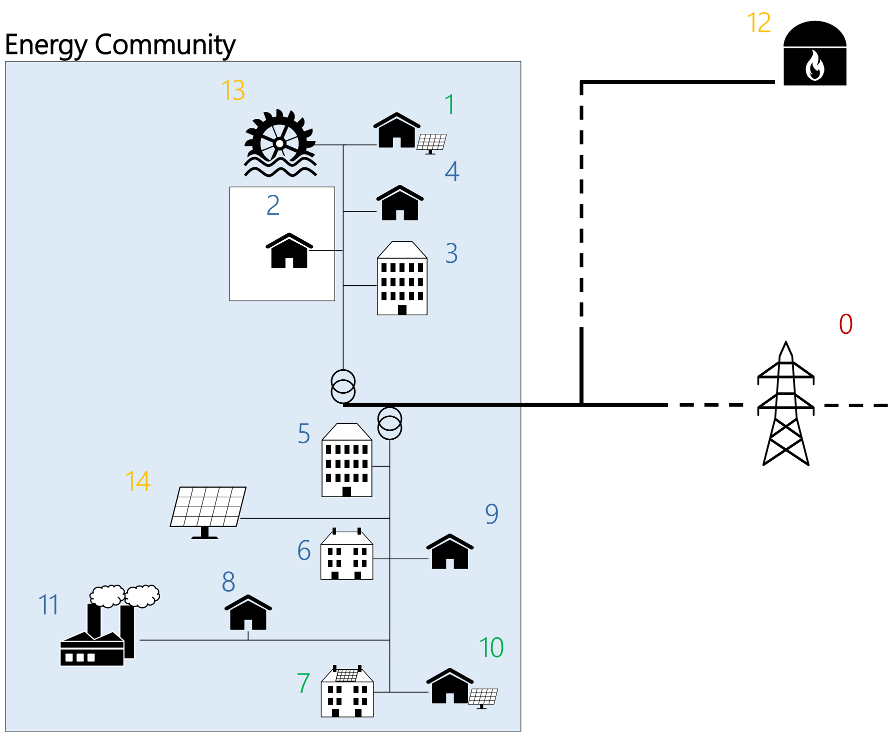


Figure 5-6: Schematic representation of the case study with consumption (blue), renewable energy, RE (yellow), a prosumer (green) and the grid (red)

The energy community has a regional direct marketing contract with a biomass micro combined heat and power plant (biomass micro-CHP, 12) within 4.5 km to cover residual loads.

For reasons of simplicity, the data of the case study is a modified local subset of the simulation framework. The agents in Figure 5-6 all consist of individual load profiles (household loads, electric vehicles), a small enterprise (11) and renewables, as described in section 5.2. The simulation is conducted for a full year. Both case studies are based on the same data.

Supply and demand of the depicted energy community are relatively balanced with a median $\widetilde{SDR}$ of 1.11 and a surplus in 59 % of all time steps. Additional data is provided in Table 14-1 in the appendix.

### 5.5.2 Model Assumptions

Current legislation, processes and infrastructure are barriers for the realization of the use cases. This leads to process constraints, increased costs, and even economic infeasibility. These challenges and corresponding model assumptions will be summarized in the following.

**Considered Participants**

REC and CEC, as intended by the EU, are primarily for private consumers, producers, and small renewables. Since SMEs are not the main target group and, moreover, load profiles are not available in sufficient resolution and variety, they are therefore not considered in the simulation of municipalities. However, in this case study, a single SME is included. To ensure the compatibility of the use cases, only renewables ≤ 2 MW are considered, since this is the delimiting factor of RDM.

**Household Prices**

The household electricity price in Germany is composed of multiple components including electricity price, taxes, and levies. Only a small proportion is directly related to the actual generation price, paid by consumers to their utility. For the year 2019, electricity price, procurement, and sales (charged by the utility) only accounted for 7.09 ct/kWh or 23.3 % for household customers. The total price was 30.46 ct/kWh. The remaining 76.7 % were comprised e.g., of grid fees (7.39 ct/kWh), VAT (4.86 ct/kWh), EEG (6.41 ct/kWh) and others (e.g., 2.05 ct/kWh electricity tax) [158]. Since the share of the utility is divided into electricity price, procurement, and sales (including security and a margin), the actual share of the electricity exchange price in the household price is determined in the following.

**Wholesale Prices**

The basis for LEMs and LES is a retail and a wholesale electricity price. While both are known for 2019, the wholesale prices for 2035 are not known for the used scenario.

A goal of this work is the comparison of different pricing mechanisms in 2019 and 2035. To ensure better comparability of the pricing mechanism based on different compositions of the municipalities, the prices of 2019 are therefore also used for the scenario 2035 [A3]. Accordingly, statements can only be made regarding how the expansion of RE in the municipalities will affect the relative price development, influenced by endogenous changes within the community. Exchange prices are hence considered exogenous variables in this work.

**Retail Price in Energy Communities**

Utilities procure their electricity for the most part as futures in the year prior to delivery and buy or sell residual quantities on the spot market [159]. Based on this, the actual electricity price in the household price can be estimated by the average volume-weighted prices of electricity on the futures market in the year prior to delivery. The basis for 2019 is the "EEX Phelix-DE Baseload", which includes the average prices and quantities paid per business day in 2018 [160]. The average volume-weighted price in 2018 for the year 2019 was 43.44 €/MWh ranging from 32.75 €/MWh to

56.65 €/MWh on 251 days of trading on the EEX. Therefore, the average exchange price (i.e., procurement) in the household price was 4.34 ct/kWh, leaving 2.75 ct/kWh for costs and margins of the utility.

For the use cases involving a pricing mechanism, a retail price is required. Based on [A3] and [A4] the retail price in the simulation framework for 2019 and 2035 is 7.09 ct/kWh. For reasons of comparability of the pricing mechanisms, the $p_t^{retail}$ and $p_t^{export}$ in 2035 are set identical to 2019 to exclude impacts of external factors.

**Taxes, Levies and Charges**

As depicted, a significant proportion of household prices is comprised of fixed costs, including taxes, levies, and grid charges. EU legislation directives aim to change "network charges, as well as relevant charges, levies and taxes, ensuring that they contribute, in an adequate, fair and balanced way, to the overall cost sharing of the system in line with a transparent cost-benefit analysis of distributed energy sources developed by the national competent authorities" [161]. Since this directive has not yet been implemented in Germany, it is questionable which shares will in fact be removed for energy communities. As shown in section 4.3.3, electricity produced and consumed within 4.5 km is already free of electricity tax. It seems reasonable to reduce upstream grid costs, due to local grid use.

If ECs are exempt from some or all of these additional price components, this has great impact on the local market price, since the cost advantage to energy, sourced on the electricity exchange (= retail price), increases by this amount. As an example, if energy distributed within an EC (independent of pricing method) is 76.7 % percent cheaper by default, due to an exemption of all grid, tax and, levy related costs, then even if the price paid is equal to the exchange price, the difference would be included in the local market price.

Assumptions in this area have a large impact on local price. To ensure comparability between market mechanisms, it is not assumed in this work that any taxes, levies, and grid fees are reduced within an EC. Hence, it is assumed that the retail price for 2019 is 7.09 ct/kWh. For reasons of comparison, it is also assumed that today's 2.75 ct/kWh, which covers costs, risk and margin of the utility, is the same in 2035.

**Grid Fees**

The share of lower voltage grid fees is not known. Since in many countries, a reduction of grid fees for local energy consumption and generation is granted, the costs for the case study in section 5.5 are approximated. Based on [162], the total costs and the cost rollup between voltage levels is known for 2013. Based on this, about 11 % of lower voltage grid (LVG) fees are due to TSO costs. About 18 % are due to higher- and medium voltage grid (HVG/MVG) and 70 % from the lower voltage grid. Accounting for the estimated cost of metering (included in the grid fees), which make up about 0.9 % (or 0.27 ct/kWh) of the household prices [158], and assuming a constant share, the lower voltage grid fees are about 4.98 ct/kWh for household consumers. Conversely, this means that 2.09 ct/kWh of the grid fees are due to medium, high and transmission system costs.

The goal of this work is to calculate the potentials of the use cases presented in section 4 for all German municipalities. The use cases presented in section 4 have a strong local reference. For example, in the case of regional direct marketing, a distance of 4.5 km, a temporal resolution of generation and consumption data of 15 minutes is required by law [163, 164]. In the other use cases too, the requirements in terms of spatial and temporal resolution are equivalent and usually refer to individual, small-scale consumers and generators whose load profiles must be determined and simulated individually.

### 5.5.3 Case Study 1: Allocation by Proximity

**Description:** in this case study, a utility provides a local energy product which includes the allocation of electricity according to the proximity of supply and demand in the area.

**Allocation:** the electricity is allocated according to the distance between the consumers and RE. The use case is regional electricity.

Result: Both sides (supply and demand) are shown as a percentage in Figure 5-7. Consumers 2, 11, prosumer 7 are depicted with their individual shares. The allocation is made according to spatial proximity. Hence, supply from 1 and 13 are primarily allocated in the northern LVG and supply from 7, 10 and 14 in the southern LVG. Especially the southern LVG has high simultaneity of supply, due to three PV systems producing simultaneously, depending on weather conditions. Hence, the relatively constant supply of the small hydropower plant (13) is allocated completely within both grids to cover shortfalls. The grey electricity is mainly allocated among consumers 7, 10 and 11 since they are the furthest away from RE 12 and 13. Residual electricity is either sold or bought from the grid (0).

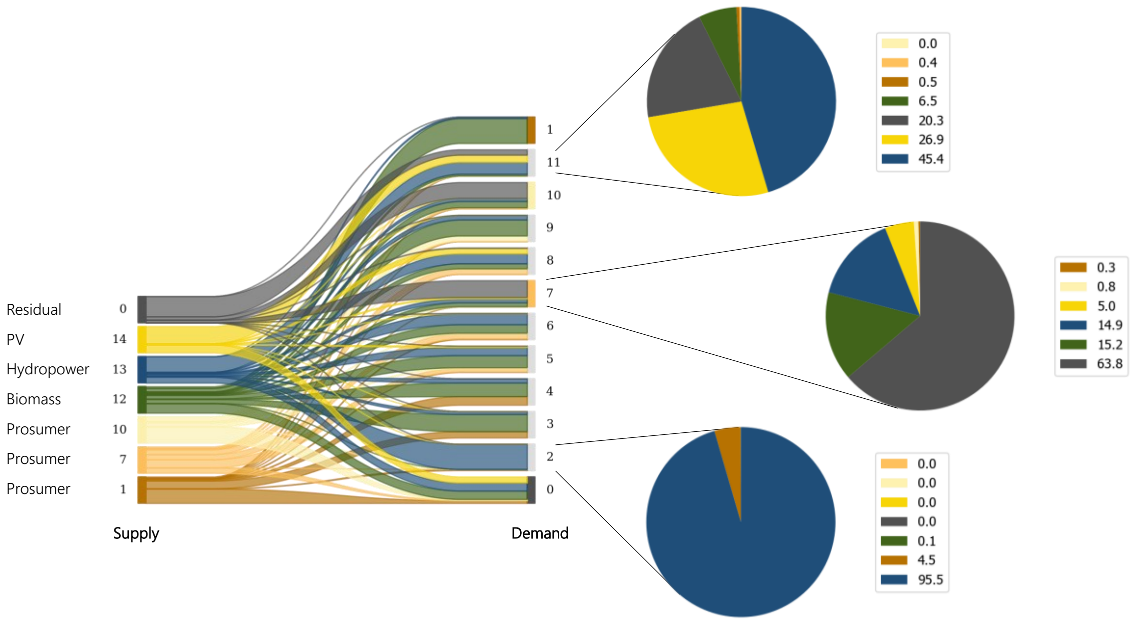


Figure 5-7: Sankey diagram of the allocation result in percentage, and individual results for three consumers, considering proximity.

**Application of the Labeling Framework:** the labeling framework is used to perform the allocation, as shown in Figure 5-7. The results are provided individually to all consumers via a graphical (user) interface. They are verified using ZKP. Additionally, based on the individual electricity consumption, individual information on the respective GHG emissions is provided to all consumers. The German Environment Agency (UBA), which is in charge for correct allocation, can verify the correctness of the process via the ZKP.

### 5.5.4 Case Study 2: Allocation by Use Cases

**Description:** an energy service provider (ESP) handles the processes of a local energy community, considering multiple use cases and verifying the results to various stakeholders via the labeling framework.

**Allocation:** instead of proximity, use cases and their respective costs are considered in the allocation. The following assumptions are made for the costs in the case study:

- All consumers and prosumers (except consumer 2) are part of the energy community.
- Simultaneous supply and demand within the community is free of taxes and levies and hence cheaper than electricity from external sources.
- Grid fees are charged, depending on grid use. Therefore, simultaneous supply and demand within the same LVG is only charged with LVG grid fees. If electricity is transferred from the northern to the southern LVG, the MVG is used and hence LVG and MVG fees apply (use case: consideration of grid topology).
- The community has a regional direct marketing contract with a biomass micro-CHP (12). Electricity from this plant is not obligated to pay electricity taxes for all quantities, supplied to the community. It is hence cheaper than buying electricity from the exchange (use case: consideration of proximity/regional direct marketing).
- The SME (11) has an offsite-PPA with the biomass micro-CHP (12) and bought the small hydropower plant (13) (RSC) to avoid the high amounts of grey electricity (see case study 1). Hence, the SME is prioritized over other consumers and the community in case of 12 and 13.
- The SME (11) together with prosumer 7 and consumer 8 invested collectively in the ground mounted PV (14) (use case: renewable self-consumers/asset sharing).
- For reasons of simplicity, the electricity costs (procurement) for residual quantities are considered static.
- Consumer 2 receives electricity primarily from his own utility (i.e., the grid) since he is not part of the community. However, if the community has more supply than demand, he receives the surplus for the market price.

Based on these assumptions, data provided in [158], as well as the earlier considerations in section 5.5.2, the household price compositions including different costs per use case are depicted in Figure 14-2 in the appendix.

**Result:** the goal is to allocate energy production to individual consumers in such a way that use cases with financial benefits are mapped first in order of their benefits. The goal of the linear optimization is the minimization of the cost of all consumers. The results are depicted in Figure 5-8.

As demonstrated in Figure 5-7, electricity is allocated accordingly. Contrary to the proximity-based allocation (Figure 5-7), Consumer 2, who does not participate in the community, now receives 54.2 % grey electricity. If surpluses from the community were sold to the market rather than to him, he would receive 100% grey electricity. The share of grey electricity of the SME (11) is reduced from 20.3 % (Figure 5-7) to 9 %. However, in times of a general shortage of green electricity, a full coverage is still impossible without storage, flexibility or additional RE in the community. Prosumer 7 can increase the share of PV in his electricity mix by his investment in 14. However, due to the high simultaneity to his own PV system, the overall share is only increased from 5 % to 11 %. Since the SME (11) acquired electricity from 12, other demand (including prosumer 7) receives lower shares from this source.

**Application of the Labeling Framework:** These results, provided by the labeling framework, allow the executing ESP to proof the correctness of this process and input data to involved stakeholders in the community and external third parties. This can be done in a transparent, GDPR-compliant and tamper-resistant way via smart meters, Merkle proofs and ZKP. The blockchain-technology serves as shared platform to avoid double spending and ensure transparency towards stakeholders (especially regulators). External stakeholders in this case, are the DSO as well as multiple authorities, providing refunds on grid fees, levies and taxes. Instead of receiving and checking the underlying data, these third parties can verify the correctness of the allocation by the provided ZKP. This allows for quick processing of refunds (even in real time, if necessary).

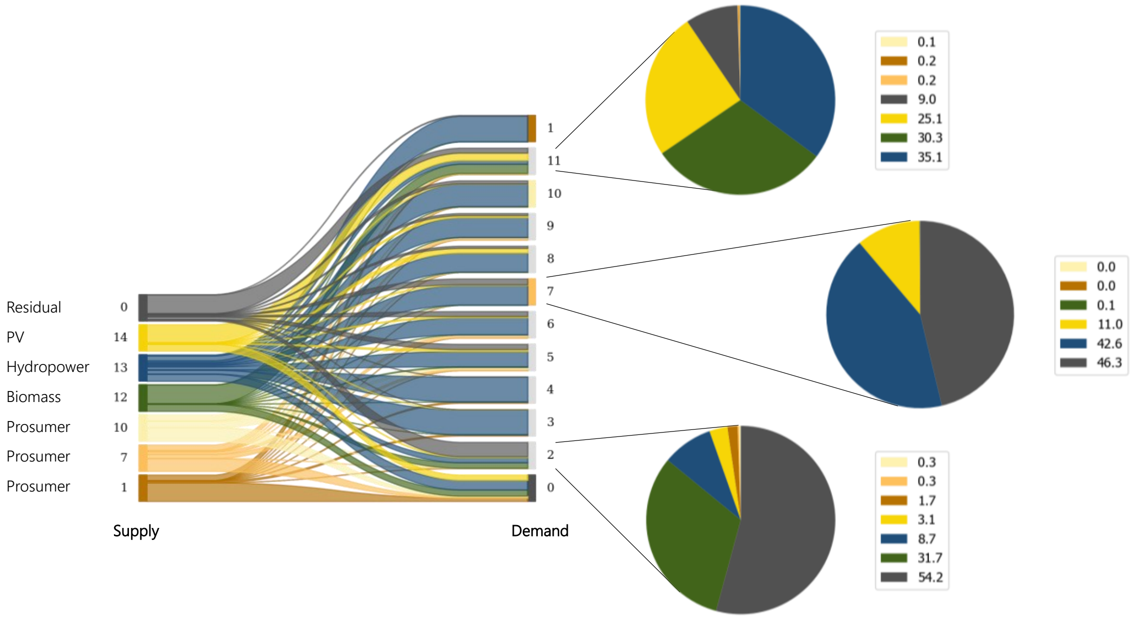


Figure 5-8: Sankey diagram of the allocation result in percent and individual results for three consumers, considering cost.

Both case studies show the viability of the simulation framework as well as the applicability and flexibility of the allocation, to incorporate multiple different use cases. The runtime of the computation of individual time steps is low, which allows this to be done in near-real time. However, the case studies also show that the runtime of the simulation is relatively high if about 12,000, significantly larger municipalities than in the case study have to be simulated and optimized for an entire year. For this reason, computational costs are analyzed in more detail below.

## 5.6 Computational Costs

The goal of this work is to calculate the potentials of the use cases presented in section 4 for all German municipalities. The use cases presented in section 4 have a strong local reference. For example, in the case of regional direct marketing, a distance of 4.5 km, a temporal resolution of generation and consumption data of 15 minutes is required by law. [163, 164] In the other use cases, too, the requirements in terms of spatial and temporal resolution are equivalent and usually refer to individual, small-scale consumers and generators whose load profile must be determined and simulated individually.

In this section, the time required to simulate the use cases is present and possible improvements shown.

### Method

As described in [A3] and section 7.3, 1,323 municipalities were generated once but only 50 typical hours were simulated per municipality, in the use cases RDM and LEM, due to computational cost. Every type hour represents a known amount of hours, adding up to 8,760 h/year. The time to generate results was logged per municipality and use case module.

The time to simulate the full 8,760 h per municipality can be estimated by multiplying the number of hours a type hour represents and adding up the results. To estimate the simulation time for the full population, a linear- or polynomial function is fit on the simulation time and number of inhabitants. Since the number of inhabitants is known for all municipalities, the time can be estimated for a full simulation.

### Community Generation Module

Figure 5-9 shows the generation time for 8,760 time steps of 1,323 municipalities. This generates necessary data (e. g., load profiles, penetrations of different elements) for the optimization or other use cases. Based on this data, the TSA is conducted to determine type hours for the more computationally expensive use case modules.

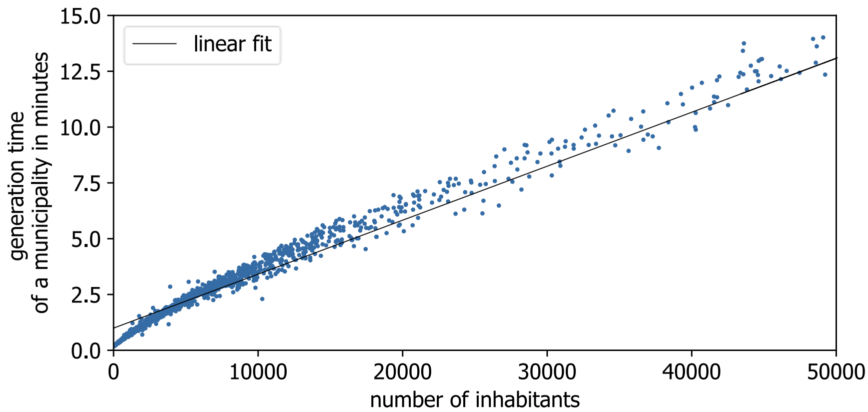


Figure 5-9: Generation time for a sample of *n=1,323* municipalities in 2019

The generation time $t$ in minutes of a municipality $m$ with 8,760 time steps (excluding the TSA) can be described as a linear function of the number of inhabitants $x$ by $t_m = 0.00024 * x + 0.99$ with an $R^2$ of 0.988. Applying this function on the known number of inhabitants of all ca. 12,000 municipalities, this would require 21.7 days (2019). As shown in [A3], the generation of all 11,973 municipalities took 13.78 days. The difference in simulation time can be explained by the model complexity which increased in the meantime as well as varying server workload.

A result of this process is $supply_t$ and $demand_t$, necessary for the SDR pricing and MMR pricing in LES. Based on this input data, Equations (5-2) and (5-3), the prices can be calculated in any municipality, if $p_t^{export}$ and $p_t^{retail}$ are known.

### Regional Direct Marketing

The simulation is based on different mathematical principles. The use case "regional direct marketing" is a linear optimization problem, defining the allocation (for details of the allocation, see section 4.3.3).

The total time to optimize a sample of 1,323 municipalities with 50 time steps initially was 14.97 days with an average of 16.3 minutes per municipality and 19.5 s per time step. The time complexity of the linear optimization model increases not only with the number of producers and consumers, but especially with their ratio. The more balanced their ratio and the more actors involved, the longer the runtime. Accordingly, a simulation of the entire German territory is computationally not feasible. For any big municipality and in any future scenarios, the number of small prosumer PV systems is especially high, increasing computational costs. To tackle this, instead of treating every single producer and consumer individually in the linear optimization, they are aggregated in square cells (i.e., 100 x 100 m). Households etc. are still generated individually, but the resulting supply and demand are summed up in this area. The resulting "own consumption" in a cell is added to the total RDM potential. The residual load is transferred as supply (if supply > demand) or as demand (if demand > supply) into the optimization. Figure 14-3 in the appendix shows the resulting effect on the relative number of participants (supply & demand) in different municipalities (representatives are described in section 6) and their effect on the optimization. It shows an "elbow" at a grid of 100 x 100 m with the greatest decrease of participants. A subsequent analysis showed no losses in result accuracy for a resolution of 100 x 100 m. Hence, this approach is used to improve optimization time. Optimizing 1,323 municipalities with 50 time steps without this simplification required 14,97 days. With this simplification the runtime decreased to 17.5 hours (0.95 s per time step).

Figure 5-10 shows a rather low predictive power of inhabitants, due to the high spread of datapoints. A 2nd degree polynomial ($t_m = 7.4 * 10^{-11}x^2 + 3.95 * 10^{-5}x - 1.13 * 10^{-1}$) with an $R^2$ of 0.61 can be used to estimate the optimization time for 50 type hours and all municipalities. The overall simulation time of 11,973 municipalities with only 50 time steps would take approx. 4.3 days. However, this would require that these municipalities have already been created, which would require additional 21.7 days per scenario. An optimization with a full 8,760 time steps for all municipalities in 2019 would take approx. 544.24 days (1.49 a). For 2035, due to more renewables, the optimization time goes up to 1064.14 days (2.92 a). Without the aggregation of supply and demand on a 100 x 100 m grid, the simulation would have required ca. 19,195 days (52.6 a).

This approach is not valid for LEMs, since the number of market participants has an impact on the market results. For RDM however, prior aggregation using a cell size of 100 x 100 m yields the same results as the simulation of individual participants.

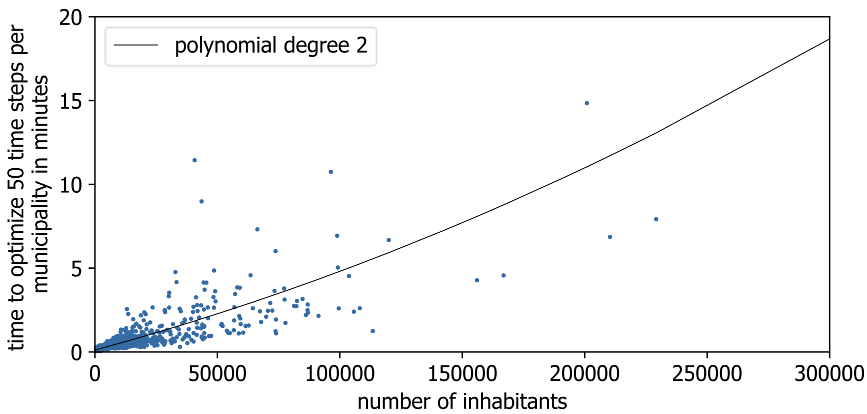


Figure 5-10: Optimization time for a sample of *n=1,323* municipalities with 50 time steps per municipality in 2019 and an aggregation on 100 x 100 m.

**Pricing in LEMs**

Figure 5-9 depicts the simulation time of the multi-agent model to determine prices in 50 time steps per municipality, as described in section 4.3.2.

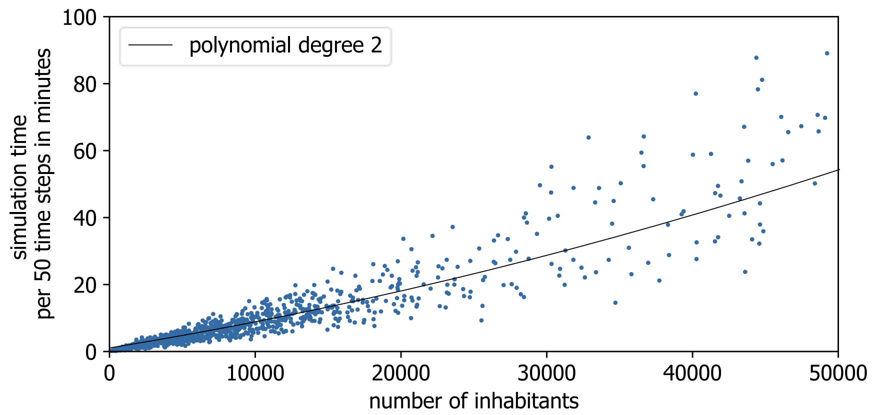


Figure 5-11: Multi-agent-based simulation time for a sample of *n=1,323* municipalities with 50 time steps per municipality.

The total time to generate prices for 1,323 municipalities and 50 time steps was 11.03 days with an average of 12.01 minutes per municipality.

The simulation time $t$ in minutes of a municipality $m$ with 50 time steps can be described as a 2nd degree polynomial function of the number of inhabitants $x$ with the function $t_m = 7.7 * 10^{-9} * x^2 + 5.53 * 10^{-4} - 5.01 * 10^{-2}$ with a resulting $R^2$ of 0.89. Using this as predictor in conjunction with the known inhabitants of all 11,973 municipalities, the modelling process with 50 time steps each would have taken approx. 155.83 days. A simulation with a full 8,760 time steps per municipality (weighting the type hours by their frequency) would have taken approx. 27,517 days (75.4 a), excluding the time to generate the municipalities. In the 2035 scenario (due to an increased number of prosumer and supply agents), the simulation time would have gone up to 122.5 a.

Since the multi-agent model does not scale linearly to inhabitants, larger municipalities require significantly more computational power and slow down the process considerably. Therefore clusters 6, 11 and 17 are excluded from the simulation. Additionally, at an $SDR_t \geq 18$, the price on the LEM was considered to reach the wholesale price (details see section 14.2.3., in the appendix)

The runtime of both use cases (RDM and LEM) depends on the number of consumers and producers within the time steps. As shown, a high number of producers with a high surplus slows down the computational time.

Ways to improve computation time include obtaining more computing capacity, scaling using cloud service providers, optimizing or parallelizing code and reducing model complexity, i.e., by model abstraction, homogenization or simplification of input data [165]. In this dissertation, however, the focus will be set on the possibilities of machine learning within the modeling process, to keep losses in accuracy low and increase runtime performance considerably.

## 5.7 Preliminary Summary

In this section, a description of the developed simulation framework was provided, answering **RQ 2: How can the potentials of the use cases be modeled and evaluated using a simulation framework?** The goal of the community generation module is to create a digital representation of a municipality with relevant energy-economic objects such as renewable generation, consumers and prosumers with home storages and electric vehicles. All objects are modeled in high detail including time series data on consumption and generation as well as location.

The simulation framework is comprised of multiple components. The community generation module is a means of selecting available data and generating a municipality with all defined parameters (such as scenario, temporal resolution or selected timeframe). It builds on energy-economic datasets such as the MaStR and Census, to depict the status quo as realistically as possible. Based on future scenarios, additional capacities of PV and onshore wind, HSS, BEV and rooftop PV can be modeled in the simulation framework. In section 5.3 the resulting model is introduced and validated with reference data. Results show a high temporal and spatial accuracy in modeling consumption, generation, households, electric vehicles and home storage systems.

For any generated municipality, use cases can be simulated and implemented via independent "use case modules". These use case modules allow to calculate potentials of regional direct marketing, prices in local energy sharing communities and local energy markets. Additional use cases can be implemented in the future, as shown in the case study in section 5.5. Based on the structure of the community generation module, the simulation framework is a bottom-up model. The framework allows the implementation of multiple different types of models (i.e., optimization, simulation, accounting or multi-agent models) [166]. The introduced use case modules include a bottom-up simulation model (LES), a bottom-up multi-agent model (LEM) and a bottom-up optimization model (RDM).

To show the functioning of the simulation framework, the allocation method as well as the pricing mechanisms, multiple case studies were performed. In [A6] the multi-agent model for LEM was developed and used to determine prices. In [A3] and [A4], prices of supply demand ratio pricing and mid-market rate pricing (pricing mechanisms in LES) were determined and evaluated for selected few municipalities. In section 5.5, a case study was introduced to show the viability of the optimization-based allocation method. In the first case study, the allocation of electricity within an energy community was done, based on proximity. In the second case study, multiple use cases were implemented, defining prices and costs between involved stakeholders. These include the consideration of grid topology, proximity (i.e., regional direct marketing), and renewable self-consumers. The case studies show that within a time step the costs or distances are minimized so that the overall optimum is achieved.

Certain energy-economic and model assumptions are required for the case study. These are presented in section 5.5.2. Assumptions include the focus on prosumer communities, i.e., the crafts and trade sector as well as the industry are not included in the framework due to the lack of high-resolution consumption data. Additionally, prices, taxes, levies and charges are considered or excluded for different use cases in the case study.

Since these use cases require a high level of detail, and high spatial and temporal resolution, the computational complexity and hence computational costs are high. Therefore, the simulation of the entire population of approx. 12,000 municipalities is computationally expensive, and if multiple use cases and scenarios are considered, almost computationally infeasible even with existing, dedicated hardware. As shown in section 5.6, the generation for the approximately 12,000 municipalities would require about 21.7 days. This process has to be done for both analyzed scenarios. While this community generation is enough to simulate prices in LES, LEM (multi-agent model) and RDM (linear optimization model) use case modules require even more computational power. The full optimization of all time steps of all municipalities for both scenarios with regional direct marketing would require ca. 1,100 days. A full multi-agent modeling of all municipalities would require approx. 75.4 years per scenario. This illustrates the computational infeasibility to model all municipalities in an hourly resolution with the given framework and use case modules.

An alternative to decrease computational costs of these methods is provided by machine learning. Unsupervised machine learning is capable of reducing the temporal resolution down to only necessary and representative time steps and can reduce the population e.g., by excluding outliers or simulating only representative municipalities. Supervised Machine Learning can be used for emulation or surrogate-modeling in order to substitute the complex and knowledge-based community generation module in favor of a data-based machine learning model. These models (once trained) are capable of outperforming simulation models due to their fast application at the cost of minor losses in model accuracy. They use the expensive simulation only as long as it takes for the machine learning algorithms to adequately mimic the simulation and generate results for un-simulated datapoints faster than the simulation framework.

The application of machine learning in the modeling process is evaluated in the next sections, starting with a cluster analysis of the German municipalities, which are the basis of the simulation.

# 6 Cluster Analysis of German Municipalities

The following section describes the methodology and its application for selecting clusters and representative data points from a dataset. The presented content (sections 6.1 to 6.5) has already been published in [A2] and is based on the works of Hennig et al. [167, 168, 169, 170].

One focus of this dissertation is the identification of representative regions for energy-economical use cases utilizing unsupervised machine learning. These identified clusters and their respective representative regions are used for the potential assessment of the use cases presented in section 4, as well as the emulation of the simulation (see section 7). It will be further assessed how unsupervised learning may be included into energy-economic modeling processes, based on the experience gained from this work. Clustering is one application of unsupervised machine learning. In the following, the used data, the methodology, and application on ~12,000 German municipalities is described. The results are interpreted from an energy-economic perspective in section 6.6

## 6.1 Goals and Challenges

Clustering, as depicted in this chapter, is a viable part of the methodology to sample municipalities on the one hand and aggregate time series data on the other. This is an important step to emulate the simulation model, as depicted in section 7. Additionally, representative municipalities help with interpretation and serve as representative examples. Hence, the goal of this work is to identify clusters in a given dataset, without prior knowledge about its structure. Existing knowledge should be used in the best possible way to validate the results. Since the number of “true” clusters is unknown beforehand, it is part of the research field of “unsupervised clustering" [171]. The following contents and methodology were already published in [A2].

According to [172], clustering can be described as ”method of creating groups of objects, or clusters in such a way that objects in one cluster are very similar and objects in different clusters are quite distinct”. Clustering is a part of "unsupervised machine learning". The challenge compared to "supervised machine learning" is that there is no known ground truth on which to train the model or validate a result.

Clustering can serve the following purpose:

1. Pattern recognition: by forming groups of similar data points, patterns can be detected. Similarity is quantified by a distance measure in feature space $d_{i,j}$ between two data points (details see chapter 6.4).
2. Outlier detection: by pattern recognition it is possible to identify outliers that do not show similarity to the other data points. This makes it possible to detect anomalies (e.g., in spam filters) [173].
3. Information compression: instead of considering each point individually, representative datapoints (medoids) or centroids $c_i$ of the respective cluster $C_i$ are identified. These can be used instead of the entire dataset, e.g., for simplified downstream calculations [173]: Thus, the amount of data can be reduced, while the feature space $R^n$ is preserved.
4. Dimensionality reduction: while in information compression the number of features (spanning the feature space) of input and output are identical and only the number of data

points is reduced, dimension reduction can also reduce the feature space or dimensionality $R^n$. This can be done by projecting the data into a new space $R^m$ with reduced dimensionality ($m < n$), while maintaining the underlying information as best as possible [174, 175, 176].

5. Knowledge expansion: Clusters or their representatives can help to create a better understanding for the underlying data, especially for large datasets. For example, in marketing, customers are segmented to identify so-called "personas" [177].

This dissertation makes use of four out of five of the listed purposes. Pattern recognition helps to better understand the characteristics of all ~12,000 communities and to quickly identify relationships and distinctions between them. For each cluster of municipalities, a representative is determined mathematically. This allows to investigate or simulate only one representative municipality instead of many thousands and to transfer the results to the rest of the municipalities in this cluster (information compression). Additionally, a time series aggregation is used in conjunction with an emulation approach, to reduce the computational complexity of the simulation model (see section 7). Dimensionality reduction can be used to project high dimensional data to a 2-dimensional space to illustrate its distribution or to reduce the time needed for clustering itself or for supervised learning. In section 6.6.2, the clusters are used for knowledge expansion in order to highlight the energy-economic implications of the results.

The aim of this work is to determine whether clustering can be used as a basis for various sampling methods, to aggregate time series data and to interpret modeling results. For this purpose, a methodology for clustering was developed and introduced in [A2] to derive clusters and representatives for municipalities in Germany. In section 7, these methods are used to develop sampling methods and to interpret and display the results. Additionally, clustering algorithms are applied to aggregate time series in section 7 in order to reduce the complexity of input data for the simulation model, introduced in section 5. This can considerably reduce computational complexity and hence improve the simulation time.

## 6.2 Literature Review

The following section is a summary of the findings in Bogensperger et al. [A2] on the current state of science in the context of cluster analysis.

**Definition**

Clustering can be described in a very general sense as a "method of creating groups of objects, or clusters in such a way that objects in one cluster are very similar and objects in different clusters are quite distinct" [178]. More detailed definitions of clustering always use "metrics" to describe their goals, as shown in the definitions in [178] by Bock (1989) and Carmichael et al. (1968). The authors describe objects in a cluster as closely related in terms of their properties with high mutual similarities (= low distances) and other objects out of the same cluster in close proximity. All clusters in a dataset should be clearly distinguishable, connected and dense areas in n-dimensional space. They should be surrounded by areas of low density in n-dimensional space. These definitions show that, with a greater level of detail, the definitions of clusters vary strongly and might even be contradictory. It also shows that assumptions about the clusters have to be made in order to find a clustering result. Lorr (1983) proposed splitting clusters into two groups:

- compact clusters have high similarity and can be represented by a single point or a center.

- "[a] chained cluster is a set of datapoints in which every member is more like other members in the cluster than other datapoints not in the cluster" [178]

In literature and open-source software (e.g. scikit-learn), countless clustering algorithms are available. Moreover, within the individual algorithms different hyperparameters can be set, which determine the result. This creates the challenge for users to choose the right algorithms for their use case on the one hand and to select the best solution from the results on the other. Since unsupervised machine learning is involved, the result cannot be compared and evaluated with a known ground truth (external validation). From the literature analysis in [A2], it becomes clear that for validation, "cluster validation indices" are used. Internal validation makes use of internal information generated by the clustered data, in order to compare clusterings without external information (ground truth). Relative validation is used to compare the results of a single clustering algorithm but with multiple hyperparameters [179].

By means of cluster validation indices (CVIs), properties of a clustered dataset are described mathematically. If these describe an individual property of a clustered dataset (e.g., the mean distance of all points to their respective centroid), they are referred to as single cluster validation indices (sCVI). sCVIs can be found in

Table 14-4 in the appendix. If these single CVIs are in turn mathematically combined to form a single, more complex CVI, they are called composite cluster validation indices (cCVI). Composite CVIs often combine several properties or sCVIs and express the result in one value to describe the cluster quality. Commonly used composite CVIs in the literature include the Calinski-Harabasz index, Davies-Bouldin index, Silhouette index, Dunn index, and many more [A2].

While a single CVI describes individual, very basic properties, composite CVIs are complex and describe multiple properties at once. Yet, evaluating a cluster result with only one sCVI is usually not sufficient. This is often due to the complexity of the target on the one hand and the limited information content of individual sCVIs on the other [A2].

This becomes clear with the average within-cluster distance ($CVI_{avg_{wc}}$) in formula 6-1 [169].

$$CVI_{avg_{wc}}(C) = \frac{2}{\sum_{j=1}^{K} n_j(n_j - 1)} \sum_{j=1}^{K} \sum_{x \neq y \in C_j} d(x, y) \tag{6-1}$$

As the number of clusters $K$ increases, the size of the individual clusters decreases. This leads to a decreasing average within-cluster distance (the notation can be found in section 14.3.1 in the appendix). Thus, $CVI_{avg_{wc}}$ is decreasing with increasing cluster number $K$. With two clusterings $\mathrm{C_a}$, $\mathrm{C_b}$ (conducted with the same clustering algorithm, e.g., k-Means), and for the same data set $D$: $CVI_{avg_{wc}}(\mathrm{C_a}) \leq CVI_{avg_{wc}}(C_b)$ with $K_a \ll K_b$. Therefore, in the case of comparing different clusterings $C$ in the same dataset $D$, this index will always prioritize large $K$. Accordingly, a trade-off with the number of clusters is reasonable and necessary.

By combining a selection of single CVI, multiple clustering characteristics can be assessed simultaneously. This is often achieved by computing a weighted sum of the respective CVI, resulting in a highly customized composite index. For example, the Dunn Index utilizes compactness of clusters, the variance within the datapoints of each cluster and the separation of the clusters [179]. Thereby, different clusterings can be compared with respect to multiple individual characteristics. However, their higher mathematical complexity makes the composite CVI more difficult to interpret. It is also difficult to select the right composite CVI for the individual task at hand [A2].

[169] provides the mathematical basis for normalizing and weighting various sCVIs, but points out the difficulty of using industry-specific expertise to provide meaningful weighting.

## 6.3 Methodology

An alternative method for using multiple single CVIs in conjunction is presented in [A2], building on the previous work of Hennig [169]. The methodology is shown in two examples. The modified method can be taken from Figure 6-1.

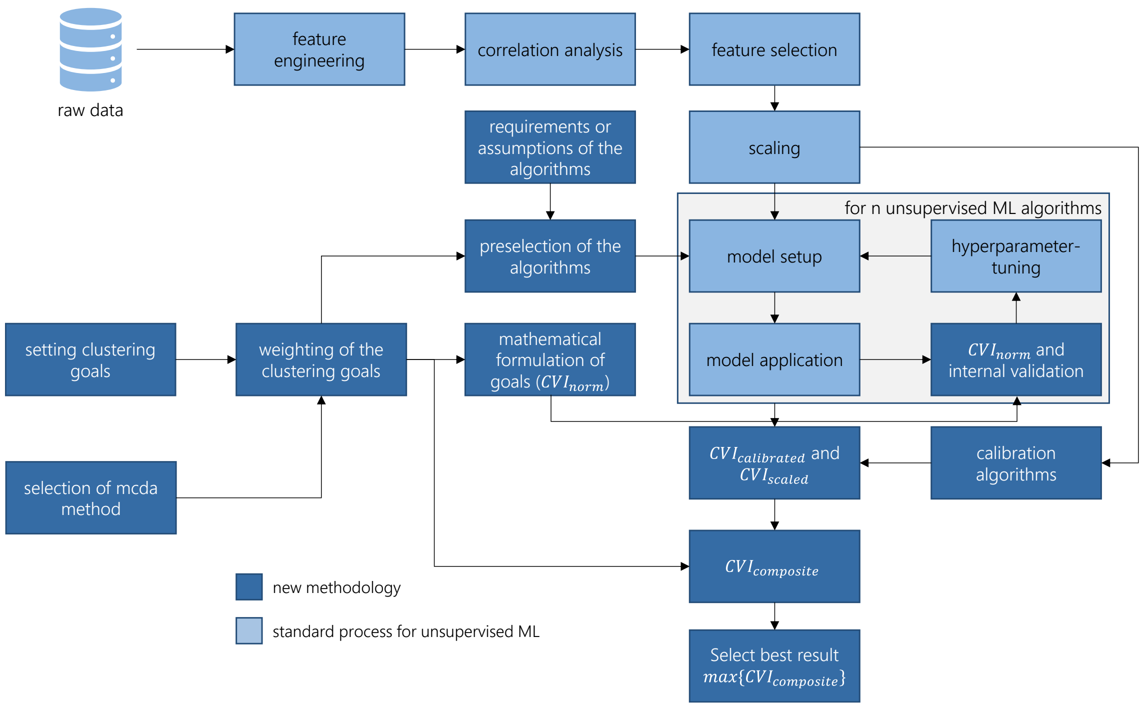


Figure 6-1: Depiction of the method for developing valid clusters using multiple single CVIs and combining them with a MCDA method according to [A2].

The process, as depicted in Figure 6-1, can be divided into multiple methodical steps. On the one hand, raw data must be processed in such a way that it can be processed by the unsupervised machine-learning models (unsupervised ML). On the other hand, the experts from the respective field must define the goals and then mathematically formulate and weight the single CVI.

The standard process for unsupervised learning starts with the raw dataset. Features need to be engineered in such a way that they can be interpreted by the unsupervised ML (feature engineering). In the next step, correlated features are removed and the final features are selected. This is done using correlation analysis, as described in section 6.4. The dataset is scaled and then the unsupervised ML fits to the data. The ML is validated relatively, hyperparameters optimized and the algorithms fit again until an optimal result is obtained. If the clustering process is computationally expensive due to large amounts of data and many features (= high dimensionality), the dimensionality of the dataset can be reduced by unsupervised dimensionality reduction (i.e., via Principal Component Analysis PCA, t-distributed Stochastic Neighbor Embedding t-SNE or Uniform Manifold Approximation and Projection for Dimension Reduction UMAP).

To evaluate the results, qualitative goals are set by domain experts. The objectives are weighted by means of an MCDA method (multiple methods see [A2] and [180]) and the target variables are formulated mathematically (or incorporated from [169]). These selected single CVIs, as well as the processed and scaled data, can then be used to select the algorithms of interest. It is crucial to match the objectives of used unsupervised ML with the weighted single CVI to obtain optimal results. For example, if the focus is set on information compression to represent a dataset by a substantially lower number of representative datapoints, k-Means or k-Medoids should preferably be used, since they optimize towards the representation of a centroid or medoid.

The MCDA method as well as the mathematically formulated clustering goals can be transferred into multiple single CVIs. CVIs, as introduced in [A2] and based on [169], can be calculated in different forms depending on the need of the practitioner:

- Raw CVI ($CVI_{raw}$): based on a clustering result, raw CVIs are calculated. Since there is no normalization or scaling involved, they cannot be used in conjunction with weights or to compare the properties of different CVIs.
- Normalized CVI ($CVI_{norm}$): Hennig [169] introduces normalized CVIs to counteract this problem by using, e.g., the maximum distance of datapoints within a dataset- to achieve $CVI_{norm} \in [0,1]$. Appendix 14.3.3 depicts normalized CVI for toy datasets.
- Calibrated CVI ($CVI_{calibrated}$): while normalized indices are already within a range between 0 and 1, multiple clusterings may yield very similar results or very different variance. Applying multiple naïve random clusterings, as proposed in [169] and [170], and using their mean and standard deviation to calibrate the results, counteracts this problem [170].
- Scaled CVI ($CVI_{scaled}$): since the value range of a $CVI_{calibrated}$ is not strictly limited between 0 and 1, a composite index based on weighted aggregation of selected indices could be dominated by single indices, which would distort the original weighting [A2]. To simplify the weighting process, an additional scaling process was proposed in [A2]. The resulting $CVI_{calibrated}$ values are rescaled, with the best value of all compared clusterings for any CVI set to 1 and the worst to 0.
- Composite CVI ($CVI_{composite}$): the $CVI_{scaled}$ is weighted using individual weights, according to [A2] and the weights in section 6.5. Since multiple $CVI_{scaled}$ clusters are merged into one, the $CVI_{composite}$ is a composite index [170]. The weights were determined using an MCDA method.

The preselected unsupervised ML are subsequently fit on the data. The single CVI are applied individually to the results and hyperparameters of unsupervised ML optimized towards a high $CVI_{composite}$. The clustering with $maxCVI_{composite}$ is the most suitable from the practitioner's task at hand. In the last step, this result is validated, interpreted and evaluated in terms of energy-economics. The presented processes are taken from [A2], based on [169] and [170].

The CVI ($CVI_{raw}, CVI_{norm}, CVI_{calibrated}$ $and$ $CVI_{scaled}$) can also be used for relative cluster validation to improve the results of unsupervised ML using hyperparameter optimization. $CVI_{norm}, CVI_{calibrated}$ and $CVI_{scaled}$ can be utilized for internal validation to compare the results of different unsupervised ML by a single property [A2]. Since $CVI_{composite}$ includes multiple $CVI_{scaled}$and their weights, the clustering with $maxCVI_{composite}$ is the most suitable from the practitioner's task at hand. This allows practitioners to decide for a certain result with only a single, tailor-made index.

In the following, this method is applied to German municipalities.

## 6.4 Dataset

The dataset for German municipalities contains various features. These are displayed in Table 14-5, in the appendix. If data is not available at the municipality level, they are assigned by means of the existing polygons from [181].

The selected and engineered features describe structural parameters of municipalities relevant to the energy sector. These include:

- Data on population (e.g., number of inhabitants)
- Data on the potential of renewable energies (e.g., PV potential)
- Description of residual load structure or self-consumption structure (e.g., self-sufficiency)
- Generation data (e.g., wind, PV, hydropower, biomass)
- Building structure (e.g., share of old buildings, number of buildings per building class)
- Settlement structure (e.g., area, settlement area)
- Site conditions (e.g., wind speed)
- Consumption structure (e.g., electricity consumption of different consumption segments)

The preprocessing steps (feature correlation and selection as well as scaling) are shown in section 14.3.2 in the appendix.

## 6.5 Application of the Methodology

The methodology for this work was already described in [A2]. In [A2], a MCDA-method was applied with domain-experts. The weighted results are displayed in Table 6-1.

Table 6-1: Clustering goals and decision rules for municipalities determined by a Simos method with f = 13.2 in [A2]

| Goal | Explanation | Mathematical formulation | Simos Rank | Weight in % |
|---|---|---|---|---|
| Members of a cluster should be well represented by a specific data point within the dataset. | This is necessary in order to a) simulate a real municipality and b) let it be as similar to other points in the cluster as possible. Input-features are a lower dimensional representation of municipalities. | $\max\{CVI_{cp2cent}\}$ | 13 | 21,7% |
| The number of clusters should be as low as possible | Since the resulting clusters are the basis for a subsequent optimization with high computation time, a lower number is favored | $\max\{CVI_{Parsimony}\}$ | 9 | 15,0 |
| Clusters should be clearly distinguishable | Since one goal is to analyze key characteristics of the clusters in order to improve explicability, clusters should be distinguishable. | $\max\{CVI_{\mathrm{p-sep}}\}$ | 9 | 15,0 |
| Communities within a cluster should be structurally similar. | As similarity is defined by Euclidean distance, pairwise distances should correlate with cluster affiliation. | $\max\{CVI_{Pearson}\}$ | 9 | 15,0 |
| The number of clusters should be between 5 and 20 to 25. | The experts of the simulation software preferred an upper limit of 20 to 25 possible simulations. In order to make the clustering viable, a minimum of 5 clusters was determined by the participants. | $\max\{CVI_{\mathrm{targetRange}}\}$ | 7 | 11,7 |
| Within-cluster dissimilarities should be small | This makes sure that not only the representative but also all data points in a cluster are comparable. | $\max\{CVI_{\mathrm{avg_{wc}}}\}$ | 7 | 11,7 |
| Clusters should be describable by a low number of features | Next to having unique and distinguishable characteristics, the number of characterizing features should be as low as possible to be interpretable. | $\max\{CVI_{\mathrm{PPS}}\}$ | 5 | 8,3 |
| Clusters should be relatively even in size | A clustering with 90% of the datapoints in one cluster is not desirable. Hence the participants agreed on this parameter. | $\max\{CVI_{\mathrm{Entropy}}\}$ | 1 | 1,00 |

The resulting weights were applied on the results of multiple clustering algorithms, as shown in the following section.

## 6.6 Result Interpretation

In the following, the selected CVIs and clusters will be interpreted from a general and an energy-economical perspective.

### 6.6.1 Cluster Validation Indices

The methodology for clustering was applied according to [A2] and [169]. A total of 156 clusterings were conducted on the dataset. Since an additional hard limit to the maximum cluster size (50 % of the data) was set by the project team, only 121 clusterings with varying algorithms and cluster sizes remained. The applied clustering algorithms are compared in Figure 6-2.

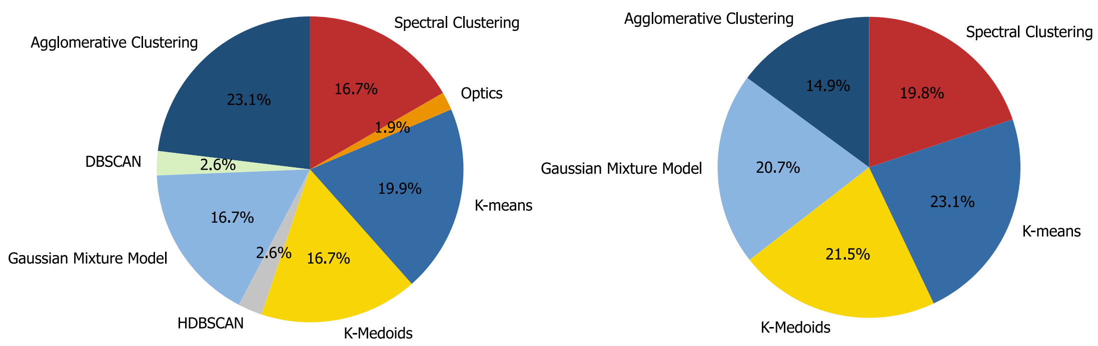


Figure 6-2: Share of applied clustering algorithms for 156 clusterings (left), without the size constraint set by the project team of a maximum cluster size of 50 %, and the remaining 121 clusterings with maximum cluster size constraint (right).

Figure 6-2 shows that density-based algorithms such as Optics, DBSCAN and HDBSCAN yielded only results which violated the maximum cluster size constraint of 50 %. Likewise, results of Agglomerative Clustering violated the constraint as well. The algorithm was applied with several linkage methods. Single linkage performed especially poorly and only yielded results with single clusters containing sometimes almost all datapoints. In contrast, ward linkage provided viable results that did not conflict with set constraints. Figure 14-7 in the appendix depicts the resulting maximum cluster size per algorithm and number of clusters, showing decreasing cluster sizes with the increasing numbers of clusters. In particular, k-Medoids provide relatively small clusters.

An interpretation of the results of all individual algorithms for all $CVI_{raw}, CVI_{norm}$, $CVI_{calibrated}$ and $CVI_{scaled}$ clusters in high dimensional Euclidean space is out of the scope of this work. Akhanli and Hennig provide deeper explanations of the behavior of certain sCVIs in [170]. Detailed plots of all eight CVIs relevant for this work are provided in appendix 14.3.3. In Table 6-2, a summary of the resulting $CVI_{scaled}$ is provided.

Table 6-2: Summary of the resulting scaled cluster validation indices

| $CVI_{scaled}$ | Weight in % | Interpretation |
|---|---|---|
| $CVI_{cp2cent}$ | 21,7 | The $I_{cp2cent}$ is an index to determine whether a cluster is well represented by a single point closest to the centroid. Since k-Means and k-Medoids (details see Appendix 14.3.3) tend to form spherical clusters, to minimize the sum of squares towards the centroid, they optimize towards a low average distance to the centroids within clusters. If a real datapoint is close by, this leads to a high $CVI_{avg_c p2cent}$. Agglomerative Clustering and GMM form non-spherical clusters and hence have lower values for $CVI_{avg_c p2cent}$. Since Spectral-Clustering relies on k-Means clustering to assign points to a cluster, and results are relatively high(details see Appendix 14.3.3). The highest values are achieved by k-Means > 12 clusters. |
| $CVI_{parsimony}$ | 15,0 | Parsimony is a linearly decreasing index which has its highest value for $k = 1$ and its lowest for $k = 30$. It is the same for all clustering algorithms and hence only penalizes clusterings with an increasing k. |
| $CVI_{p_s ep}$ | 15,0 | The p-separation index quantifies the separation in between a proportion $p$ (here: 10 %) between two clusters. This index increases with well separated clusters. Figure 14-10 in the appendix shows an increase of this index towards higher numbers of clusters. Agglomerative Clustering and k-Means show an almost linear increase towards $k = 30$. This indicates the presence of relatively well-defined local clusters. |
| $CVI_{pearson}$ | 15,0 | The $I_{pearson}$ indicates a high pairwise correlation of datapoints to their cluster affiliation and hence high structural similarity of datapoints within a cluster. Hierarchical Clustering performs particularly well with this index, since in the bottom-up approach, close points are assigned to the same cluster. Additionally, k-Means, GMM and Spectral Clustering perform relatively well. |
| $CVI_{targetrange}$ | 11,7 | Target range, like Parsimony, is the same for all algorithms and only depends on the number of clusters. Since the experts in section 6.5 preferred clusters up to a size of 20 to 25, the index decreases between these values and is 0 for all $k \geq 25$. |
| $CVI_{avg_{wg}}$ | 11,7 | The average widest gap ensures that all data points in a cluster are well connected, and no subclusters exist. The higher the index, the smaller the gaps within a cluster. All algorithms except GMM perform relatively well with a tendency towards a higher number of clusters, since this leads to the emerging of these sub-clusters within their own cluster. |
| $CVI_{pps}$ | 8,3 | The $I_{pps}$ was introduced in [A2] to show whether clusters can be described using only a low number of features. Agglomerative Clustering, k-Means and Spectral Clustering perform relatively well, which will be shown in detail in section 6.6.2 by the energy-economic results. |
| $CVI_{entropy}$ | 1,00 | Entropy is an index to prefer the formation of even-sized clusters. K-Medoid performs relatively well for entropy, since it is more prone to outliers than e.g., k-Means [182] |

For calibration purposes, as described in [169], a total of 200 calibration runs split between two different random clustering algorithms were conducted per cluster size. Since this was calculated for cluster sizes between 5 and 30, a total of 5,000 naïve random clusterings were applied on the dataset for reasons of calibration. The scaled cluster validation indices for every clustering were calculated and weighted according to the weights in Table 6-1. The results are displayed in Figure 6-3.

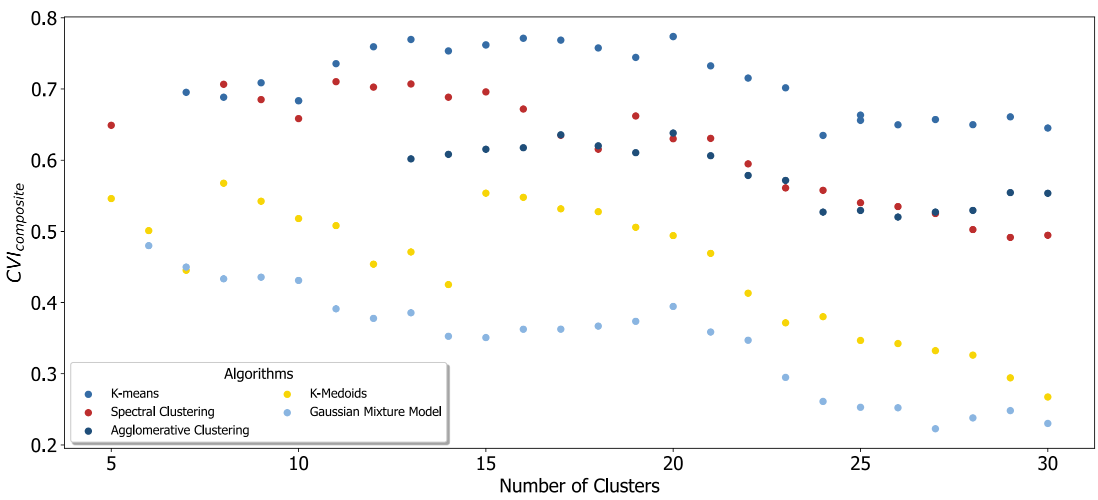


Figure 6-3: Calibrated, scaled, weighted and aggregated cluster validation indices for German municipalities

Figure 6-3 shows the resulting calibrated and weighted cluster validation indices. Since k-Means performed particularly well for many CVIs with high weights and a lower number of clusters is preferred, a k-Means with $k = 20$ yields the best overall results. In the following, the results are discussed in detail from an energy-economic perspective.

### 6.6.2 Energy-Economic Results

The main goal of this section is to determine and describe energy-economically viable clusters of German municipalities, using the methodology provided by [169] which was modified and extended in [A2]. In the following, an in-depth energy-economic assessment of the resulting clusters is provided. In the appendix (section 14.3.4) the cluster representatives are introduced in individual profiles.

In Table 6-3, the resulting clusters as well as their key characteristics are described from an energy-economic perspective. For each cluster, the representative is presented and its characterizing properties highlighted. Detailed data for the representatives as well as the overall cluster is provided in the appendix (see section 14.3.4.)

Table 6-3: summary of clusters, representatives, overall share and number as well as their key characteristics

| Cluster | Representative | Share | Key Characteristics of the Mean Municipality |
|---|---|---|---|
| 1 | Gerlingen | 8.0 % | 957 small suburbs with low installed RE and high population density |
| 2 | Weilbach | 15.9 % | 1,913 rural southern municipalities with low population and very low RE |
| 3 | Krummwisch | 10,3 % | 1,230 small northern municipalities with low population and high wind potential but low installed wind capacities |
| 4 | Detmold | 1.1 % | 132 densely populated cities with high rooftop-PV potential and high consumption. |

| | | | |
|---|---|---|---|
| 5 | Laage | 1,5 % | 174 medium sized, eastern municipalities with high installed ground mounted PV. |
| 6 | Cologne | 0.0 % | Cologne, Munich, Frankfurt, Hamburg with high population, many electric vehicles and high PV potential |
| 7 | Löbitz | 12.8 % | 1,543 small municipalities with low population density, low consumption average RE generation |
| 8 | Anröchte | 0.3 % | 32 highly self-sufficient northern municipalities with high installed wind and ground mounted PV capacities |
| 9 | Henschtal | 2.5 % | 305 small rural municipalities with very low population and number of buildings, almost no installed renewables with low consumption |
| 10 | Weener | 1.6 % | 191 big northern wind regions with predominantly low wind turbines, high wind and PV potential |
| 11 | Berlin | 0.0 % | Capital city of Berlin with highest population, biggest area, highest energy consumption and most electric vehicles. |
| 12 | Gilten | 2.3 % | 273 northern wind regions with high wind speeds, high self-sufficiency and high RE-surplus |
| 13 | Hofgeismar | 7.3 % | 876 big and highly populated medium-sized cities and towns with hydropower, rooftop PV and high consumption |
| 14 | Bad Füssing | 0.3 % | 36 southern hydropower regions with high generation and surplus |
| 15 | Sosa | 21.7 % | 2,598 middle and eastern, small rural regions with low population, least annual generation of renewable energy and low RE potential |
| 16 | Sprakebüll | 0.4 % | 44 very small, northern rural municipalities with lowest population, very high wind capacities with lowest energy consumption and high surplus |
| 17 | Dresden | 0.2 % | 19 major cities with large population, buildings, electric vehicles and energy consumption. High RE generation but low surplus. |
| 18 | Köthen (Anhalt) | 0.2 % | 21 east German municipalities with high wind and highest ground mounted PV installations, high RE potential and high energy consumption |
| 19 | Rettenbach | 13.5 % | 1,621 predominantly southern, with many newer buildings, average PV, hydropower and some minor biomass capacities |
| 20 | Jüterbog | 0.3 % | 33 large, northern municipalities with highest RE capacities including high PV installations, potentials, most wind power and highest wind potential |

The summary of the energy-economic cluster characteristics shows very different cluster properties. It becomes clear that especially the smaller clusters often show very clear and distinct characteristics. E.g., cluster 14 (Bad Füssing) includes all hydropower regions in the south, cluster 18 (Köthen) is characterized by ground mounted PV and cluster 8 (Anröchte) are highly self-sufficient municipalities with high wind installations. However, due to the multiple features, there are also overarching properties that encompass several clusters.

Thus, multiple clusters are wind energy regions. However, they differ in the type or age of the turbines, their size or other properties. Cluster 3 (Krummwisch) has high wind energy potential yet low installations. Cluster 18 (Köthen) is dominated by ground mounted PV with additional wind capacities while cluster 8 has some ground mounted PV next to predominantly old wind turbines, which is important e.g., for repowering. Cluster 10 (Weener) is characterized by many low wind turbines and high PV potential. Cluster 16 (Sprakebüll) has very high wind installations with strong wind turbines but almost no local consumption, resulting in a high surplus. Cluster 12 (Gilten) has the strongest wind turbines and Jüterbog the highest wind RE generation. This demonstrates that while these could all be described as "wind regions" and are all located in the norther part of Germany with higher than average wind speeds, they are still different in their properties.

Even though single municipalities within a cluster are well describable and well characterized by few properties, the cluster size is an important factor. While some clusters are only average in many features (e.g., installed PV capacities), their cluster size can lead to them becoming relevant e.g., for nationwide observations. In the following figures, this discrepancy between the key characteristics of the municipalities in a cluster and the cluster size for multiple selected features is shown.

Figure 6-4 depicts features from the category "consumption". The features include the number of HSS, electric vehicles and total annual electricity consumptions in private households, crafts and trade sector and the industry.

The comparison of the mean values (Figure 6-4, left) for each cluster shows the highest mean consumption in all features within the clusters that contain the biggest cities. These include (in descending order): cluster 11 (Berlin), cluster 6 (Cologne), cluster 17 (Dresden) and cluster 4 (Detmold). Due to the cluster sizes, the overall importance of cities is diminished, if considering the sum instead of the mean (Figure 6-4, right). Especially larger clusters or those with above-average consumption in conjunction with larger clusters have the highest overall contribution. The clusters with the overall highest values in the category "consumption" include cluster 13 (876 medium-sized cities and towns), cluster 4 (132 cities), and cluster 1 (957 suburbs). Cluster 6 (Munich, Hamburg, Cologne and Frankfurt) has the highest demand for annual electricity consumption in the craft and trade sector while clusters 19 (1,621 southern municipalities) and 2 (1,913 southern and rural municipalities) already have the second and third most installed HSS. Even though they only have average PV and HSS installations within each municipality, their sum is high due to their large cluster sizes.

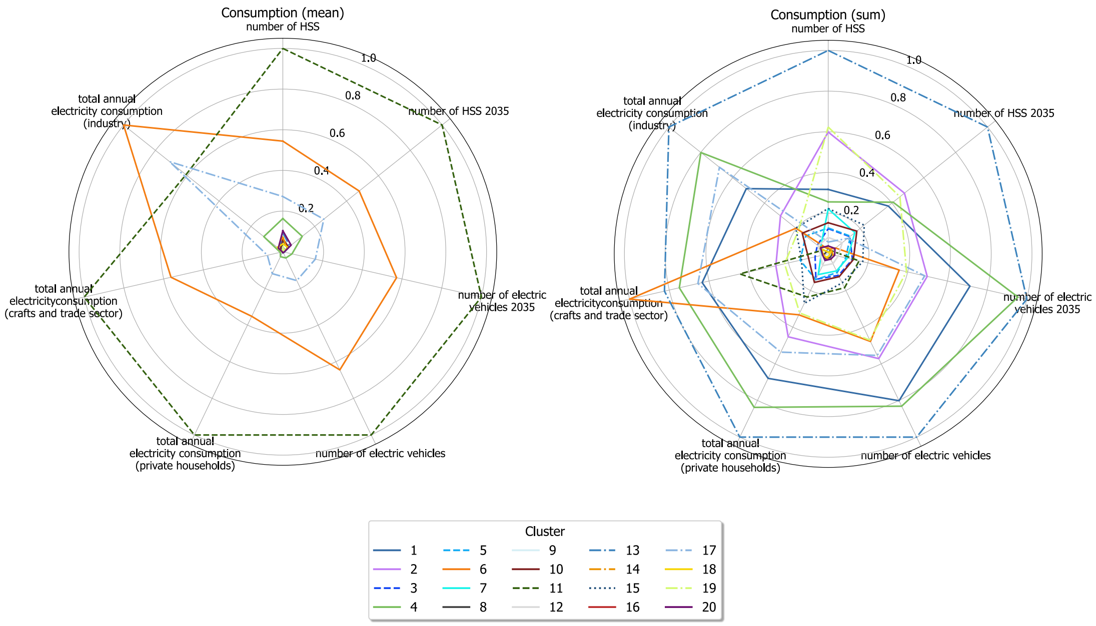


Figure 6-4: Features of the 20 clusters for the category "Consumption" as mean and sum for each cluster with a scaling to the range of [0, 1]

Figure 6-5 depicts features from the category "generation". These include installed capacities of wind, PV, hydropower and biomass as well as total annual RE generation. In contrast to the category "consumption" there is no clear correlation to the population within the municipality.

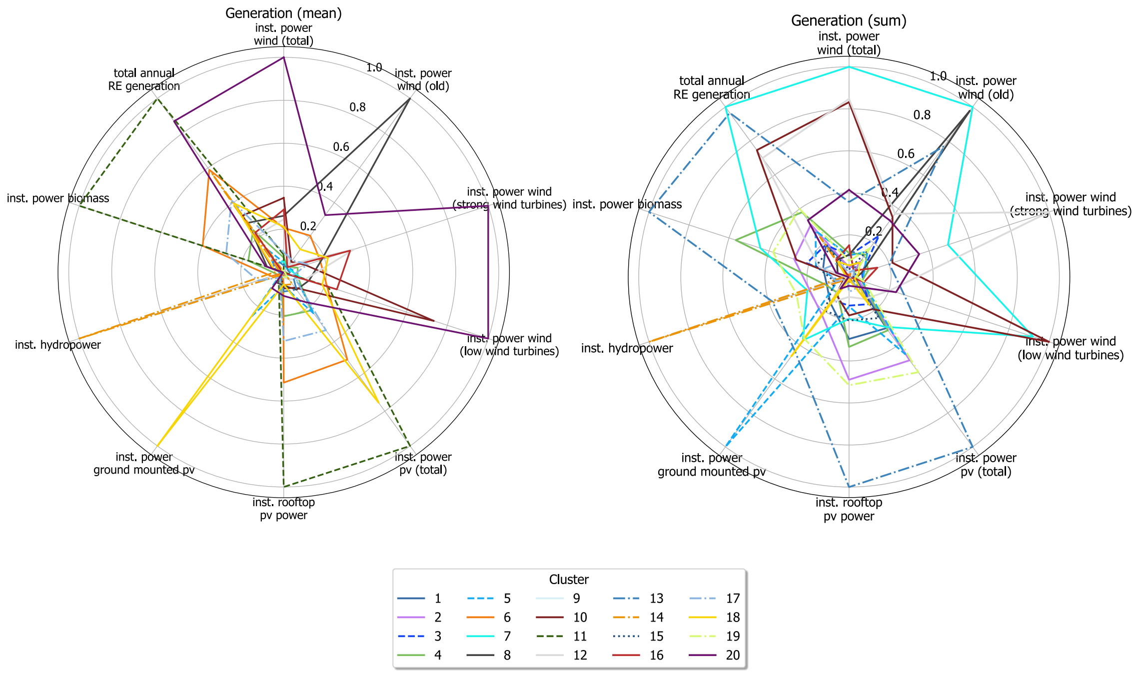


Figure 6-5: Features of the 20 clusters for the category "Generation" as mean and sum for each cluster with a scaling to the range of [0, 1]

The clustering results in the category "generation", as depicted in Figure 6-5 are interpreted in the following:

- Installed capacities for rooftop-PV are high in cities with large populations and roofs (e.g., clusters 11, 6, 17 and 4). Mean ground mounted PV is especially high in cluster 18 (Köthen). Cluster 18 has the 2nd highest total installed PV capacities, due to these ground mounted PV plants. Considering the clusters' contributions to the entire German rooftop PV installations, cluster 1 (957 suburbs), 19 (1,621 southern municipalities) and 2 (1,913 southern and rural municipalities) dominate, due to their cluster sizes. Ground mounted PV is dominated by cluster 5 (174 medium sized) which has the 2nd highest installed ground mounted PV power. While this is much less on average, the 174 municipalities compensate for this.
- Total installed wind capacities are high on average in rural northern municipalities. These include clusters 20 and 10. Additionally, installed wind turbines in cluster 8 are predominantly "old" wind turbines (e.g., 75% of them built between 1996 and 2005 with the median 2000). Considering the overall installations in Germany, cluster 7 (1,543 small, rural municipalities in middle and northern Germany), 12 (273 northern wind regions with high wind speeds), and 10 (191 big northern wind regions with predominantly low wind turbines) contribute the most.
- Hydropower is a special case, since 39.2 % of German hydropower capacities are installed in cluster 14 with only 36 southern regions. Hence, they offer the highest mean and absolute hydropower installations and electricity generation from hydropower.
- Biomass capacities are primarily located in bigger cities since they are often used for thermal and electrical power (i.e., for local and district heating or industrial use) and are therefore close to heat demand. Additionally, since biomass is continuously provided by sewage treatment plants, big cities like Berlin (cluster 11) have high capacities. Overall, clusters 1 (957 suburbs) and 4 (132 densely populated cities) provide the most electricity from biomass, due to their cluster size.
- Total annual RE generation (sum) is dominated by bigger clusters 7 and 1, 10 and 12: Cluster 7 due to the installed old and low-wind turbines in 1,543 rural middle and northern

municipalities; Cluster 1 due to biomass and rooftop PV in 957 suburbs: Cluster 10 due to predominantly installed low wind turbines in 191 big northern wind regions: and Cluster 12 due to strong wind turbines in 273 northern wind regions with high wind speeds.

Figure 6-6 depicts renewable energy potentials for PV and wind. ItFigure 6-6 shows the highest wind potentials in 2035 on average for cluster 20, which consists of 33 large, northern municipalities with already the highest RE capacities. The potential for ground mounted PV is the highest on average in cluster 18 (21 east German municipalities), which also has relatively high consumption. Rooftop PV potential is highest in municipalities with the most rooftops, as given in urban municipalities with the highest population, including 11 (Berlin), 6 (Cologne) and 17 (Dresden).

Considering the overall cluster size and hence the cumulated potential per cluster, clusters 7, 10 and 12 dominate in terms of installed wind capacities 2035. Cluster 7 includes 12.8 % of all municipalities with low or average wind potential while clusters 10 and 12 on the other hand only represent 1.6 % and 2.3 % of municipalities but are both located in the north with high wind speeds. The difference between clusters 10 and 12 lies in the predominantly low wind turbines installed in cluster 10, in contrast to cluster 12 with high wind turbines. Cluster 13 (Hofgeismar) has both high wind and PV potential in 2035. In contrast to other urban clusters (i.e., clusters 11, 6, 17), these municipalities are relatively big in size and less densely populated, even though the population is 5th highest on average. They hence offer both enough rooftops and suitable areas for wind and ground mounted PV around the more densely populated settlements. In addition to cluster13, clusters 2 (Weilbach) and 19 (Rettenbach) also have high potential for rooftop PV due to their large cluster sizes of 1,913 and 1,621, and their location predominantly in southern Germany. Cluster 5 (Laage), even though only 3rd highest on average for ground mounted PV in 2035, has the highest overall ground mounted PV potential as a cluster.

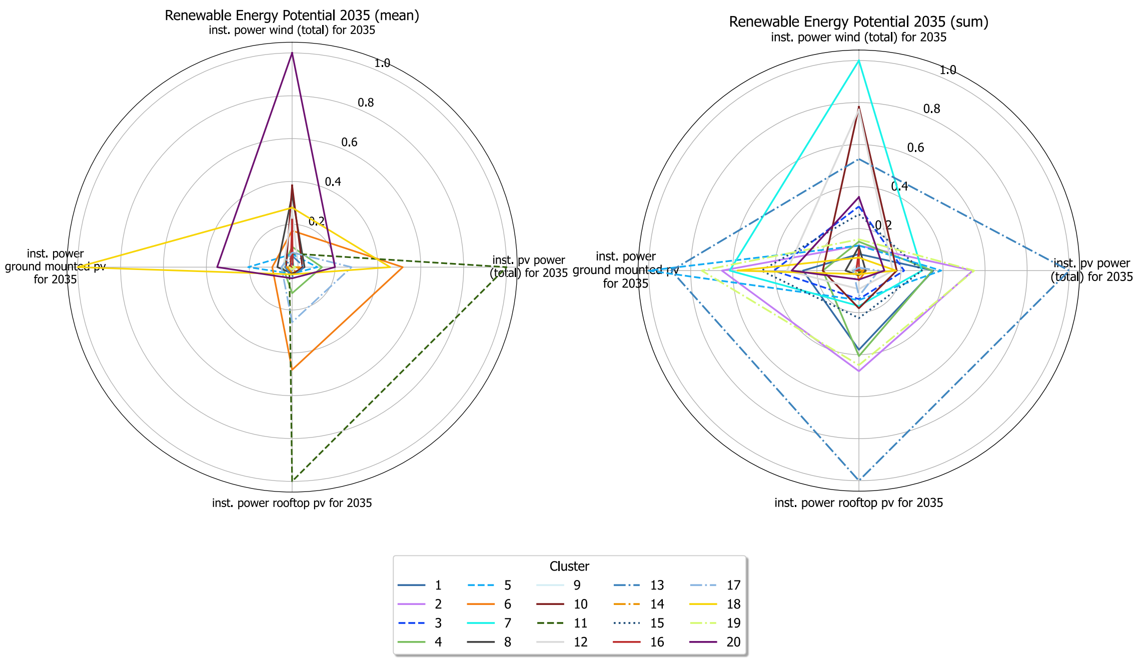


Figure 6-6: Features of the 20 clusters for the category “Renewable Energy Potential 2035” as mean and sum for each cluster with a scaling to the range of [0, 1]

The installed renewables as well as the local consumption lead to different characteristics of residual loads. The residual load can be described by the following metrics:

- The annual average balanced self-sufficiency rate is defined as the total RE generation divided by the total energy consumption [183]. A value of < 1 indicates that a municipality produces less electricity from RE within a year than its overall consumption. A value > 1 indicates more generation than consumption within a year. The metric does not provide information about the simultaneity of generation and consumption.
- The share of load profiles with RE-surplus quantifies how often within a year a municipality exports or imports electricity. A high value indicates high exports while a low value indicates imports. A municipality with a share of 0 % does not export electricity at any time. The metric, however, does not quantify the proportions of imports and exports.
- The annual average own consumption rate is defined, according to [183], as the quotient of the energy used directly within the municipality at the time of generation and the total energy supplied by the RE. An own consumption rate of 100 % hence indicates that all locally produced electricity by all RE can be consumed immediately. Municipalities with low generation, low surplus and simultaneously high consumption (e.g., cities like Berlin, Cologne and Dresden) usually have a high annual average own consumption rate. Municipalities with high shares of renewables and a relatively low local consumption have a lower rate.
- The annual average self-sufficiency ratio puts the locally generated and simultaneously self-used energy from RE in relation to the total energy consumption [184]. This metric shows whether the local electricity consumption can be covered by the locally generated renewable electricity. Municipalities achieve higher values if the consumption is lower than the generation.

The introduced metrics help to describe the structure of the residual load within a municipality. On their own, their explanatory power is limited. Only by combining the metrics communities can be clearly described. Figure 6-7 depicts these metrics as a mean for all municipalities within a cluster.

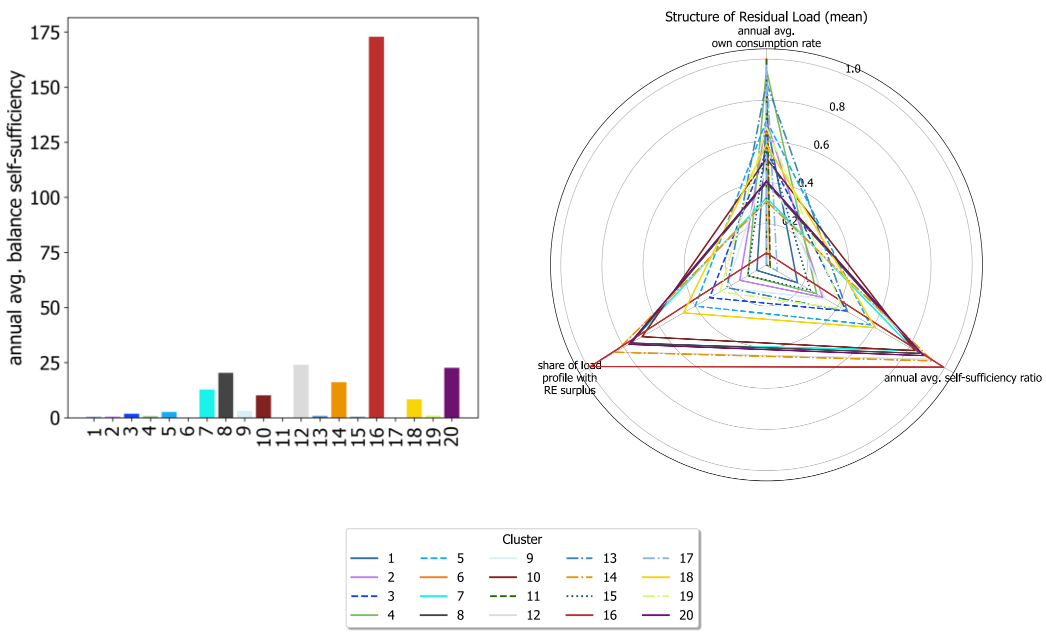


Figure 6-7: Features of the 20 clusters for the category “Structure of Residual Load” as a mean for each cluster (right) and the annual avg. balance self-sufficiency (left).

Figure 6-7 (left) depicts cluster 16 (Sprakebüll) as an outlier in terms of the annual average balanced self-sufficiency. The municipalities of the cluster are characterized by low population and low energy consumption. Renewable energy generation is high due to high wind speeds and proportionally high installations of wind (see Figure 6-5). This leads to a considerably higher quantity of generation than consumption and hence to a high average balanced self-sufficiency. Other municipalities with higher generation than consumption are in clusters 12 (wind), 20 (wind), 8 (wind), 14 (hydropower), 7 (wind), 10 (low wind) and 18 (ground mounted PV). Especially windy regions in the north are often sparsely populated and thus responsible for a proportionally large surplus.

Figure 6-7 (right) characterizes the structure of the residual load. A high annual average balanced self-sufficiency ratio correlates to high shares of RE surplus and to a low annual average own consumption rate. These correlations are depicted in Figure 6-8.

In municipalities with a high annual average self-sufficiency ratio, all local consumption can be covered by the local generation. This is the case for clusters 16, 14, 12, 20, 8, 10 and 7 which all have annual average self-sufficiency ratios of more than 80 %, predominantly due to high wind installations and hydropower (cluster 14) and relatively low consumption. Clusters with high ground mounted PV installations (cluster 18) have much lower self-sufficiency and RE surplus, due to the volatility of PV.

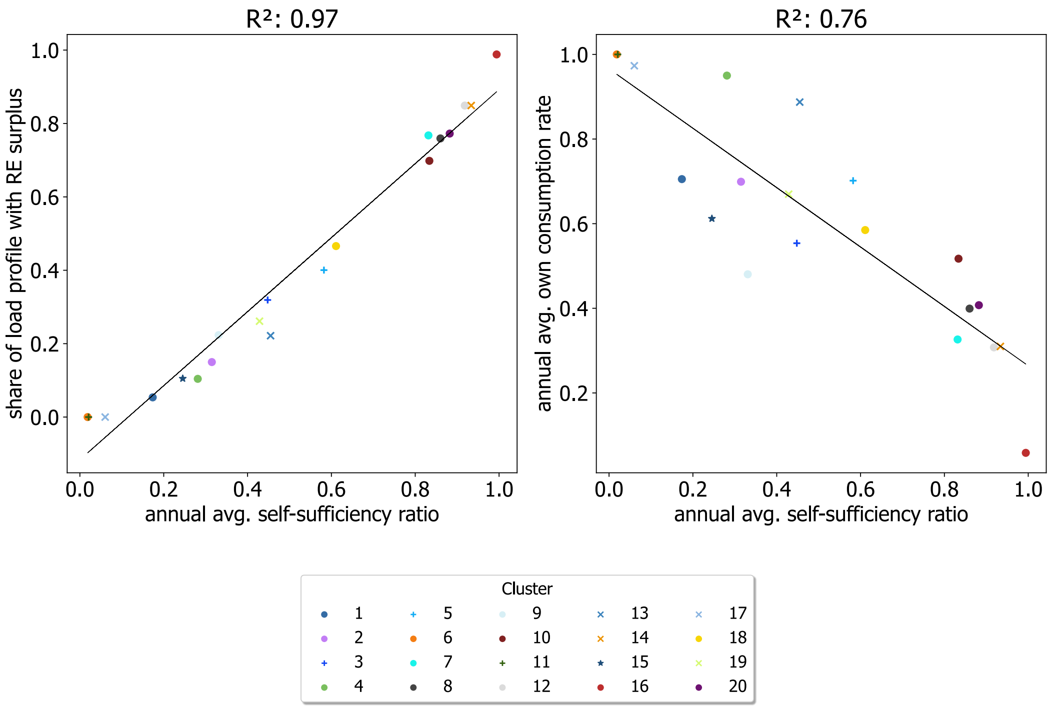


Figure 6-8: Correlation of the annual average self-sufficiency ratio with the share of RE surplus (left) and annual average own consumption rate (right).

**Representatives**

Table 6-3 depicts the clusters as well as their characteristics and representatives. The latter are those municipalities closest to the centroid of a specific cluster. The accuracy with which a representative reflects a cluster depends on how different features are distributed within a cluster as well as how close a representative comes to the respective mean value.

The mean coefficient of variation ($mcoe_c$) as well as the mean absolute error ($mae_c$) between representative and respective centroid are used to illustrate the clustering results. Alternatively, the

$CVI_{cp2cent}$ can be used as well, to calculate a standard deviation of Euclidean distances within the cluster towards their respective representative to achieve a relatively similar goal as $mcoe_c$.

$$mcoe_C = \frac{1}{F}\sum_{f=0}^{F}\left|\frac{std_{f,C}}{mean_{f,C}}\right| \tag{6-2}$$

| | |
|---|---|
| $C$ | Cluster $C$ |
| $F$ | Number of features $f$ in the dataset (or selected group of features) |
| $std_f$ | Standard deviation of feature $f$ in a cluster $C$ |
| $mean_f$ | Mean value of feature $f$ in a cluster $C$ |

A low $\frac{std_{f,C}}{mean_{f,C}}$ implies a low $\mathrm{std}_{\mathrm{f,C}}$ in relation to the $mean_{f,C}$ within a specific feature in a cluster. Since it is dimensionless, it can be calculated as a mean value over a selected range of features $F$ within a cluster $C$. A high $mcoe_C$ hence implicates either an overall high relative standard deviation within all features or the presence of certain outliers. This shows that the points within a cluster $\mathrm{C}$ and feature $f$ are not similar, while a low value indicates high similarity.

$$mae_c = \frac{1}{F}\sum_{f=1}^{F}\left|\frac{cr_f - mean_{f,C}}{mean_{f,C}}\right| \tag{6-3}$$

| | |
|---|---|
| $f$ | Feature of cluster $C$ |
| $F$ | Number of features $f$ in the dataset (or selected group of features) |
| $cr_f$ | Feature $f$ of cluster representative $\mathbf{cr}$ |
| $mean_{f,C}$ | Mean value of feature $f$ in a cluster $C$ |

The $mae_c$ is derived from the mean absolute error, an evaluation metric from supervised learning [185]. In this case, the representative ($cr_f$) is considered as the prediction, and the cluster centroid ($mean_{f,C}$) as the actual measurement. The $cr_f - mean_{f,C}$ shows whether a representative is over- or underrepresenting the cluster mean. The cluster representative $\mathrm{cr}_{\mathrm{f,C}}$ overrepresents the cluster in a certain feature for $\left(cr_f - mean_{f,C}\right) > 0$. The feature is underrepresented if the sum is negative. Since these values are computed as a percentage for each feature, depending on the corresponding mean value, they can be expressed as mean value over all considered features. A high $mae_c$ implies a larger discrepancy of the representative, compared to the mean within multiple features or the presence of outliers. A low $mae_c$ implies a good fit of the representative in all features.

The combination of both metrics is necessary to assess the usability of the representatives as such in certain use cases. If a representative represents a cluster well, it can be used e.g., to approximate overall economic cluster potentials (e.g., for regional direct marketing), that were only calculated for the representative, by multiplying the results of the representative with the cluster size. If, in addition, $mcoe_C$ is very low, the results for the other datapoints within the cluster are relatively similar. the representative can be used for this method as long as it has a low $mae_c$ but if the cluster has a high $mcoe_C$, no direct deductions can be made about the other cluster points. Since representatives are not the centroids of a cluster, neither very low $mae_c$ nor low $mcoe_C$are to be expected except clusters with $k = 1$ (i.e., cluster 11: Berlin). Additionally, both metrics decrease with the number of clusters in a dataset.

Figure 14-17 in the appendix depicts the $coe$ and $mae$ of all 20 clusters for features in the category "consumption". The category covers the number of HSS (today and 2035), number of electric vehicles, and total annual electricity consumption of private households, industry, and crafts- and trade sectors. It shows low (i.e., good) values for clusters 17 ($mae = 0.15, mcoe = 0.59$) and 6 ($mae = 0.25,\ coe = 0.46$). Both clusters are relatively small. The results show a low variance within the cluster features and good representation of the cluster by the representatives Dresden (17) and Cologne (6). Cluster 11 ($mae = 0, coe = 0$) is a special case, since the cluster consists only of Berlin. Cluster 16

(Sprakebüll) has a relatively average standard deviation of $coe = 0.96$ but the highest $mae$ of $1.14$. This implies a relatively low grade of representation of cluster properties by the representative. This is predominantly caused by the number of electric vehicles, which is very low on average but higher in Sprakebüll (see appendix, Figure 14-21 and Figure 14-22). The $mae$ is hence relatively high, due to the number of electric vehicles. As this cluster is already negligible in the context of electric mobility (see appendix, Figure 14-22), this feature could lead to wrong assumptions and should be excluded in these cases. For any further analysis, it is important to select relevant features to the use case and pre-select specific cluster before the evaluation.

Figure 14-18 in the appendix depicts the $coe$ and $mae$ of all 20 clusters for features in the category "generation". The category includes generation of PV, rooftop-PV, ground mounted PV, hydropower, wind (old, low and strong wind) biomass and total annual RE generation. This shows both a higher $mae$ and $coe$ for generation in comparison to consumption. This implies a higher variation of features in this category within the clusters and a less optimal representation by the cluster representatives. Clusters 15, 2, 3, 1 and 19 have particularly high values both for $mae$ and $coe$ due to the cluster size. Bigger clusters lead to higher variation within the features due to more datapoints. Additionally, these clusters (and cluster 9) are characterized by low generation as well as small municipalities in these clusters. In small municipalities, the difference in percentage is often very large because certain features are rarely or not at all present. As with Figure 14-17, these clusters are not characterized by these features which automatically leads to higher $mae$ and $coe$. Clusters with low $mae$ and $coe$ include 20, 10,8 ,13, 17, 4, 18 and 6. These clusters are all characterized by high installments of PV, wind or hydropower. Additionally, cluster sizes are rather small (except cluster 13, Hofgeismar).

Cluster 16 is an outlier with a high $mae$ due to more PV installations in the representative than on average in the cluster (details see Figure 14-17 in the appendix). Since the cluster is dominated by wind energy and PV is not a factor, the big difference in these features is that many communities have no PV installed at all. This leads to a high percentage deviation and hence to a high $mae$.

All in all, this evaluation shows that both the variance within a cluster ($coe$) and the representation by its representative ($mae$) are low for characterizing features and high for non-characterizing features. For example, if a cluster is characterized by wind-power, both $mae$ and $coe$ are low for these features. This implies a high level of similarity for this particular feature. Other, non-characterizing features display a higher variability and lower representation. Choosing representatives for a specific goal should hence only be used for clusters which are characterized by this feature for more solid results. The use of representatives should therefore be avoided, since qualitative statements can only be made with them in special cases.

This allows the following conclusions:

- Using representatives for, e.g., a potential assessment, should be avoided since they only represent a cluster well in its characterizing features.
- If the potential of a use case is to be assessed only in selected clusters (e.g., for wind energy), the respective representatives can be utilized if they are characterized by features relevant to the use case. Still, due to the representative being not the centroid, an extrapolation of the results will result in high error. Additionally, as shown in Figure 6-4 and Figure 6-5, clusters may contribute to a certain feature by cluster size, even though they are not being characterized.
- Instead of using a clustering with many generalized features, individual clusterings should be conducted with only the relevant features for a given use case. This, however, increases the computational complexity and could negate time savings gained by looking at representatives instead of more datapoints in the cluster.

Based on these results, it is summarized how clustering can be integrated into energy-economic modeling processes, to answer research question 3 (RQ 3).

## 6.7 Clustering in Energy-Economic Modeling Processes with large Populations

Various goals can be achieved through clustering. They include pattern recognition, outlier detection, information compression, dimensionality reduction and knowledge expansion. In this section, German municipalities with multiple features were described, an MCDA method was applied to derive generalized clusters, and these results were used to tailor an individual composite cluster validation index to choose the best clustering result. In section 6.6 the results of the cluster validation indices as well as the energy-economical perspective were interpreted.

The calculated CVI showed the necessity to determine individual and task-specific clustering goals and to apply a weighting method to simplify the decision process. The method helps practitioners to set task specific goals without in-depth knowledge about the process of clustering itself. In contrast to exploratory data analysis, however, the approach is not completely unbiased, which is why the result is only suitable for the respective use case.

From an energy-economic perspective, Table 6-3 shows that the clusters can be clearly distinguished from each other and can also be clearly described with a few key characteristics. The resulting clusters are characterized by very different properties. From the analysis in section 6.6.2, it becomes clear that the mere consideration of a representative is not sufficient, due to the very different size of the resulting clusters. A representative should not be considered without including the impact of the whole cluster on a feature to avoid false assumptions. As an example, cluster 7 (Löbitz) ranks only 11th in installed wind capacities and 9th in hydropower, but due to its size of 1,543 municipalities, 23.0 % percent of German wind capacities are installed in these areas, 10.6 % of biomass and 8.2 % of hydropower and 9.6 % of ground mounted PV capacities. The municipalities contribute 15.5 % of German renewable energy and characterized by high shares of load profiles with a surplus of renewable electricity. This implies that the selection of suitable clusters for certain purposes (like the economic assessment of use cases) requires both the consideration of typical properties and the size of the cluster.

The features used to conduct the clustering are derived from the municipalities and only reflect selected properties. They can be considered as a lower-dimensional representation of a municipality. This process only works in one direction, therefore, it is not possible to apply centroids in the simulation but only real municipalities. A representative municipality can only be approximated, since a centroid does not represent a real municipality and cannot be used in the simulation. The representative is therefore not the exact centroid of a cluster, but the municipality that is most similar (i.e., has the smallest Euclidean distance) to it. The lower the similarity between centroid and representative, the less the latter can be used to utilize the results of the simulation of this point to infer the entire cluster. Better results for a cluster mean can be achieved by focusing only on high values for the $CVI_{cp2cent}$ at the expense of other CVIs. Representatives should therefore only be used to better describe and understand a cluster or to make qualitative statements about a cluster, if they are not the centroid. The representatives give practitioners a better idea of the datapoints in the cluster, yet they are too imprecise for exact quantified assessments of the whole cluster. Two metrics help to assess how well a representative reflects the typical characteristics (=mean) of a cluster:

- The $mae_c$ is a metric, derived from supervised machine learning, to evaluate whether a representative is close to being the centroid. A low $mae_c$ implies a good representation of the included features. In terms of CVI, the $CVI_{cp2cent}$ is a comparable metric, based on the Euclidean distance.

- The coefficient of variation or relative standard deviation $mcoe_c$ illustrates the variance within individual features or several features. A high $mcoe_c$ implies lower similarities between the points within a cluster, while a low $mcoe_c$ indicates higher similarities.

However, since both metrics are relative, they are susceptible to outliers. Their interpretation should therefore only ever be carried out with relevant features that are relevant in the cluster.

Even though it can be inaccurate to draw quantitative conclusions about the entire cluster from a single representative, clustering can still be used to improve a quantitative potential assessment, which this work pursues. In this work, this means that either an individual potential is shown for each data point (here municipalities), or a total potential is shown for all municipalities. The aim is to achieve the highest possible accuracy, which can be provided by the simulation framework (see section 5). The most accurate potential assessments are possible with the simulation of each individual municipality at a high LoD. However, as this is often computationally expensive, it is not computationally feasible for large populations (here: ca. 12,000 municipalities). The individually simulated value (e.g., the economic potential of a municipality in a use case) is hence considered a benchmark for the quality of the results. The alternative ways of calculating potentials as accurately as possible in a realistic time, on the basis of the simulations, are summarized in the following:

1. Result approximation by cluster mean: with a low $mae_c$, the result of a simulation of the representative can be used to approximate the cluster potential e.g., by multiplying it with the number of datapoints in the cluster[3].
2. Result deduction by similarity: with a low $mae_c$ and $mcoe_c$, the result of a simulation of the representative can be used to approximate the results of the other datapoints in the same cluster, since they will be relatively similar.
3. Cluster pre-selection: the resulting clusters can be used in combination with domain expertise to exclude those from the simulation that are unimportant for certain use cases. For example, if a cluster has no or only very small numbers of electric vehicles, it can be excluded for use cases in this area. This can be achieved by simulating only those clusters that are relevant for these features based on the known functional relationship of the simulation. As another example, if potentials for repowering of wind turbines are to be assessed, clusters with no or only little wind can be excluded.
4. Level of detail (LoD) assessment: clusters can also be used to choose the level of detail or the assumptions and simplifications of a model. For clusters of low importance within a use case, low fidelity models with much lower levels of detail can be applied, since the resulting error does not have a significant influence on the overall result. For more important clusters, high fidelity models yield better results but at the cost of simulation time.
5. Stratified sampling: the resulting clusters can be used as strata for a stratified sampling approach, as proposed in [A3]. The resulting samples can be simulated and the results used in conjunction with regression analysis, surrogate, meta or emulation modeling.
   - Result Inter- and Extrapolation: to inter- and extrapolate the results for other datapoints in the same cluster from a sample, regression models can be applied.

[3] Assuming that the features cover all important properties of a cluster that are relevant for a use case.

Simple regression in this case does not achieve the same level of detail as the simulation.

- Surrogate-/meta-model: These models are a special case of regression model, if they are trained with data from a simulation model only, achieve the same level of fidelity and substitute the simulation model [A3]. The strata can be used to determine optimal input features to achieve high levels of accuracy.
- Emulation model: Emulation models, like surrogate- or meta-models are trained with simulation data and achieve the same level of fidelity. These models only substitute parts of the simulation model, retaining the remainder.

6. Time series aggregation: clustering can also be used to simplify time series and thus reduce the computing times. Details can be found in section 7.

The primary goal of this dissertation is the model-based energy-economic potential assessment of the introduced labeling use cases. Since the level of detail is high in the simulation model (details see section 5), all the above-mentioned options are considered in sections 7 and 8.

Based on these learnings, to achieve optimal results for a potential assessment using any of these methods, the workflow in Figure 6-9 is proposed.

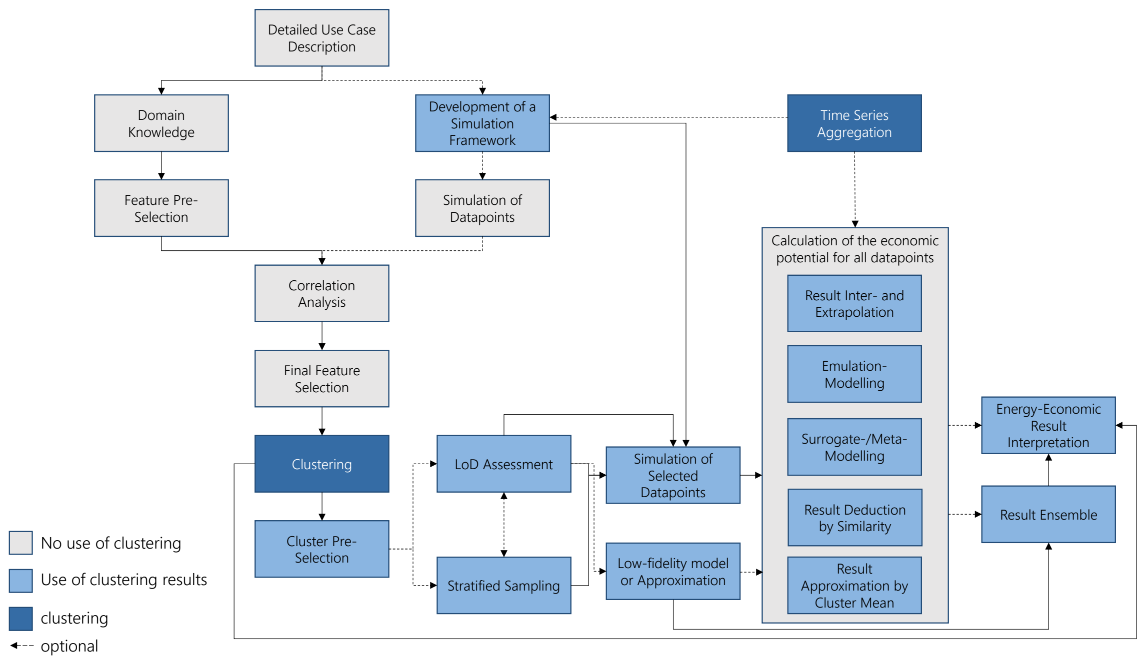


Figure 6-9: Workflow for the energy-economic potential assessment for a large population (e.g., municipalities) including the unsupervised clustering approach, introduced in [A2]

The depicted workflow starts with a detailed use case description, as introduced in section 4. Derived from the use case description, a simulation framework is developed, as described in section 5. Domain knowledge or simulation results, generated on random samples is applied, to pre-select suitable features with a high correlation (e.g., by feature correlation as introduced in appendix 14.3.2) to the known (by the simulation) or expected (by domain knowledge) outputs of the simulation framework. In this work, the simulation framework was not yet developed at the time of the clustering. Hence, domain knowledge and the introduced preprocessing steps (including correlation analysis), as shown in section 6.4 were employed.

The selected features were used for the clustering of the dataset, as introduced in [A2], section 6.5 and evaluated in section 6.6.

The resulting clusters are the foundation to compute energy-economic potentials of different use cases. The clusters as well as their energy-economic assessment, as done in section 6.6.2, should be used to either perform a LoD assessment or for the sampling of relevant datapoints (more details see section 7). Clusters with low importance within a certain use case can be excluded or simulated with a lower LoD to reduce computational costs. For the remaining datapoints, a specific sample including the representatives or centroids should then be simulated. The energy-economic potential for all datapoints will then either be simulated for all datapoints (if computationally feasible) or calculated using one of the introduced methods. These methods include the inter- and extrapolation of results, ESM, result deduction by similarity or approximation by cluster mean. An alternative to the direct evaluation of the results is the use of the different calculation methods in conjunction as ensemble. This allows for the quantification of uncertainty.

Section 6.6.2 shows relatively high $coe$ and $mae$ for the representatives. Result deduction by similarity or approximation by the cluster's mean is hence not a suitable option in this work. Only doing a simple regression, inter- or extrapolation on the results (i.e., a sum) is not sufficient, as a high temporal resolution is necessary for the evaluation in section 8. Therefore, machine learning based meta/surrogate and emulation models are assessed in the following sections.

## 6.8 Preliminary Summary

In this section, unsupervised machine learning was integrated into the modeling process, answering **RQ 3: How can clusters and representative regions be determined by unsupervised machine learning methods and applied in the modeling process of German "Energy Communities"?**

A challenge in the domain of unsupervised clustering is the evaluation of the result, since no ground truth is available. Validation is hence done by the application of either single cluster validation indices (sCVIs), or composite cluster validation indices (cCVIs). The latter are able to combine multiple mathematical properties of a clustering result into one index. This comes at the expense of interpretability and may stand in contrast to the individual goals of a domain-specific task. Selecting a suitable composite index for an individual task is still a challenge. Single CVIs can describe only one individual cluster property in detail. Therefore, it is challenging to select the best indices for the individual goal and to choose the best out of multiple clustering results. In [A2], methods from multiple criteria decision analysis (MCDA) were applied in conjunction with sCVI to integrate domain knowledge and multiple stakeholder perspectives into the process. This is achieved by describing single CVIs in a non-mathematical way in order to explain them to the domain experts. Experts are then capable of selecting and weighting the sCVI according to the task at hand by MCDA methods. The selected and weighted sCVIs are combined mathematically to a single, tailor-made index for a task at hand. This methodology was initially introduced in [A2] and applied in two different real-world cases to prove the validity and practicability of the methodology

Furthermore, the method was applied on a dataset of approximately 12,000 German municipalities in section 6.5. A total of 156 clusterings were conducted on the dataset and the selected sCVIs were calculated for every result. Applying the methodology, the best clustering was selected and the results both from a CVI and an energy-economic perspective evaluated. Due to the selection and weights of the CVI, the former shows a clear tendency to prefer k-Means clustering over the other applied clustering algorithms (Spectral Clustering, Optics, k-Medoids, HDBSCAN, Gaussian Mixture Models, DBSCAN and Agglomerative Clustering). This can be explained due to the tendency of k-

Means to form spherical clusters with low distances to a center point and relatively well separated clusters. K-Means was not the best choice for every single CVI, but always provided solid results. This led to the selection of a k-Means clustering with $k = 20$.

Based on this clustering, the energy-economic results were interpreted. In particular, smaller clusters are often characterized by high similarity with respect to certain features. Most of these clusters can be described using only a few features which make them unique. This showed that the clusters can be clearly distinguished from each other. From an energy-economic perspective, a discrepancy arises from the key characteristics of the individual datapoints within a cluster and the respective cluster size. For larger clusters, this results in the individual datapoints not being characterized by few individual features. The cluster, due to its size (relative to the overall population) may still contribute significantly to a single feature. This suggests that if all municipalities within a cluster have a rather small population, but the size of the cluster is large, they may still be important. As shown in section 6.6.2, this leads to a challenge if cluster representatives are to be used to quantify overall cluster properties or to derive an overall potential by extrapolating the results of the representative as if it was a centroid.

All in all, the resulting clusters help to better understand the data structures, key characteristics of datapoints and their distribution. Cluster representatives are helpful to validate simulation results. Six ways to incorporate clustering into the modeling process to approximate results for either municipalities, either individually or collectively, were identified, based on this research. These options include result approximation by cluster means, result deduction by similarity, cluster pre-selection for the simulation, level of detail assessment, stratified sampling in combination with different forms of regression and time series aggregation to reduce the computational cost of the simulation model. Based on this research, a clustering workflow is proposed in Figure 6-9.

# 7 Emulation-/Surrogate-Modeling

An advantage of supervised machine learning algorithms is their processing speed (examples see section 7.1). Once trained, they are capable of very high performant calculations. For this purpose, methods from machine learning (ML) are investigated to emulate the simulation framework and respective use cases in chapters 4 and 5. The following content (until section 7.6) was already published in [A3]. The most important results from this publication are summarized below.

## 7.1 Summary of the Literature Review

The literature review in [A3] shows that the emulation of simulation software (also called surrogate or meta-modeling, or sometimes reduced-order models [186]) with ML models is currently an area of interest in many research fields. The terms are often used interchangeably. However, [A3] distinguished emulation from surrogate and meta-models by the fact that emulation models must still retain parts of the original model.

Reviewed papers make use of this approach, e.g., in chemistry and medicine [187, 188, 189, 190], the automotive industry [191, 192], geoscience [187, 193], astrophysics [187], fluid dynamics [194], or various engineering challenges [189, 195]. Use cases in the energy sector include fusion simulation [196], the heat demand of buildings [197], an urban energy simulator [198], vehicle energy consumption [199], and smart grids [189, 200, 201].

The goals of the reviewed papers include the reduction of computational complexity and speed increases by machine learning [189, 193, 194, 195, 196, 197, 198, 200] as well as the calculation of in-between states that are hard or impossible to calculate by the simulation model [190, 191, 192, 194, 196]. The advantages in saving time through the reapplication of the trained ML models are especially emphasized but vary considerably. The increase in runtime performance, compared to their respective simulation model, ranges from increases by a factor of 12 [195], 700 [194], 2500 [198], up to 2 billion [187]. The challenge in [A3] and the use cases in section 8 deviate from the literature since the runtime performance increases are not solely considered for the reapplication of the emulation model but also for the initial combined process of simulation and emulation to generate results for a known population.

The importance of sampling methods in conjunction with small amounts of training data is highlighted and applied only in [199, 200, 202]. The main challenge is the generation of sufficient and high-quality training data for the ML by simulation to achieve the desired accuracy. Other papers, e.g., [189] and [195]still rely on simple random sampling to choose the appropriate training data if only a limited number of simulations are feasible. Most papers have sufficient training data available [187, 190, 192, 193, 194, 196, 197, 198] and hence the effects of sampling methods are diminished [202].

The literature review shows ESM as an emerging field of science in many areas of research, including the energy sector. In the reviewed works [200, 202, 203], samples are drawn from multidimensional distributions, i.e., arbitrary datapoints from the feature set can serve as input data. Hence, sampling methods such as Monte Carlo Sampling [200], Latin Hypercube Sampling [203], and Halton/Sobol [202] are used in these works. However, this does not apply to the problem in [A3] and this work, where the input data consist of a finite number of existing municipalities in Germany.

Based on existing literature and the research in [A3], the method used in this work for ESM, including sampling of a finite population and time series aggregation is provided in the following.

An important step of applying machine learning is the use of intelligent sampling methods to choose sampling units to maximize the variance of the outputs to achieve high accuracy in the learned model, without the need for more input-datapoints [A3]. The sampling in this work is introduced in the next section.

## 7.2 Sampling

In [A3], the importance of sampling methods in the results of ESM were shown. For reasons of scope in this work, section 4 of [A3] is summarized in the following.

**Sampling Methods**

In [A3], four sampling methods were compared. These methods included:

- Simple Random Sampling: samples are drawn randomly from the population, with each point having the same probability of being selected. This sampling method is viable for large-enough sample sizes and served as benchmark [A3].
- Balanced Sampling is a stratified sampling approach, based on Tipton [204]. The sampling units are selected proportionally to the cluster size for each stratum (cluster). Furthermore, the selection process is not random, but is determined by a distance ranking preferring the closest points to the cluster centroids [A3].
- Cluster sampling is a stratified sampling method using unsupervised clustering. A sample is created by specifying the number of clusters $k$ as the desired sample size and then the closest points to the respective centroids are drawn as sampling units. The goal of this sampling strategy is to obtain as much variety as possible in terms of the feature composition in the training set [A3].
- Adaptive Sampling is based on the active learning from the field of supervised machine learning. Adaptive sampling techniques, or active learning, are characterized by an iterative sampling scheme, which aims for datapoints that provide the most valuable information for the ESM at each iteration [A3].

**Method of Comparison**

To compare the sampling methods, three datasets with a known ground truth were utilized in [A3]:

- Dataset 1 included estimated potentials of regional direct marketing in German municipalities. The prediction variable was calculated as the sum of locally available generation of RE ≤ 2MW.
- Dataset 2 contained regionalized flexibility potentials of decentralized energy resources as introduced in [205] by Müller et al. for German municipalities.
- Dataset 3 contained ~35,000 datapoints (time series) of Spanish electrical consumption, generation, pricing and weather data from [206]

For each dataset, the introduced sampling methods as well as a random forest regressor from the scikit-learn framework were used. The sampling process was repeated ten times for each sample with different sample sizes ratios (0.5%, 1%, 5%, 10%, 25%, 50%, and 75 %).

**Result Interpretation**

The results in [A3] show an increase in model accuracy with increasing sample size (sample ratio) for almost all sampling methods and datasets. K-Means cluster sampling and adaptive sampling yield the overall best model accuracy for large and medium sample ratios for all datasets on their respective test sets.

However, while k-Means cluster sampling also performs best for lower ratios (1–10%), adaptive sampling sometimes requires higher ratios to reach the same (or better) accuracy than k-Means cluster sampling. Adaptive sampling focuses on data with high uncertainty in a model's prediction (here: Random Forest) on unseen data. Therefore, for large samples, only average data remain in the test set, which is easier to predict. For lower sample ratios, it seems that these samples often contain too many outliers for the model to generalize well on the test set. K-Means cluster sampling also integrates outliers into the sample, e.g., when they are regarded as a separate cluster (particularly with an increasing number of clusters, i.e., sample size), but in general, more distributed samples are generated at lower sample ratios, which leads to a better training effect.

All in all, the sampling methods have a considerable impact on model accuracy, especially in cases of small sample sizes, extending the results in [199] that compared a stratified sampling technique and SRS. However, the results on multiple datasets show that there is no "one-size-fits-all" approach. The choice of the best sampling approach is highly dependent upon sample sizes and model complexity. The results also show that model accuracy does not always increase with increasing sample size, and adaptive and k-Means cluster sampling in particular yield better results, since only "average" points remain in the test set.

An advantage of k-Means cluster sampling is its simple implementation. Even though k-Means clustering is relatively inexpensive and well optimized, compared to other clustering algorithms (details see [207] and [208]), its time complexity of $O(knd)$ [209] still leads to high computation times for large datasets ($n$), high-dimensional data ($d$), and high numbers of clusters ($k$). If the samples are not enough to achieve good model accuracy, re-sampling cannot be performed using k-Means again. Resampling is therefore only possible using e.g., a simple random sampling (as done in [199]) or an adaptive sampling approach. This is a big disadvantage of its "one-shot" character [203]. While k-Means cluster sampling leads to challenges when increasing the sample sizes but is the simplest to implement, adaptive sampling provides very good results for increasing sample sizes but is harder to implement. K-Means sampling is hence the best option if a maximum number of simulations is determined prior to the sampling and cannot realistically be increased after the simulation. Adaptive sampling provides good results with low sample sizes and, due to its iterative approach, offers the advantage of stopping the sampling process once a desired model accuracy is achieved. Additionally, random forest regression provides relatively good scalability with a training time complexity of $O(n * \log(n) * d * k)$ with $k$ as the number of decision trees [210].

The three datasets show very different results considering minimum viable sample sizes. While in the simplest, dataset 1, ~5% of the data are already enough for the model to achieve most of its accuracy, with increasing difficulty of the functional relationship, the number of data needed increases. In dataset 2, ~25% already yields good results, while in dataset 3, a steady increase in model accuracy, depending on the sample size, can be observed. This shows that determining the sample size prior to the simulation is challenging and depends on many factors.

Experience shows that a combination of methods is also viable. Since k-Means cluster sampling is very easy to implement, the sampling units can be generated relatively quickly. Yet, if the model accuracy with the initially estimated $k$ is not sufficient, further sampling units can be generated, using adaptive or simple random sampling.

In [A3], well-established and new sampling methods were introduced and compared on three datasets. Especially, the newly presented sampling approaches of k-Means cluster sampling and adaptive sampling using Random Forests have shown good results. For smaller sample sizes (<10%), however, k-Means cluster sampling led to the best results, which is why this sampling method was chosen for the case study presented in [A3] and the use cases in section 8 of this work.

[A3] also shows an increase in model accuracy with an increasing sample size. From a sample size of 10 % (~1,200), the model accuracy only increases slightly with an increasing sample size.

## 7.3 Time Series Aggregation

In addition to the ESM with supervised ML, unsupervised ML can also be utilized to reduce the runtime of a simulation model. This can be performed by identifying typical periods (e.g., hours, days, weeks). However, it can only be applied in cases without dependencies of the time steps to each other (e.g., due to battery storages), since in these cases, the sequence is essential and skipping time steps or ignoring their order distorts the result. A previous study [211] provides a comprehensive review of multiple time series aggregation methods. Time series aggregation (TSA) can be performed in a time- or feature-based nature and via resolution variation or typical periods. Clustering provides a feature-based approach with typical periods that exploits repeating time series patterns and automatically identifies similar patterns while not merging similar adjacent time steps [211]. In [212], Kittel et al. show that time series can be compressed to below one percent while still retaining the global characteristics of the input data. Additionally, they evaluated and compared hierarchical and partitional cluster methods for electricity system modeling. The results show best results for WARD and k-Means which are among the most used algorithms for this purpose. The authors suggest to apply k-Means for "applications that model dispatch and investment decisions for energy infrastructure with strong seasonality or diurnal structures in demand or supply (…)" [212].

The energy-economic model (details see [A3] and section 5) is capable of simulating all ~12,000 German municipalities individually with a temporal resolution up to one minute. In the simulated case study in [A3], time steps are independent and represent one hour. Overall, this results in around 105,120,000 time steps. Since this is computationally infeasible, typical periods for every municipality need to be identified to reduce the computational complexity of the model [212]. According to [212], k-Means is an optimal algorithm for TSA for the given model and use case. In [A3] the python framework TSAM (time series aggregation module, https://pypi.org/project/tsam/), developed by the authors in [211], to identify typical periods using feature-based merging with a clustering approach, was utilized.

Typical hours of the year using k-Means clustering, as described in [211], were identified. Instead of the resulting centroids (= cluster mean), real time steps were needed, since the features used in the clustering only represent selected features in the simulation framework (see [A4]). Hence, cluster medoids, which are defined as those datapoints with the minimal sum of dissimilarities to all other datapoints in their respective cluster, were identified in [A3].

**TSA Validation**

To avoid the clustering process for ~12,000 municipalities, representative municipalities were identified in [A2] and described in section 6. For an iteratively increasing number of typical hours, the feature values (sum of the year) from the typical hours were derived and compared to the actual values using the mean absolute percentage error. The process of selecting typical hours is performed using the implementation of k-Means in the tsam package [211], while random sampling is used as a benchmark.

The evaluation in [A3] shows that the MAPE drops below 1.3 % in all representative municipalities for ≥50 typical hours with the clustering and thus outperforms random sampling by a factor of about

10. An error of 1.3 % for the model is acceptable. Hence, this methodology will be applied in further simulations and is capable of reducing the model's input time steps by 99.4 % and, thus, the computational costs significantly.

**Energy-Economic Result Interpretation**

As already shown, the MAPE of 50 typical hours is already less than one percent for representative municipalities. In [A3], this method was applied with 50 typical hours to the time series of all German municipalities and distinguished the input time series in the following parameters:

- Load/consumption is defined as the sum of all consumption within a municipality, regardless of own consumption within households.
- Generation is defined as the sum of all generated electricity within a municipality regardless of own consumption within households.
- Demand is defined as the sum of the remaining load after own consumption of all prosumers.
- Supply is defined as the sum of the remaining feed-in of electricity of all prosumers after own consumption.

Both demand and supply are important factors for the use case described and modeled throughout this dissertation.

Supply and demand, which were directly included in the time series aggregation (clustering) yield results with errors below 1 % for demand and a distribution around 1.3 % for supply. The features not included in the clustering process have a slightly higher error, which is still less than 5 % for 98.2 % (load) and 95.5 % (generation) of all municipalities. The model hence provides very good representation of 8,760 h with only 50 typical hours. This leads to a theoretical reduction in the necessary simulation time per municipality of 99.4 % if the model scales linearly.

If a use case does not have a sequential dependency of the input time-series, this method provides good results. In other cases, typical days or weeks need to be sampled instead of typical hours to provide valuable results instead.

Based on these results from [A3], the following method is used in this work.

## 7.4 Methodology

In [A3], a hybrid emulation/surrogate-modeling (ESM) approach for bottom-up energy-economic models was presented. The goal of ESM is to accelerate the simulation model for the initial simulation of a known population of parameters as well as the reapplication of the model, while achieving high levels of accuracy. ESM revolves around the intelligent sampling of simulation parameters to generate the input data for the ML. According to the current literature, intelligent sampling can achieve better ESM runtime performance, even with smaller amounts of data. Since a lack of scientific studies was identified in [A3] that include TSA in the process of ESM, a novel approach of combining TSA and emulation models to reduce simulation and training time alike and evaluate the synergy of these two methods was used. Additionally, aggregated and hence lower-level time series data were used as the input to train the emulation model, but the prediction and evaluation of the model were conducted on non-aggregated, higher-level time series data.

Deviating from most publications, the methodology in [A3] (and this dissertation) is viable when parts of a known population (here municipalities) are simulated with a high level of detail (including high-resolution time series) and the simulation is too computationally expensive for all members of the population (i.e., all German municipalities). The objective is to make the best possible use of the available simulation runs to be able to substitute (parts of) the simulation with supervised ML (here: regression). In contradiction to the current literature, the population of input parameters for the simulation is known, discrete, and not uniformly distributed.

The method used in [A3] is the same as was used in this work. Its viability was shown via a case study in [A3]. The methodology used in [A3] and subsequently in this work is summarized visually in Figure 7-1.

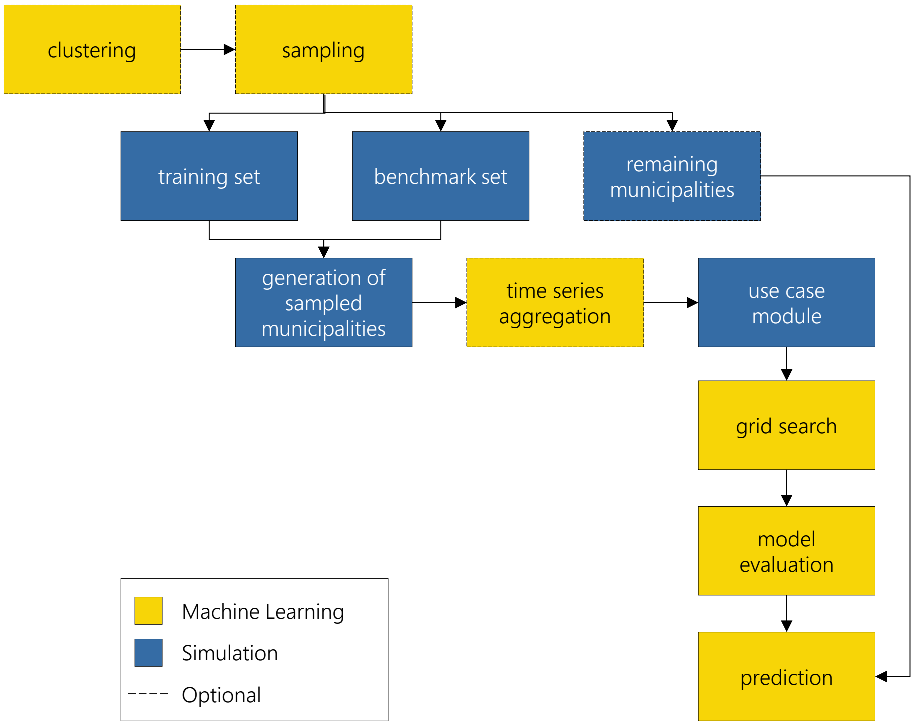


Figure 7-1: ESM methodology

Based on the results of [A3], cluster sampling and a cluster-based time series aggregation are used in this dissertation. Cluster sampling (details see section 7.2) is applied on the already identified clusters in section 6. Within each cluster, the sampling method selects 10 % of relevant sampling units (for training and testing) which are to be simulated. This sampling size provided sufficiently accurate results in [A3]. The generation of ca. 10 % of all the approximately 12,000 municipalities (with 8,760 h each) is time consuming but computationally feasible (see section 5.6). It is required to generate the necessary data to conduct the time series aggregation.

Using a prior clustering and time series aggregation are optional steps. The former is used throughout this dissertation, since the sampling is only conducted once for all use cases. The RDM and LEM use cases are computationally expensive. Hence, they are only applied on 50 type hours of the 10 % simulated municipalities. The type hours are identified with the TSA method in section 7.3.

For the ESM, the simulated data of the samples (training set) is used to train different machine learning algorithms. To achieve optimal training results, a grid search is applied for each ML algorithm. The results are evaluated on a benchmark dataset (testing), as analyzed and used in [A3]. The trained ML models are evaluated using evaluation metrics such as MAE, MSE and $R^2$ and the benchmark dataset. Since multiple models may yield relatively similar results, they are compared with these metrics, runtime and model complexity. Based on the fundamental principle of Ockham's razor [213], a simpler machine learning model with almost equal results to a more complex one is to be preferred. In addition, simpler models are less computationally expensive to train and apply on unseen data and less prone to overfitting.

## 7.5 Case Study and Method Validation

This section was initially introduced in [A3].

The goal of this dissertation is the energy-economic potential assessment of multiple use cases by simulation. Since they are computationally expensive (details see section 5.6) alternative means, based on machine learning, are to be used. The method introduced in the previous sections is applied in the following on the pricing of the use case prosumer LES. The difference between [A3] and this work is that in [A3] only SDR and MMR pricing in local (prosumer) energy sharing communities were determined. For this reason, the regional differences were relatively small, since all communities are very similarly composed. In this dissertation, on the other hand, all other RE supply below 2 MW is also taken into account. The two applied pricing mechanisms are described in section 4.3.1. The used simulation model is described in section 5.

The focus of the following case study is the ESM as well as its validation. The method model validation and results were initially introduced in [A3].

The emulation of the simulation model focuses on the generation of the supply and demand in each municipality. Since this step is time consuming, the emulation model in [A3] was introduced to speed it up.

The simulation framework applies features at the municipality level to create data for individual households. These data includes household size, number of inhabitants, installed rooftop-PV, number of electric vehicles, as well as home storage systems. Based on a Markov-Chain and additional information (e.g., employment status), individual load and driving profiles are generated, according to [122]. Driving data are used to generate a load profile for every electric vehicle. Depending on local solar radiation, PV generation profiles are generated for every building. Based on this time series data for every building, an individual household residual load and a battery storage load profile are generated. The resulting residual load is divided into surplus and shortage for every household in every time step and the results are summed for the entire community. This leads to the necessary inputs required for the pricing mechanisms, described in section 4.3.1. Household consumption and rooftop-PV generation, as well as the number of electric vehicles and battery storages, are known for any municipality without simulation and can hence be used as input for the emulation.

The process of calculating own consumption at the building level and calculating the resulting supply and demand is substituted by the emulation model. Since training data are generated by the simulation model and parts of the simulation framework still persist (e.g., the pricing modules, as described in section 5.4.2), according to [A3], this is a hybrid emulation model utilizing ML-based regression.

**Regression Model**

As a regression model for the hybrid emulation, a random forest regressor was applied. It provided the overall best accuracy in [A3], is prone to overfitting, and is not sensitive to outliers [214]. The scikit-learn standard implementation was used [215] and GridSearchCV [215] applied for grid searching of the optimal hyperparameters.

Additionally, a multi-layer perceptron ANN (MLP) and AdaBoost were tested on the TSA-data and yielded considerably less accurate results.

**Training Data and Sampling Method**

The inputs include static features such as the number of inhabitants, electric vehicles, buildings per building type, number of households, and battery storage systems. Additionally, installed PV capacity is provided. Time series data for each municipality include the total PV-generation and total household consumption. The model needs to learn the impact of own consumption within all prosumer households in each municipality. Supply and demand must be considered separately, because at each time step, there can be PV surplus due to (some) prosumer households, while other households (especially pure consumers) demand electricity. In cases with very low to no prosumers, the supply is (almost) zero and demand equals the total consumption. With increasing amounts of prosumers present, the effect of own consumption, and hence the impact of the simulation/emulation model within a community, increases.

Due to the results in [A3], the k-Means cluster sampling method was utilized. It provided optimal results for 10 % of the dataset (1,200 municipalities), which is a reasonable amount of simulation runs that can be conducted for this use case.

**Model Validation**

Sampling methods have a substantial impact on the model's runtime performance as shown in section 7.2. This not only accounts for the training of the ML models but also for the testing. If testing requires an additional 5–10 % of the dataset, this leads to additional simulation time. To validate the accuracy of the emulator on the remaining data, in practice, no large simulated dataset with a known ground truth is hence available. Instead, a representative subset of the dataset needs to be specified and simulated to evaluate an ML model's accuracy. This is called the benchmark or training set.

For this purpose, the results from a cluster analysis, introduced in [A2] and evaluated in section 6, were used. The resulting clusters helped to define a representative benchmarking dataset to test the ML model results. Similar to [199], a stratified random sampling, using the clusters from [A2] as strata, was applied. A sample of roughly 1 %, or 123 of all municipalities, was taken proportionally to the size of the clusters. To additionally show the validity of this approach, a ground truth of all remaining 90 % of the data was used as a test set in comparison. The described training, test and benchmark data was simulated for 8,760 h and used for the evaluation of the model results in Table 7-1

Table 7-1: Error metrics for supply and demand models

| Error Metric | | Supply no TSA | Supply TSA | Demand no TSA | Demand TSA |
|---|---|---|---|---|---|
| Test | MAE | 15.196 | 19.787 | 19.904 | 19.979 |
| | $R^2$ | 0.993 | 0.991 | 0.990 | 0.989 |
| benchmark | MAE | 16.695 | 22.230 | 25.470 | 26.735 |
| | $R^2$ | 0.990 | 0.988 | 0.996 | 0.994 |

The model quality as well as the method presented in section 7.4 are to be validated using the simulation framework. For this purpose, a simulation of all ~12,000 municipalities was conducted for [A3]. This was done despite the simulation time of 13.78 days, to obtain a ground truth for the validation of the results for the chosen use case and a single scenario.

In addition, the emulation model accuracy was not only evaluated with the remaining data, but also with the benchmark set (about 1 % of all municipalities). To show the impact of time series aggregation on accuracy and model runtime performance, a training with TSA and without was performed, resulting in four different regression models in total. Each model was then evaluated on the remaining test data and the benchmark set.

The MAE as well as the coefficient of determination ($R^2$) [185] were used as evaluation metrics. In Table 7-1, these two metrics for the described cases on the benchmark and test set are summarized. The resulting error metrics show relatively low overall errors. The errors of the supply model are lower than the ones of the demand model. This can be explained by the considerably higher impact of own consumption on demand than on supply, due to the high installed capacities of rooftop-PV. Additionally, supply is only available in about half of the time steps (due to the availability of solar radiation), which reduces the possibility for errors. Hence, the model is capable of predicting the resulting supply and demand relatively well.

While a time series aggregation (TSA) decreases simulation and training time alike (details see next subsection), it affects the resulting accuracy of the model. In the given cases, it affects the result of the supply by an MAE of 4.59 kW for demand by 0.07 kW. While for supply this is a relative increase of 30 %, it still is a relatively low absolute loss in accuracy compared with the average consumption or generation in most German municipalities.

Upon calculating the error metric on the benchmark set, the results show a slightly higher MAE (22.23 kW for supply and 26.74 kW for demand) and $R^2$ (≥0.988) for the two models. While this does not exactly match the values obtained with the evaluation of the ground truth for the remaining data, the results are still very good. A very small test sample hence leads to only minor underestimations of model accuracy compared to the entire remaining dataset. This, however, further increases the simulation time.

#### Improvements of Simulation Time

A goal of [A3] was to reduce the simulation time of the model by emulating it with ML. Figure 7-2 depicts the necessary time for simulation, TSA, sampling, training, and prediction.

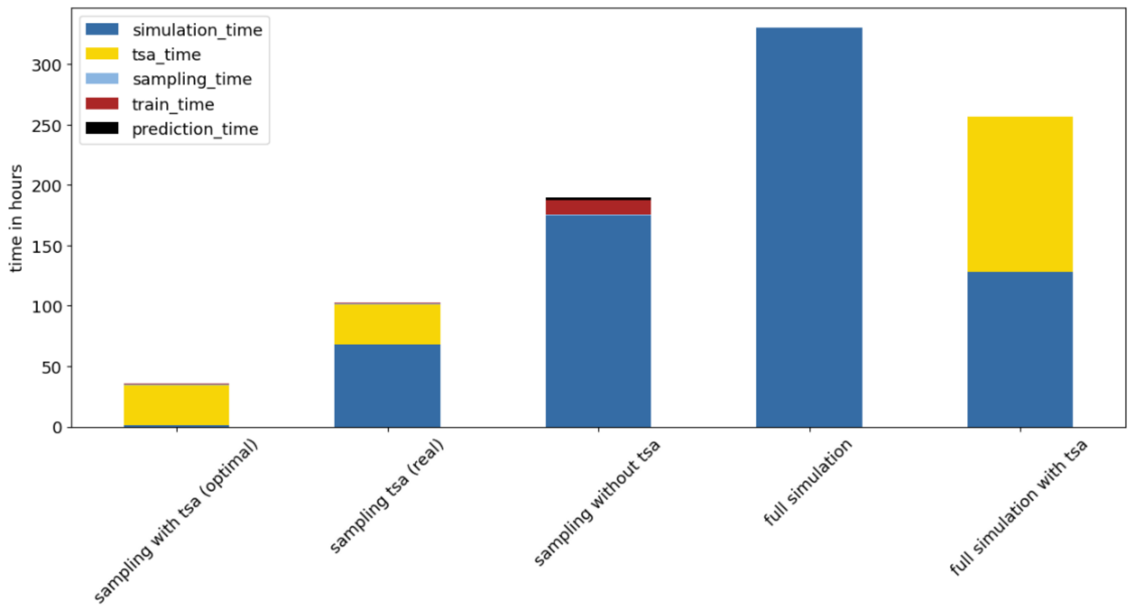


Figure 7-2: Simulation sampling, training, testing, and benchmarking time of the supply and demand model with and without time series aggregation [A3]

Figure 7-2 shows the runtime improvements for the entire process. This includes the necessary computation time for sampling, TSA, simulation, testing, and prediction. The results show an initial improvement of 42.6 % with an ESM workflow (sampling without TSA) compared to the full simulation of all ~12,000 municipalities. Even though only 11 % of municipalities were simulated, the 11 % sampling units included many relatively large municipalities. As a result, the simulation time was not reduced in a linear way by 89 % but only by 47 %, since large municipalities are more computationally expensive to simulate. This approach decreases the initial overall time to calculate supply and demand (11 % simulated, 89 % emulated) by 42.6 % (see sampling without TSA in Figure 7-2), compared to a full simulation. In the given case, the main restriction for emulation is the simulation time for the necessary sampling units.

Time series aggregation can accelerate the training time of the ML models considerably, while only small additional losses in accuracy occur. With time series aggregation down to 50 typical hours, the simulation time can be reduced up to 99.4 % if the simulation framework is adapted accordingly and scales in a linear way (see sampling with TSA (optimal)). Including the necessary time for the TSA, this leads to a potential decrease in the initial runtime of 88.9 %, compared to the full simulation.

The introduced simulation framework in section 5 is not yet designed for this, which is why it is not yet possible to achieve this full potential. Currently, a reduction of simulation time by 79 % was achieved with TSA (sampling TSA (real)), compared to the full simulation of 8,760 h for every municipality. This approach is 61 % less time consuming compared to the simulation of 1,323 municipalities for training and testing (sampling without TSA). Adopted on the simulation of ~12,000 municipalities, TSA offers the possibility to include more municipalities in the sampling and training process. This inclusion of more municipalities, but with fewer time steps per municipality, improves model accuracy. When all municipalities were simulated with a TSA and the simulation framework, the runtime was improved by only 22.4 % due to the computational expense of the TSA process (full simulation with TSA).

The main improvement can be seen by reapplying the emulation model, e.g., for different use cases. The time of 330.6 h for the simulation of ~12,000 municipalities could be decreased to 2.4 h without the TSA with the random forest. The random forest with TSA performs better and predicts all 8,760 h for all ~12,000 municipalities in 0.34 h. This is an increase by factors of 156 and 1,100 (with TSA). The difference in performance can be explained by the different size of the random forest. In particular, default hyperparameters of the scikit-learn RF do not restrict the depth of the trees, which can lead to arbitrary complex models. Furthermore, larger training sets lead to more input data variance, which might also increase complexity of the RF.

All in all, this section and [A3] show three main parameters for emulation: sample-size, sampling method, and time series aggregation. The more samples used, the better the model. Lower amounts of samples can be compensated for with more intelligent sampling methods. The more detailed the time series of the samples are used, the better the result. All these increases in complexity and detail come at the cost of simulation time. However, the results also show a non-linear increase in model accuracy with the increase in sample size and time series (see [A3]).

By intelligently selecting the number of typical hours for the TSA, sample size, and sampling methods for the respective application and capacities of the simulation, the result can still retain a high quality. TSA and emulation were able to speed up the initial modeling process in our case study by up to 88.9 % compared to the simulation of all ~12,000 municipalities. Reapplying the model increases the time required to calculate all municipalities by a factor of 1,100 (including TSA). In cases with optimal improvements in the simulation framework (e.g., linear dependency of simulation time and simulated time steps), TSA as an input of simulation can considerably decrease runtimes and increase the amount of sampling units for the emulation. For non-linear dependency of the simulation time and time steps, fewer samples with a more detailed time series may provide equally good results).

Based on this case study on local prosumer energy sharing communities, important conclusions were drawn for the application of ESM in this dissertation. For sampling, 10 % of the municipalities with a time series aggregation on 50 time steps is sufficient. For the validation of the results, 1 % of the municipalities is sufficient. Both data sets must be sampled intelligently, as described in [A3]. The clustering in section 6 is a valuable (but optional) basis for clustering. ESM can increase the runtime performance considerably while retaining a high accuracy. However, since parts of the computationally expensive simulation model are still needed to generate the samples, the runtime performance gains are dependent on the sample size and the number of necessary simulations.

Based on these findings, the method from section 7.4 is applied to the use cases of this thesis, in the following.

## 7.6 Method Application

In this section, the introduced methods (TSA, sampling and ESM) are applied on the simulation framework and the three use cases selected for the energy-economic potential assessment in section 4. In the following, the necessary background for the method application is provided.

**Sampling Method**

The municipalities were only sampled once for all use cases, using the k-Means cluster sampling approach with a sample size of 1,200 municipalities (ca. 10 %) for training and cross-validation and 123 municipalities for benchmarking purposes, as described in [A3]. The sampling was conducted using a two-step approach. In step one, the clusters from section 6 were used to determine their share of the sample size (10 %), proportional to the cluster size [199]. In step two, the cluster sampling, as introduced in section 7.2, was applied on each cluster individually to determine the sampling units [A3]. The simulation time in this dissertation is highly correlated to the number of consumers and producers within a municipality, as shown in section 5.6. The urban clusters (6, 11, 17) only contained a few municipalities with the highest number of inhabitants. To reduce simulation time, these clusters were excluded in the benchmark and sample set, according to the method in Figure 6-9 (i.e., cluster preselection). These sampling units were used for all following use cases.

**ESM Model Types and Dependencies**

Figure 7-3 depicts the workflow and model dependencies in this thesis. The basis for all ESMs is the simulation results.

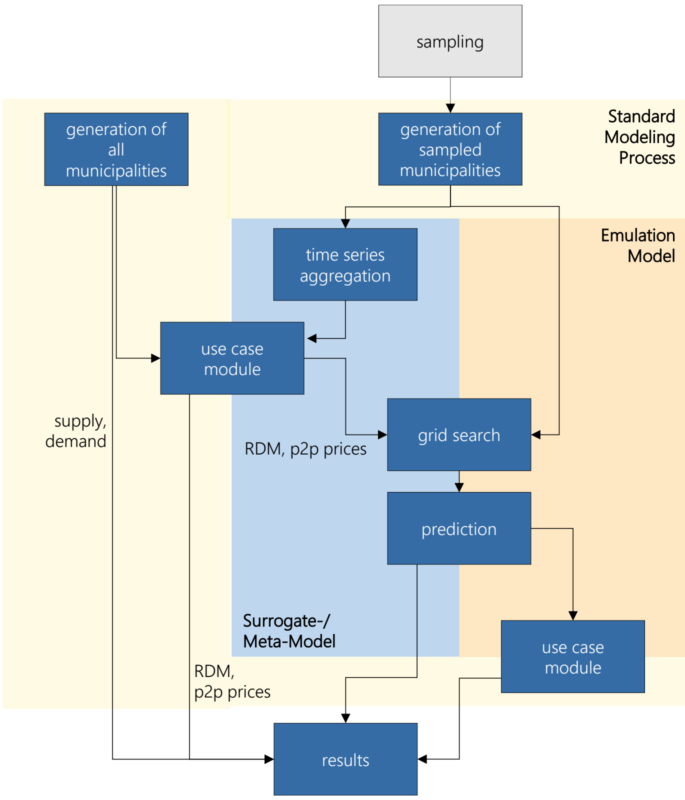


Figure 7-3: Workflow and dependencies of the multiple ESM models and reference model

The demand and supply of prosumers is necessary to calculate $SDR_t$ as well as SDR and MMR pricing. The ESM is trained on simulation data which needs to be generated by different model components (depending on the use case). Since P2P prices and RDM volumes correlate to the $SDR$, supply and demand are used as features in these machine learning models as well.

The dependencies show that SDR and MMR pricing use supply and demand in a local energy sharing community to determine the community buy and sell prices. Since the simulation framework is not completely substituted (i.e., the pricing module is retained), it is an emulation model. P2P prices and RDM volumes do not retain parts of the simulation model but substitute it completely. They are hence surrogate- or meta-models.

### Supervised Machine Learning Algorithms

Supervised machine learning algorithms automatically learn functional relationships or patterns from sample (training) data and apply them on unseen data to make predictions [216]. Supervised ML hence "relieves the human of the burden to explicate and formalize his or her knowledge into a machine-accessible form and allows to develop intelligent systems more efficiently" [216]. Supervised machine learning can be distinguished in shallow and deep learning. However, a clear line cannot be drawn between them [216]. Shallow learning models are generally simpler; often white boxes [216] that require small amounts of input data. Deep learning (i.e., deeply nested neural network architectures), needs big datasets, more computing power, and the capability to solve more complex tasks such as natural language, image or video processing [216]. However, in cases with lower-dimensional input datasets and less complex functional relationships of input and output, shallow MLs still produce superior results and provide better interpretability [217].

Since the datasets in this dissertation are generated by a simulation model and hence the amount of training data limited by the simulation models' computational complexity, shallow learning is chosen for the ESM.

In the context of this work, the word "model" is used for an ML algorithm (e.g., random forest regressor or k-nearest neighbors regressor) that was trained with data and is capable of making predictions. A model is described by the used ML algorithm, the applied hyperparameters and resulting error metrics describing the model accuracy.

There are many different shallow machine learning algorithms that can be considered for the ESM task. In this dissertation, the focus is set on ensemble methods. They combine multiple machine learning models (= base estimators) to generate regression results. The results of these models are either averaged (i.e., Bagging Regressor or Random Forests) or boosted[4]. The former uses independent base estimators in a parallelized way [218]. Training data is split in random sub-samples (= bootstrapping) to train multiple models and aggregate them to a single value by using their average. Hence, this process is called bootstrap aggregation (bagging). Boosting on the other hand uses sequentially built base estimators and reduces their combined bias (i.e., Ada Boost and Gradient Boost) [215].

Ensemble methods are robust to overfitting and produce more accurate results than single models. They can be applied on linear and non-linear data. However, this comes at the cost of interpretability. Additionally, the models come with more computational cost and require more storage space [218]. Another advantage of these models is the usage of the multiple base estimators to quantify uncertainty [A3]. This can then be used to simulate datapoints with a high uncertainty instead of predicting them with ML or including the simulation results into the training data (see active learning or adaptive sampling in [A3] and section 14.4.2 in the appendix).

The used ML ensemble algorithms in this work include Random Forest Regression, Bagging Regression, Ada Boost Regression and Gradient Boost Regression.

**Grid Search and Hyperparameter Tuning**

The grid search is necessary to conduct the tuning of hyperparameters of the used machine learning models. In this work, the grid search is conducted exhaustively considering all set parameter combinations. The grid search is conducted using a k-fold cross-validation (with $k = 5$). Hyperparameters are optimized (using $R^2$) on the training data. The resulting model is applied on the benchmark set and the error metrics (of model and benchmark set) are used in this work to assess model accuracy. The time required for the grid search is subjective and depends on the parameter selection, size of the dataset, number of features, available processing power and repetitions to minimize random factors.

The best model will be selected, based on multiple evaluation metrics, introduced in the following.

**Model Evaluation**

To evaluate the regression models in the next section, the metrics described in Table 7-2 are used. Let $n$ be the number of samples, $y$ be the results of the ground truth simulation, $\hat{y}$ be the predicted values.

[4] In addition to boosting and bagging, there is also stacking, blending, etc. However, these are not considered in the context of this dissertation.

Table 7-2: Applied evaluation metrics

| Name | Formula | Explanation |
|---|---|---|
| Mean Absolute Error (MAE) | $\frac{\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert}{n}$ | The MAE calculates the average absolute difference between real and predicted results. This metric is not scale invariant, meaning data with very large range or skewness will cause large variations in MAE. The MAE is in the original dimension, the most easily understood and interpretable error metric. |
| Mean Squared Error (MSE) | $\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ | The MSE squares the difference between real and predicted values. This penalizes larger errors much more than small ones, which can speed up convergence when using gradient-optimization based regression models. However, like with the MAE, any heteroscedasticity or large sample ranges will unevenly weigh the error. |
| Coefficient of Determination ($R^2$) | $1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$ | The coefficient of determination is usually interpreted as the proportion of explained variance or the total variance explained by the model over the total variance. The $R^2$ is scale-free and hence irrespective of whether the values are large or small. It is a measure of explanatory power, not fit. Its best value is 1. [219] |

As shown in [A3], applied evaluation metrics are usually interpretable if applied on values within a comparable scale. However, they are hard to interpret if the values are in different scales, since they are not scale invariant (except $R^2$). All error metrics are hence interpretable on a single municipality level; however, multiple municipalities with different sizes are not. This implies that if a regression model is capable of predicting all values within a municipality with an accuracy of 99 %, the one percent error may be 10 kW on average in a small municipality and 10 MW in another, and vice versa when applied on percentage errors. A large percentage error in a small municipality may therefore only be 10 kW, whereas a small percentage error in a large municipality could be 10 MW. A mean value of these errors loses its explanatory power.

The provided metrics offer more insight into model accuracy when comparing regression models in the same use case, to determine the best regression model in the grid search. They are also useful if analyzing the regression quality in a single municipality. With the exception of $R^2$, which is scale invariant, no other metric is useful from a global perspective. Hence, $R^2$ will be the focus of the evaluation of model accuracy since it is capable of determining the extent to which a regression model can explain the variation in a target variable, invariant of its scale.

### 7.6.1 Use Case: Pricing in Local Energy Sharing Communities

In this section, pricing in local energy sharing communities is determined, as described in sections 4.3.1 and 5.4.2. The pricing mechanisms require supply and demand, as already shown in section 5.4.2. Since the pricing mechanisms are calculated using the formulas in section 5.4.2, these models are emulation models. They predict supply and demand within each municipality individually. The training and prediction data is provided in the following.

Training and testing are performed with the following features, available for 2019 and 2035 (scenario):

- static features: installed rooftop PV capacities, number of buildings, number of electric vehicles, number of HSSs, and cluster id (see section 6.6.2) for both supply and demand; capacities of wind, PV, biomass and hydropower (for supply only).
- dynamic features: hour of the day, day of the week, consumption of households, rooftop PV generation.

- target variables: supply and demand (two separate ML models) in kWh.

The predicted variables are supply and demand within each community. As introduced in section 7.3, demand is defined as the sum of the remaining load after own consumption of all prosumers. Supply is defined as the sum of the remaining feed-in of electricity of all prosumers and renewables ≤ 2MW after own consumption.

Training a single multivariate output model requires more training data, according to [220]. Hence, two univariate models are trained. Contrary to RDM and LEM, the supply and demand is not restricted to type hours since the 1,200 municipalities for training and 123 municipalities for testing were generated with a timeline of a full year and hourly resolution; i.e. training and testing are done with all 8,760 h per municipality. The data of this process is among other things used to conduct the time series aggregation (see section 7.3).

### 7.6.2 Use Case: Regional Direct Marketing

The regional direct marketing potential is the result of a linear optimization model, according to section 4.3.3 and 5.4.1. The optimization model is completely substituted by the machine learning model, as introduced in the following. It is hence a meta/surrogate model, according to the definition in [A3].

The training is done with the following features, available for 2019 and 2035 (scenario):

- static features: number of inhabitants, area, maximum distance east-west, maximum distance north-south, settlement area, ratio of settlement area to area, average distance between settlements, average area of settlements, population density, installed capacities of (rooftop and ground mounted) PV as well as wind, hydropower and biomass, cluster ID.
- dynamic features (load profiles) of: demand of buildings, supply of prosumers from section 7.6.1, minimum of supply and demand as naïve estimation of the maximum RDM potential and household consumption.
- target variable: energy available for regional direct marketing in kWh.

The predicted variable is the available energy for regional direct marketing within each municipality. The energy can be multiplied with 2.05 ct/kWh to obtain its economic potential.

### 7.6.3 Use Case: Pricing in Local Energy Markets

In LEM, a market price is determined by a multi-agent model, as described in section 4.3.2 and 5.4.3. Since the turnover of the market only rarely covers the full supply and demand (i.e., only when $SDR_t = 1$ and all supply is sold on the market), the remaining residual load is sold or bought for the wholesale price. The resulting volume weighted average price (consisting of turnover, market price, residual load and wholesale price) is the target of the model since this price is comparable among all municipalities. This ensures that all available or needed electricity is covered for all participants.

The multi-agent model is completely substituted by the machine learning model, as introduced in the following. It is hence a meta/surrogate model, according to the definition in [A3].

The training is done with the following features, available for 2019 and 2035 (scenario):

- static features: number of buildings, consumers, prosumers and all renewables ≤ 2MW, cluster ID.
- dynamic features (load profiles) of supply, demand, wholesale prices, hour of the day.
- target variable: average LEM price in ct/kWh, including residual quantities.

### 7.6.4 Accuracy and Runtime Performance Analysis

In this section, the resulting accuracy and runtime performance of the ESM is analyzed.

**Accuracy**

Accuracy is defined in this work as the discrepancy (i.e., distance) between a true and an estimated value [221] and the explanatory power of a model. Table 7-3 and Table 7-4 show the results of the regression models on the introduced use cases, measured with the evaluation metrics.

Table 7-3: Comparison of meta/surrogate model results for demand and supply

| | Demand 2019 | Demand 2035 | Supply 2019 | Supply 2035 |
|---|---|---|---|---|
| **Regression Model** | Bagging-Regressor | Bagging Regressor | Random Forest Regressor | Bagging Regressor |
| **Base estimators** | 10 | 100 | 200 | 200 |
| **Transformer/Scaler** | - | - | Power Transformer | Power Transformer |
| **MAE** | 3.95 | 35.44 | 37.40 | 124,29 |
| **MSE** | 123.06 | 11,807.91 | 19,303.02 | 296,418,02 |
| **$R^2$** | 0.999965 | 0.996740 | 0.998886 | 0.985587 |
| **Training Time (s)** | 2,456.70 | 20,836.20 | 78,136.57 | 70,308.94 |
| **Prediction time (s)** | 2,096.94 | 4,510.00 | 7,258.39 | 6,060.05 |

The evaluation metrics show good overall results, with all $R^2$ values above 0.98. The mean absolute error of supply and demand is low in 2019 and increases in 2035. This is because the impact of generation and consumption on these two parameters increases substantially in 2035 and hence the error increases. A large proportion of the buildings have a PV system in 2035, storage and electric vehicles. This will increase self-consumption, affecting supply and demand as well as the respective error. The MAE and MSE of supply and demand are especially high in densely populated urban municipalities. Here, the impact of electric vehicles, consumption and rooftop PV is the greatest in 2035 and their absolute level is the highest.

This shows that it is challenging to quantify the accuracy of a large, heterogeneous population including time series data with MAE and MSE. Instead, individual communities must be considered in detail. The cluster representatives as well as the benchmark dataset were considered in the course of the analysis, as done in [A3]. The $R^2$ is the best measure here, because of the high accuracy and explanatory power of the model. In section 14.4 in the appendix, further evaluations on the metrics are provided.

Table 7-4: Comparison of meta/surrogate model results for RDM and LEM

| | RDM 2019 | RDM 2035 | LEM 2019 | LEM 2035 |
|---|---|---|---|---|
| **Regression Model** | Bagging Regressor | Bagging Regressor | Bagging Regressor | Random Forest Regressor |
| **Base estimators** | 50 | 50 | 50 | 50 |
| **Transformer/Scaler** | - | - | - | - |
| **MAE** | 35.05 | 47.45 | 0.1972 | 0.2155 |
| **MSE** | 11,428.99 | 27,291.87 | 0.1959 | 0.2590 |
| **$R^2$** | 0.935855 | 0.932229 | 0.929176 | 0.933564 |
| **Training Time (s)** | 141.26 | 159.03 | 74.29 | 55.71 |
| **Prediction time (s)** | 1,832.17 | 1,818.19 | 860.05 | 821.65 |

Table 7-4 shows comparable behavior. Errors increase from 2019 to 2035 due to a change in supply and demand. The $R^2$ implicates high model accuracy as all values are close to 0.93. The MSE is especially high due to outliers in municipalities with high potentials, leading to low overall average errors at the single municipality level.

Even though bagging and boosting ensemble regressors were applied on the datasets, bagging (Random Forest and Bagging Regressor) outperformed boosting regressors (Ada Boost and Gradient Boost Regressor) consistently in the grid search. Random Forest and Bagging Regressor were very close to each other. Tree based regressors are scale invariant, hence they don't require scaling. However, a Power Transformer, "to make data more Gaussian-like" [215] helped somewhat to improve the model results of demand and supply in 2035.

In all cases, the accuracy could only be improved very slightly by a higher number of estimators. Due to Ockham's razor, the regressors that achieved the best results with as few estimators as possible were selected. Additionally, the training and prediction time was considerably lower with fewer estimators, as shown in the following. All in all, the high $R^2$ values above 0.93 in all use cases indicate a high model quality and only a little loss due to the applied regression models.

### Runtime Performance Analysis

In this work, performance is defined as the ratio of the runtime of the ESMs to the runtime of the simulation model. The performance analysis aims to compare the ESMs with their simulation counterparts. To measure runtimes, they were logged at all points in the code, as already depicted in prior sections.

The following paths are compared in this thesis:

- **The full simulation (reference):** all approx. 12,000 municipalities must be generated with 8,760 h each. Every hour is simulated (or optimized) in the respective use case modules to generate results.

With machine learning, this process is modified. Instead of fully generating all municipalities, only a sample of 1,200 municipalities for training and 123 municipalities for testing (=benchmark set) is generated with 8,760 h each for each considered scenario. Based on this data, a TSA is conducted once to identify 50 typical hours per municipality and scenario.

- **Emulation Model:** the generation of 1,323 municipalities provides supply and demand data, which is the basis for the simulation of prices in LES [A3]. The supply and demand is used directly (no specific use case module needed) to perform a grid search and predict prices for all approx.

12,000 municipalities. These results are used to simulate the prices in LES, as described in section 5.4.2. Since the ML only substitutes parts of the simulation and the result is still generated with the simulation framework, this is an emulation model, according to the definition in [A3]

- **Surrogate/Meta-Model:** Based on this municipality data, a TSA is performed for all 1,323 municipalities, since the use case modules of RDM and LEM are computationally expensive [A3]. The use case modules are used on selected typical hours (TSA see section 7.3), and the results used in the grid search and prediction to directly generate the results (RDM quantities and P2P prices). Since this process substitutes the simulation framework it is a surrogate/meta-model.

It follows that the generation of the sample municipalities as well as the time series aggregation (TSA) has to be conducted once for each scenario. For every use case and scenario individually, the time to simulate or optimize the use case, model training and the prediction of non-simulated data is logged and compared to the full simulation.

As described in [A3], these steps were conducted on a local server architecture, usually applied for simulation and optimization. The machine learning was conducted on the same hardware as the modeling process. Accordingly, the results allow conclusions to be drawn about how much faster the ESM approach is compared to classical modeling, without having to use specialized hardware or cloud services. If these were used, additional costs would arise, but the performance of the ML training would be substantially higher.

Table 7-5 depicts the performance metrics of all three use cases in two scenarios.

Table 7-5: Performance increases and reference values if the use cases were to be determined independently of each other

| Use Case | Reference Type | Scenario | Runtime (days) for the entire process | | Performance increase |
|---|---|---|---|---|---|
| | | | Conventional Model | ESM | |
| LES prices | simulation | 2019 | 21.7 | 4.80 | 4.53 |
| | simulation | 2035 | 24.2 | 5.36 | 4.51 |
| RDM | optimization | 2019 | 565,94 | 5.88 | 96.21 |
| | optimization | 2035 | 1,088.30 | 6.49 | 167.81 |
| LEM | multi-agent model | 2019 | 27,538.70 | 16.17 | 1,703.07 |
| | multi-agent model | 2035 | 44,736.65 | 19.06 | 2,346.73 |

The results show that runtimes differ considerably. While all sample municipalities must be created for LES prices, about 10 % of the runtime is already determined by the conventional simulation model. In addition, as shown in [A3], the 10 % samples do not necessarily account for 10% of the computing time. Since it correlates to the number of inhabitants (see section 5.6), some large municipalities in the samples can lead to disproportionately large simulation times. With LES prices, not only typical hours but the full 8,760 h for all sampled municipalities are simulated. The emulation model can hence be trained with considerably larger datasets (i.e., with 10,512,000 datapoints). This may lead to better results, but also to increased training and prediction times, as apparent in Table 7-3. This limits the performance improvement to a factor of about 4.5.

The runtime of the conventional RDM use case module is considerably higher, since it requires the generation of all municipalities as well as a computationally expensive linear optimization, which requires ca. 544 days for 2019 and 1,064 days for 2035 (details see section 5.6). The individual steps in the ESM (2019/2035) include the sampling process (9.3/9.3 min), generation of the sampling municipalities (5,368/5,973 min), time series aggregation (2,010/2,010 min), optimization of the type hours (1,050/1,313 min), model training and prediction (32.9/32.95 min). This leads to an increase of performance by a factor of 96.21 for 2019 and 167.81 for 2035.

LEM is the use case which requires the runtime of the conventional model (i.e., 27,517 days for 2019 and 44,713 days for 2035), since all agents have to be simulated individually (see sections 5.4.3 and 5.6). While the required time of the ESM for sampling, generation of the sample municipalities and time series aggregation are the same as with RDM, the multi-agent-based simulation still requires 265 hours in 2019 and 324 hours in 2035. ESM training and prediction, however, requires only 15.57 min for 2019 and 14.62 min for 2035. Respectively, the performance increases by a factor of 1,703 for 2019 and 2,347 for 2035.

Since this analysis treats every use case individually, there are redundancies of ESM included. If they are calculated together, i.e., as per the sampling process, the generation and TSA of the sample municipalities has only to be conducted once. In addition, the goal of this work was to calculate all use cases and analyze the results. In the following, only the time required by the ESM to produce all the results needed for this work is considered. Redundancies are eliminated, as they act as synergies in this calculation. To obtain the desired data for this dissertation (for ca. 12,000 municipalities in two scenarios), the ESM improved the runtime performance of all use cases by a factor of 1874.6. This reduced the necessary time from 201.24 years, required by the simulation model, to 39.18 days, required by ESM.

The model re-application on the dataset is even faster. If the entire population has to be calculated again, the trained ESM model is applied while the simulation model must be used again. This is depicted in Table 7-6.

Table 7-6: Performance increases for model reapplication

| Use Case | Scenario | Runtime for reapplication | | Performance increase |
|---|---|---|---|---|
| | | Conventional Model (days) | ESM (hours) | |
| LES prices | 2019 | 21.7 | 3,22 | 161.7 |
| | 2035 | 24.2 | 3,55 | 163.6 |
| RDM | 2019 | 565,94 | 0,509 | 26,684.8 |
| | 2035 | 1,088.30 | 0,505 | 51,721.2 |
| LEM | 2019 | 27,538.70 | 0,239 | 2,765,392.5 |
| | 2035 | 44,736.65 | 0,228 | 470,912,105.3 |

Table 7-6 shows an increased runtime for model reapplication by a factor of 161.7 and 163.6 for LES prices. Since this is an emulation, the ESM only predicts supply and demand. Resulting SDR and MMR prices have to be simulated with the simulation model, requiring additional time. RDM improves the reapplication time by a factor of 26,684.8 to 51,721.2, and LEM by a factor of 2,765,392.5 to 470,912,105.3. Reapplication is especially important when sensitivity analyses are to be performed. This means that a model is reapplied several times with changed input parameters observing output behavior. Furthermore, it is particularly important that a model is fast. In this case, ESM outperforms conventional models enormously.

All in all, machine learning can improve runtime of a simulation, optimization and multi-agent model considerably, if they are computationally infeasible. However, the biggest limiting factor for this method remains the conventional model itself. The more model data is required and the slower the model, the slower the ESM process. Therefore, all conventional options available should be used first to accelerate the model itself. Only when this is no longer possible does machine learning offer a viable solution.

## 7.7 Preliminary Summary

In this section, insights into emulation and surrogate modeling (ESM) methodology, based on preliminary works in [A3], are provided. This sections answers **RQ 4: How can supervised machine learning improve energy-economic modeling processes?**

An advantage of this methodology, described in section 7.4, is its performance compared to a full simulation approach. In the methodology, a simulation model is only used to generate sufficient data to train machine learning models. The ML (once trained) can be applied on new, unseen data much faster, with minor losses in accuracy. In bottom-up models, this allows a much faster simulation of the population.

A key challenge in this methodology is the sampling methods, when only a small sample of a big population is used as training data. In section 7.2, insight into machine learning with small datasets and sampling methods is provided, based on [A3]. A cluster sampling approach performed well in [A3] and can be used for all use cases, without the necessity for resampling. Since the municipalities were already stratified, the clusters from section 6 can be used in conjunction with this method. To reduce the simulation time, a time series aggregation was applied on the input parameters of the simulation in section 7.3.

In section 7.5, a case study to show the viability of the method initially presented in [A3], was provided. In this case study, the emerging prices in approx. 12,000 German prosumer energy communities (consisting only of private prosumers and no additional RE), based on the pricing models in section 5.4.2, were simulated and emulated using the same methodology. As shown in [A3], this can accelerate the initial simulation of the entire population by up to 88.9 % and the model re-application by a factor of 1,100.

The methodology introduced and validated in [A3], is also applied in section 7.6 on the three use cases for 2019 and the scenario 2035. The results show very low errors in the municipalities with $R^2$ between 0.92918 and 0.99997 and low MAE and MSE in the individual municipalities. The ESM was capable of reducing the runtime from the 201.24 years required by the conventional simulation model to 39.18 days (factor of 1,874.6), while retaining high accuracy. All ESMs achieved $R^2$ values between 0.92918 and 0.99997 and low MAE and MSE in the individual municipalities. In computationally expensive and very slow models (e.g.., the multi-agent model to determine LEM prices), the runtime can be increased up to a factor of 2,346.7. Reapplying the models, for sensitivity analysis, the ESM exceeds the conventional models by a factor of 161.7 and 163.6 for LES prices, 26,684.8 to 51,721.2 for RDM and 2,765,392.5 to 470,912,105.3 for LEMs.

The evaluation shows that conventional simulation models are still needed to generate sufficient data or to simulate those parts of the model that are not substituted by the emulation model. It is therefore crucial that all available and feasible measures are first applied to accelerate the conventional model. Only then is the ESM a viable alternative. The ESM also benefits from the fact that the conventional model has been accelerated, as more data can then be generated for training.

The results of the ESM are evaluated from an energy-economic perspective in the following.

# 8 Energy-Economic Potential Assessment

In the following, the resulting potentials for the introduced use cases are assessed in detail.

## 8.1 Supply Demand Ratios and Wholesale Prices

Price models in energy communities are supposed to reflect the ratio of supply and demand within the community and serve as a link to wholesale markets. A key indicator for the local price is hence the supply demand ratio ($SDR$) and the wholesale markets ($p_t^{wholesale}$). Both factors are analyzed in the following.

### 8.1.1 Supply and Demand Ratios in Germany

As introduced in section 5.4 and [A4], a balanced energy community with a constant $SDR_t = 1$ is the optimum for both supply and demand. If the $SDR$ is imbalanced, the prices serve as incentives to balance it out by the use of flexibility and to build new (demand-oriented) renewables. The $SDR_t$ is calculated using the resulting data from section 7.6.1.

In the next sections, the following notation is used:

- $SDR$ is the supply demand ratio, with $SDR_t = \frac{supply_t}{demand_t}$
- $\widetilde{SDR}$ is the median, $\overline{SDR}$ is the mean
- SDR pricing is the corresponding price, as described in section 5.4.2

Figure 8-1 depicts the $\widetilde{SDR}$ for German municipalities for the years 2019 and 2035.

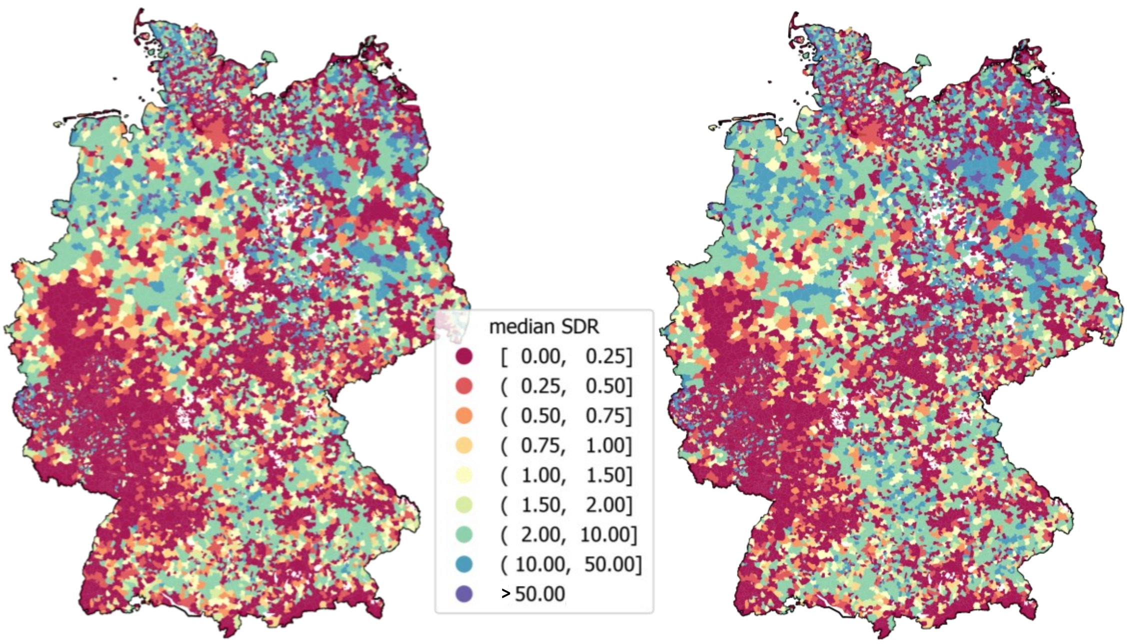


Figure 8-1: Median supply demand ratios ($\widetilde{SDR}$) per municipality in 2019 (left) and 2035 (right)

The results show low $\widetilde{SDR}$ in urban areas such as cities and suburban areas. Especially the Rhine, Ruhr and Main area in western Germany (North Rhine-Westphalia, Rhineland-Palatinate, Hesse and Baden-Wuerttemberg) have $\widetilde{SDR} = 0$, due to their high consumption but low installations of renewables < 2MW. The same goes for urban and suburban areas, i.e., in and around Berlin, Frankfurt, Munich, Dresden etc. The communities with $\widehat{SDR} = 0$ made up the largest group in Germany in 2019.

In northern Germany, regions with older wind turbines (< 2MW) are often not densely populated but are relatively large, leading to a high supply with low demand. If these wind installations are close to more densely populated areas (i.e., in Lower Saxony), the $\widehat{SDR}$ gets more balanced towards $\widehat{SDR} = 1$. In eastern Germany, both wind power and ground-mounted PV contribute to the supply. Since some areas have only a very small population, and hence a low energy consumption, the $\widehat{SDR}$ is very high, in the range of 2 to 10. The rare outliers with $\widehat{SDR} > 50$ appear primarily in this area.

In Bavaria, the overall $\widehat{SDR}$ is relatively balanced, except for urban and mountainous regions. On the one hand, this can be attributed to the relatively high number of PV installations, which account for a large share of generation, especially in Bavaria. Also, these installations are mostly smaller than 2 MW and hence contribute to the $SDR$ in this work. It should be noted that most of the nation's small hydropower plants are located in Bavaria and Baden-Württemberg. These are often under 2 MW and were historically often built near or in settlement areas along the smaller rivers, which means that the electricity can usually be consumed directly in the surrounding area.

The most balanced $\widehat{SDR}$s (0.5 to 1.5) can be observed in regions between suburban and rural municipalities. These are located outside metropolitan areas all over Germany. $\widehat{SDR}$s.

Especially smaller municipalities often show very large regional differences in the $\widehat{SDR}$. For example, in Rhineland-Palatinate, Mecklenburg-Western Pomerania or Schleswig-Holstein, small municipalities with very high and very low $\widehat{SDR}$s are often located right next to each other. In these communities, often just a few larger RE plants make the difference due to their low consumption. Also, urban communities with a high settlement density (e.g., villages or small towns) are often located directly next to rural communities.

In contrast, the $\overline{SDR}$ increases more from 2019 to 2035 than the $\widehat{SDR}$. PV has the highest impact on the increase of the $\overline{SDR}$ in almost all municipalities. The 2 MW limit assumed in this work excludes most future wind turbines, since their capacities are above 2 MW. Since most of the municipalities already had PV in 2019 and thus mainly their capacity and simultaneity is increased in 2035, the mean value increases more than the median. This leads to a very low or zero $SDR_t$ in winter and at night, while it quickly increases to values above one during the day.

Figure 8-1 (right) shows only minor changes from 2019 to 2035. There are several reasons for this. On the one hand, new wind turbines almost never count as supply, as they usually exceed 2 MW. Due to the simultaneity of volatile generation, extreme $SDR_t$s increase, but not their frequency. Since the figure shows the median, differences are only minor. However, this effect has more impact on the resulting prices and price spreads, shown in the next sections.

### 8.1.2 Wholesale Prices

All pricing mechanisms in this work resemble supply and demand within the community and the wholesale price. Figure 8-2 shows a histogram of the wholesale prices used in this work. For reasons of comparability of the price mechanisms, and to exclude the influence of exogenous variables, the 2019 prices were also used for 2035. The wholesale price used in this work is the volume-weighted average of all transactions within the three hours before physical delivery.

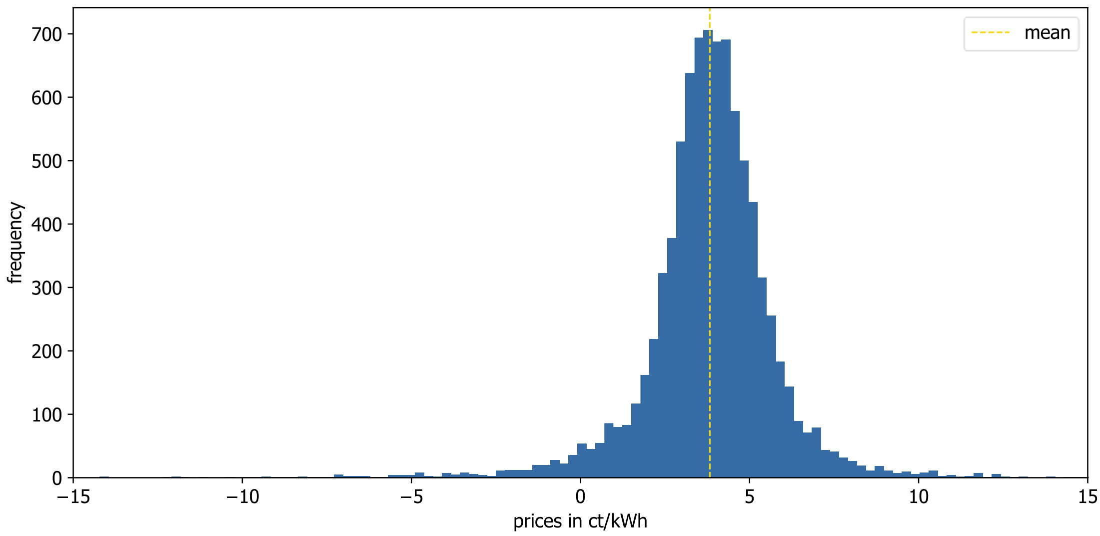


Figure 8-2: Histogram of hourly wholesale prices

The prices have a mean value of 3.82 ct/kWh and a median of 3.88 ct/kWh. They are negative in 286 hours and higher than 7.09 ct/kWh (retail price, including costs, margin and risk of the utility) in 297 h. Prices reached a minimum of - 17.95 ct/kWh and a maximum of 35.36 ct/kWh. If the electricity of households was procured on wholesale markets, their volume-weighted price would be 4.097 ct/kWh (H0-profile). For PV the volume weighted wholesale price is ca. 3.5 ct/kWh; for wind ca. 3.4 ct/kWh. This is lower than the average price, since high simultaneous PV and wind supply have a direct impact on the lowering of wholesale prices.

In general, periods of high electricity prices occur mainly at night or winter when there is little wind and solar radiation but high consumption. In times with very high generation (sunny and windy days with little consumption), prices are low or negative.

Based on this input data, the different pricing mechanisms and the RDM potentials are assessed in the following.

## 8.2 Price Analysis

The focus of this work is on the simulation and evaluation of different pricing mechanisms, introduced in section 4.3, for Germany. In this section, regional differences of the two pricing mechanisms SDR pricing and MMR pricing, as well as local energy markets (LEMs), are introduced. The resulting price spreads are analyzed, as they serve as an incentive for flexibility.

### 8.2.1 Supply Demand Ratio (SDR) Price Analysis

The SDR pricing mechanism depends on the supply demand ratio ($SDR_t$) as well as the wholesale price $p_t^{wholesale}$ which resembles the price on the wholesale markets. In cases with a high $SDR_t$, the community has a lot of oversupply. The resulting price equals the dynamic $p_t^{wholesale}$. In cases with a very low $SDR_t$, the community has very low supply but a high demand, with the price approaching the static $p^{retail}$ (here: 7.09 ct/kWh). As highlighted in [A4], the SDR pricing mechanism is not robust if $p_t^{wholesale} < 0$. Since the simulation was conducted with real $p_t^{wholesale}$, which often includes negative values, an adaptation was made in order to reflect them in section 4.3.1. Wholesale prices during this period incentivize the reduction of supply and the increase of demand. To meet these systemic requirements, whenever $p_t^{wholesale} < 0$, both buy ($p_t^{buy}$) and sell ($p_t^{sell}$) prices reflect this value. This means that the market signals are passed on directly. In times of negative prices, the price in the community is hence decoupled from the $SDR_t$.

Figure 8-3 shows the behavior of the SDR buy and sell prices (unweighted) in three different municipalities on three summer days.

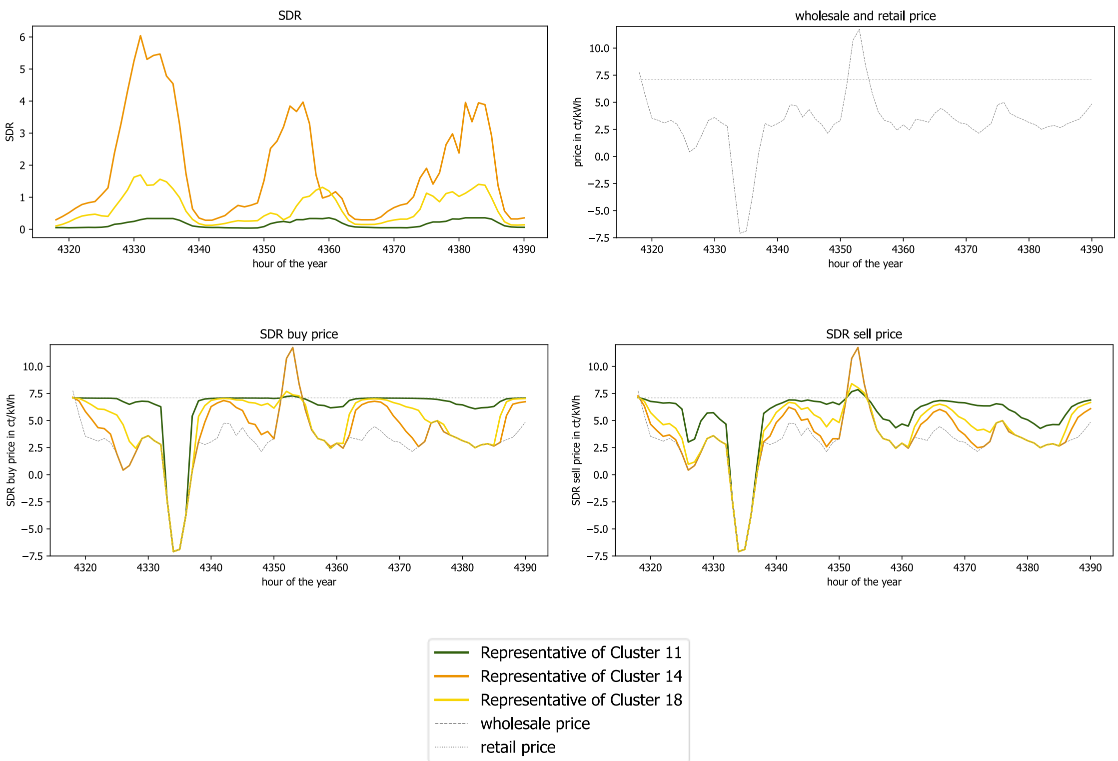


Figure 8-3: Side by side comparison of SDR prices, retail and wholesale prices as well as the supply demand ratio ($SDR_t$) on three randomly chosen summer days within three municipalities from clusters 11, 14 and 18

If the $SDR_t$ is between zero and one ($0 < SDR_t > 1$), $p_t^{buy}$ and $p_t^{sell}$ are between $p_t^{wholsale}$ and $p^{retail}$. With increasing $SDR_t$ (towards one), $p_t^{sell}$ and $p_t^{buy}$ approach $p_t^{wholsale}$. However, $p_t^{sell}$ is under $p_t^{wholsale}$, in cases with $p_t^{wholsale} > p^{retail}$, if $SDR_t < 1$. If the $SDR_t$ is above one, $p_t^{sell} \approx p_t^{buy} \approx p_t^{wholsale}$. This means that suppliers do not receive the entirety of high positive prices if the $SDR_t$ in the community is below one. Negative prices ($p_t^{wholsale} < 0$), on the other hand, are passed on directly to both buy and sell prices.

Figure 8-3 shows that the $SDR_t$ rises and falls very quickly between $0 < SDR_t > 1$, as the selected municipalities have a high simultaneity of supply. At night, the $p_t^{sell}$ in municipalities with low $SDR_t$ (i.e., if PV is the main source of supply) equals $p^{retail}$. However, almost no one can utilize this price since there is no supply available. When PV supply rises very quickly above one, $p_t^{sell}$ corresponds to $p_t^{wholesale}$. Thus, in communities with high simultaneity and high $SDR_t$, suppliers benefit little from this pricing mechanism. The revenues are only a little bit better than revenues on the wholesale market. In municipalities with a low $SDR$, only those suppliers gain a profit that can make use of the low $p_t^{sell}$. In municipalities with a balanced $SDR$, both sides profit of the pricing mechanism.

Figure 8-4 depicts SDR buy and sell prices, weighted by demand and supply in all German municipalities. This value corresponds to the annual average price of a kilowatt hour from the perspective of supply and demand. The reference retail price for demand is 7.09 ct/kWh. In 2019, 90 % of SDR sell prices were between 3.41 and 5.62 ct/kWh and 90 % buy prices between 4.10 and 6.78 ct/kWh. In 2035, 90 % of SDR sell prices are projected to be between 3.41 and 3.99 ct/kWh and

90 % buy prices between 4.17 and 6.41 ct/kWh. For a typical household (i.e., 2,500 kWh/a) cost savings by this mechanism are in the range of 7.75 – 74.75 €/a (4-42 %) in 2019 and 23.8 -73.0 €/a (13-41 %) in 2035, compared to a static retail price. Cost savings for consumers are the highest in municipalities with continuously high (over-) supply.

The average $p_t^{wholesale}$ depends on the RE technology, since their weighted prices on the wholesale market differ, depending on their simultaneity and impact on $p_t^{wholesale}$. Solar and wind have strong feedback effects on $p_t^{wholesale}$ due to their installed capacity and simultaneity. Their volume-weighted revenues on the wholesale market are lower than those of, e.g., hydropower or biomass, which (due to their base load capabilities) approach the mean $p_t^{wholesale}$ of 3.82 ct/kWh.

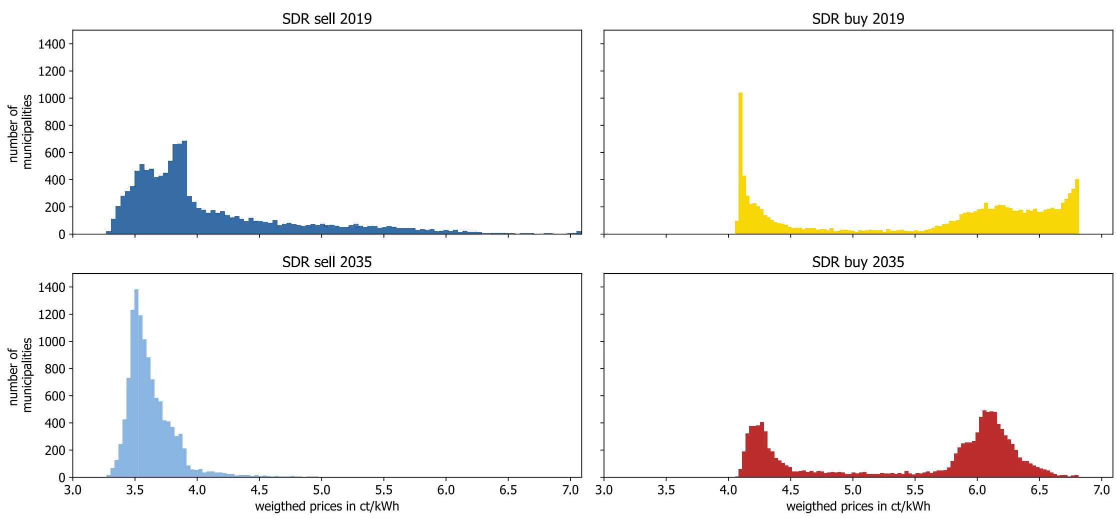


Figure 8-4: Histogram of weighted SDR sell and buy prices in 2019 and 2035

There was generally relatively little supply in 2019. For this reason, other energy sources (i.e., hydropower and biomass) besides PV still play a greater role in the supply. They receive a higher weighted price on the exchange because they fluctuate less. PV and wind, on the other hand, have a stronger influence on the exchange electricity price. The two peaks can be explained by the fact that in PV and wind-dominated areas, the average price of electricity sold on the exchanges is lower than in communities with a higher share from other energy sources (i.e., biomass and hydropower). The high simultaneity of PV and wind leads to lower volume-weighted prices on the exchange and in the community. Since the addition of new RE in 2035 is primarily PV (due to size restriction of 2 MW), the volume-weighted price in 2035 shifts downward to 3.48 – 3.54 ct/kWh as the other energy carriers play a smaller role. Due to the simultaneous behavior of PV, the supply rises and falls uniformly. If the supply is zero at night, prices are often very high (close to $p^{retail}$). However, as soon as solar radiation increases, high $SDR_t$ often occur quickly due to the simultaneity, causing the $p_t^{sell}$ to approach $p_t^{wholesale}$. Accordingly, the advantage in participation in LES with SDR pricing is rather low for volatile RE backing the observation in Figure 8-3. In contrast, non-volatile or flexible supply that generates electricity primarily during periods of low $SDR_t$ benefit the most. However, since the exchange electricity price always represents the lower limit of revenues, small increases of revenues can always be achieved compared to selling electricity on wholesale markets.

SDR buy prices peaked around the lowest prices (4.05 ct/kWh), with an increasing concentration of municipalities with higher prices up to 6.85 ct/kWh. This upper bound is always lower than $p^{retail}$ (7.09 ct/kWh) due to the consideration of negative prices in the $p_t^{buy}$. Buy prices are hence negative in 286 hours in all municipality, reducing the weighted $p_t^{buy}$. The buy price is close to $p_t^{wholesale}$ in municipalities with a high $\widetilde{SDR}$ (= oversupply), explaining the peak at the lowest price. In 2019, these were primarily communities with low-capacity hydropower plants, low-capacity (i.e., old) wind turbines (i.e. < 2MW) and PV.

In municipalities with low $SDR$, which is the case in most municipalities in 2019, the $p_t^{buy}$ came closer to the $p^{retail}$. This split of high price and low price municipalities becomes more extreme in 2035. In 2035 almost all municipalities experience periods of higher $SDR_t$, so the $p_t^{buy}$ of those municipalities that did not have supply in 2019 decrease in 2035. Since the addition of PV is the main factor until 2035 (due to the assumed size restriction of 2 MW), the $p_t^{buy}$ of these communities becomes relatively similar around 6.05 ct/kWh. As PV peaks lead to $p_t^{buy} = p_t^{wholesale}$ during the day but $p_t^{buy} = p^{retail}$ during the night, the effect of more PV on the average $p_t^{buy}$ is limited.

The municipalities with lower $p_t^{buy}$ prices, due to a higher $SDR$, are more broadly distributed around 4.15 to 4.30 ct/kWh, than in 2019. This can be explained by the fact that generation is now often not only composed of one type of generation (e.g., old wind turbines), but is supplemented by PV. This increases the diversity in 2035, which also distributes the $p_t^{buy}$ prices more homogeneously on the lower end.

Figure 8-5 and Figure 8-6 depict the weighted prices of $p_t^{buy}$ and $p_t^{sell}$ in 2019 and 2035.

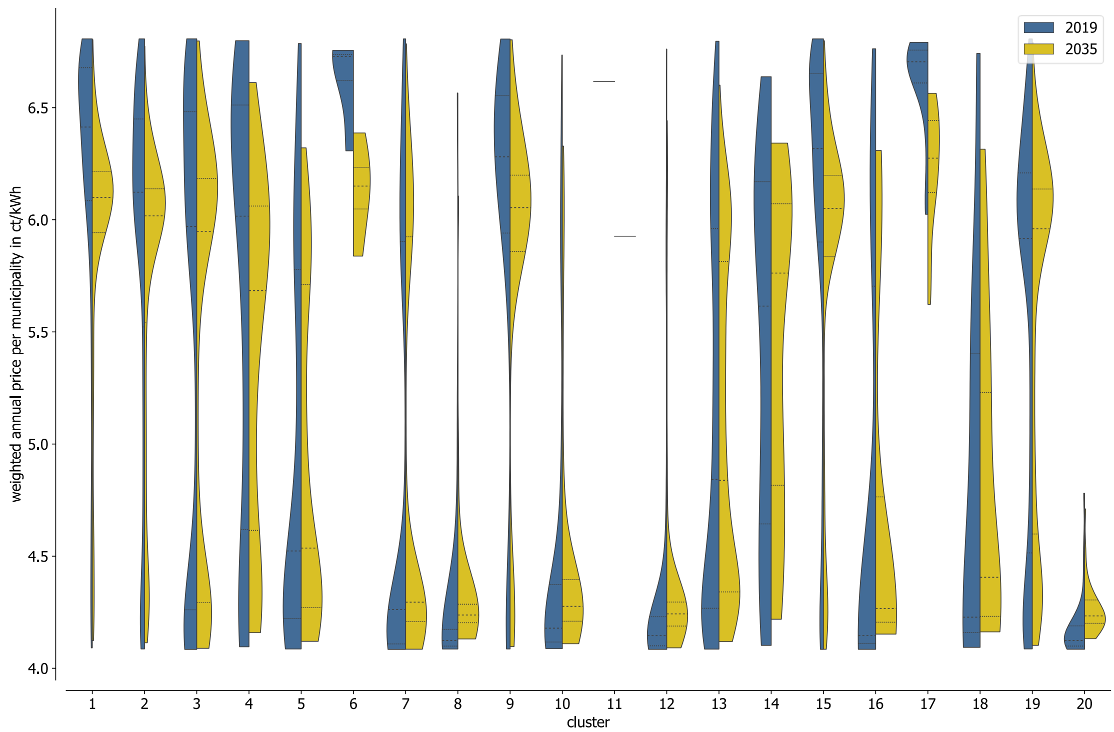


Figure 8-5: Weighted average prices of SDR buy in 2019 and 2035 per cluster

Figure 8-5 shows SDR buy prices ($p_t^{buy}$) in 2019 and 2035. Urban and suburban clusters 1, 6, 11 and 17 with low generation but high consumption (low $\widetilde{SDR}$), and small rural clusters 2, 6 and 15 with low consumption but (almost) no supply in 2019, have a high buy price.

Clusters 7, 8, 10, 12, 16 and 20 all have a high oversupply due to different RE sources. The municipalities within these clusters are relatively similar in terms of their $\widetilde{SDR}$, which means that, apart from a few outliers, the prices are all found at the lower end. Clusters 3, 4, 5, 13, 14, and 18, however, are less homogeneous since they have municipalities with high and low prices. The municipalities within these clusters have different generation and consumption structures. This also results in different prices within the clusters.

Clusters 4, 5, 13 and 18 (medium-sized towns and cities) are predominantly defined by their population, building and consumption structure, not their (rather low) generation. However, among the municipalities there are also some that have a relatively high supply, leading to a higher $\widehat{SDR}$ and hence a lower average $p_t^{buy}$. As already evident in Figure 8-4, prices in municipalities with low supply in 2019 profited the most from additional RE. On the other hand, those municipalities that already have very low prices, due to high supply in 2019, hardly change at all (i.e., clusters 5, 7, 8, 10, 12 ,16 and 20) by additional RE.

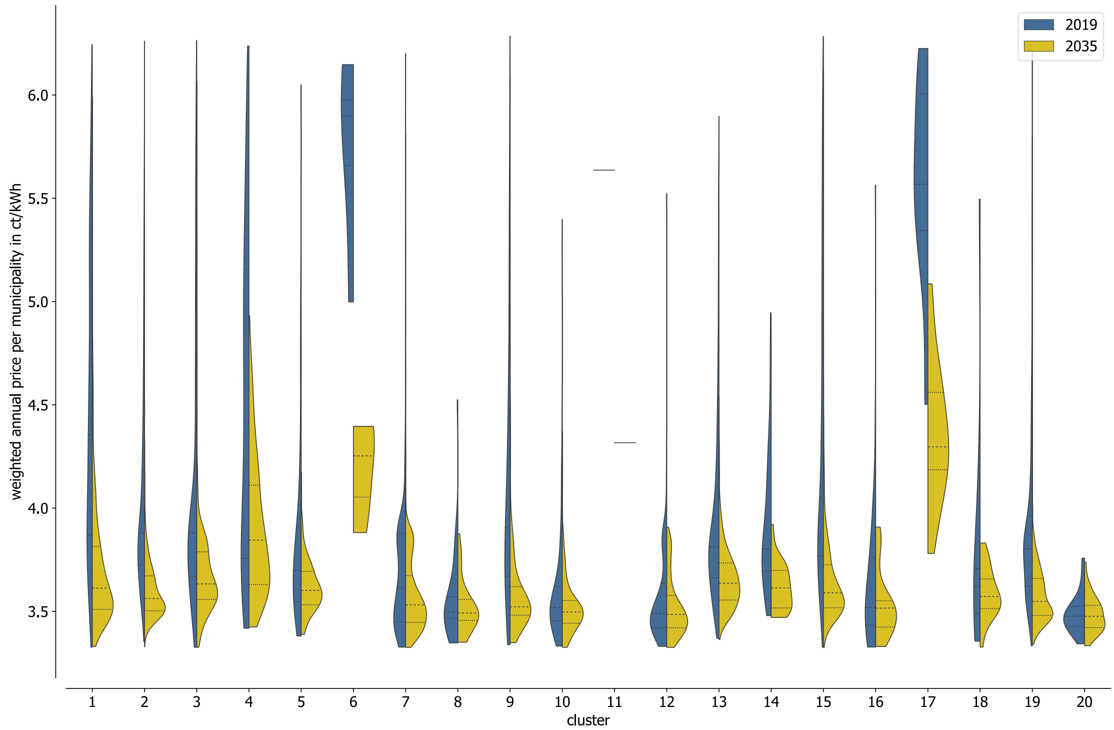


Figure 8-6: Weighted average prices of SDR sell in 2019 and 2035 per cluster

Figure 8-6 shows weighted average $p_t^{sell}$ in all clusters. In 2019, the differences in the clusters were sometimes very large, with higher price levels than projected for 2035. This is due to the fact that the municipalities rarely have oversupply and this often results from various energy sources at different times with less simultaneity. SDR pricing is highly susceptible to changes in $SDR_t$ and wholesale prices. Therefore, even small differences in generation and consumption structure within a cluster account for large differences in prices (in 2019).

High sell prices are found primarily in urban and suburban clusters (i.e., 1, 6, 11 and 17). In 2035, mostly PV plants are added (due to the capacity restriction of 2 MW), which will tend to bring prices closer together as the supply structure aligns. As already elaborated, this changes prices only slightly in communities that already had a high (e.g., wind-induced) supply in 2019 (i.e., clusters 10 and 12). The communities that already had a lot of PV generation in 2019 will see the least change (i.e., clusters 8 and 20).

Figure 8-7 depicts the average volume weighted SDR prices of demand and supply in 2019 in different municipalities in Germany.

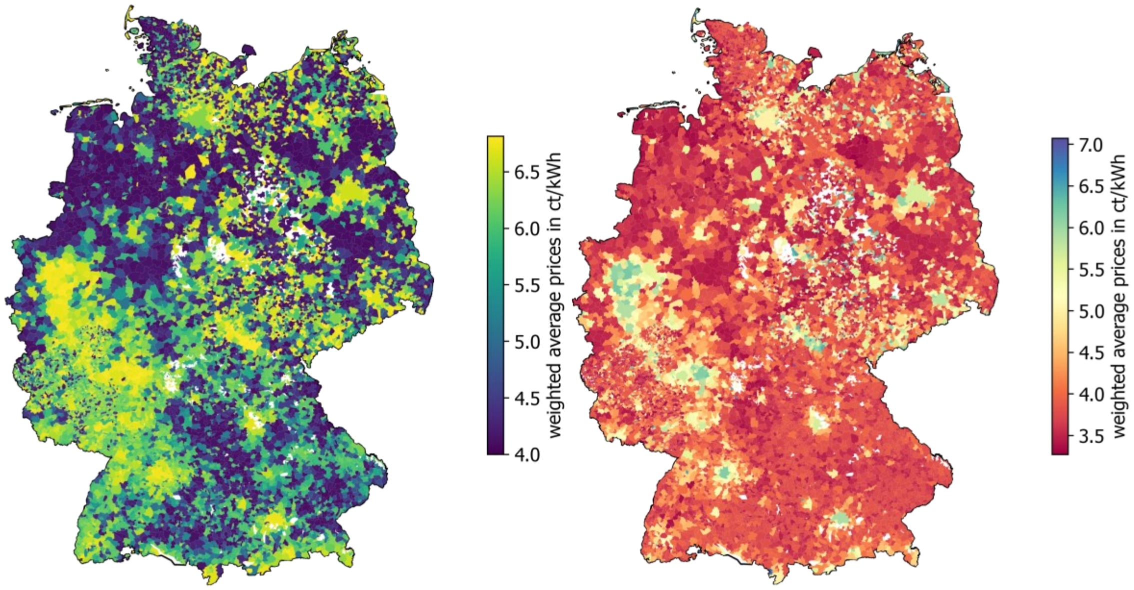


Figure 8-7: Weighted average SDR buy prices (left) and sell prices (right) in 2019

In municipalities with low supply and high demand, the $SDR_t$ is always low. Since only RE ≤ 2MW was considered, a lot of wind turbines etc. are excluded from the supply. Hence, for most small scale solar power, hydropower, biomass and old wind turbines are included. However, the volatility of PV and the resulting lack of supply during nights and cloudy days results in only minor price advantages in most municipalities. The $p_t^{buy}$ shows relatively high prices in urban and suburban areas with low supply and high demand. These are in and around big cities. In densely populated Western Germany (i.e., the metropolitan regions of Rhine-Ruhr, Frankfurt and Stuttgart) with high consumption yet low supply, only relatively high prices need to be paid by consumers. In more rural areas, such as Bavaria, North-West and East Germany, the $p_t^{buy}$ is much lower. Here, either PV (Bavaria), old and low wind turbines (North-West) or both (East Germany), provide a lot more supply and even oversupply. The $p_t^{sell}$ (right) shows a similar picture. In urban and suburban areas, a high $p_t^{sell}$ can be achieved. In rural areas with much more supply, the sell prices are much lower.

Figure 8-8 depicts the average volume weighted SDR prices of demand and supply in 2035 in different municipalities in Germany. The main difference to Figure 8-7 is in its increased supply due to the used scenario (see section 5.2.3).

Overall, buy prices $p_t^{buy}$ are lower than in 2019, due to the increase in supply. This will be particularly noticeable in those municipalities that had little generation in 2019, such as in urban and suburban regions in and around major cities and in the west along the Rhine, Main and Ruhr rivers. Sell prices $p_t^{sell}$ show the identical behavior. In areas with formerly low generation, the prices decrease slightly but still remain high, due to the high demand. In municipalities which already had high $p_t^{sell}$ in 2019, almost no changes can be seen in 2035.

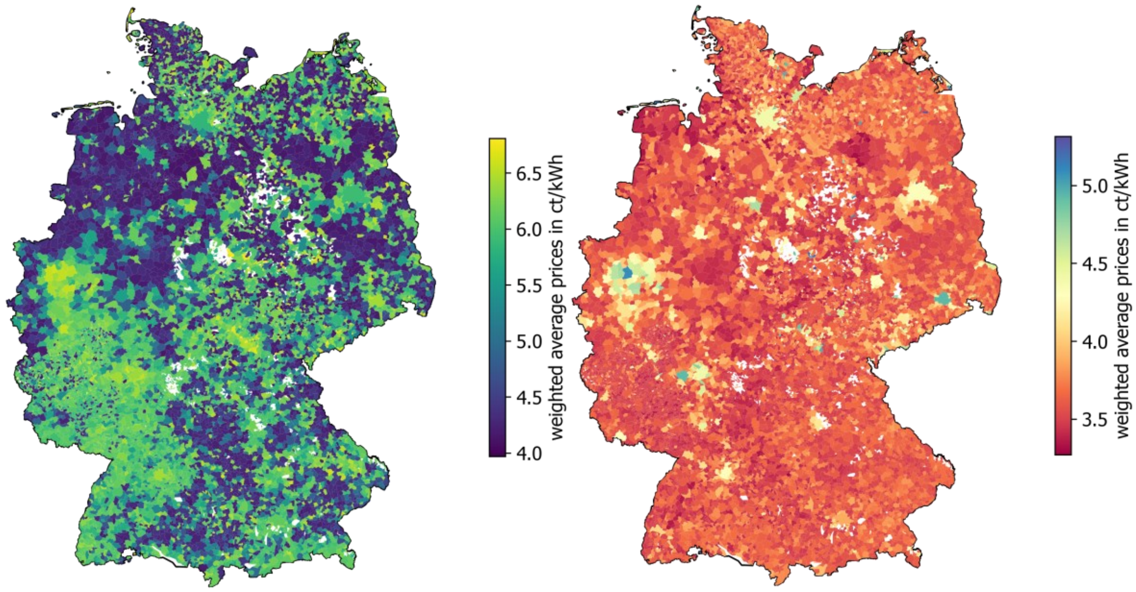


Figure 8-8: Weighted average SDR buy prices (left) and sell prices (right) in 2035

### 8.2.2 Mid-Market Rate (MMR) Price Analysis

The mid-market rate (MMR) pricing mechanism is designed to share costs and revenues within a municipality more evenly than the SDR pricing. The $p_t^{mid}$ is defined as the mean value of $p_t^{retail}$ and $p_t^{wholesale}$ and is used as a reference point (i.e., upper or lower bound) for the pricing mechanism. In cases of an imbalance, the additional costs or revenues are considered in the pricing process. For small $SDR_t$ (i.e., low supply, high demand), $p_t^{sell}$ is close to $p_t^{mid}$ while $p_t^{buy}$ approaches $p^{retail}$. For oversupply (high $SDR_t$, i.e., high supply, low demand) $p_t^{buy}$ is close to $p_t^{mid}$ and $p_t^{sell}$ approaches $p_t^{wholesale}$. As already stated in [A4], the MMR pricing mechanism behaves like the SDR pricing mechanism, with fluctuations and peaks $p_t^{mid}$.

Figure 8-9 shows the price behavior of the MMR buy and sell prices (unweighted) in the same three representative municipalities and summer days as in Figure 8-3. The MMR pricing follows the same relative behavior as the SDR pricing. However, responses to both the exchange electricity price and the $SDR_t$ are significantly lower. This is because the $p_t^{mid}$ serves as a hard cap for both $p_t^{buy}$ and $p_t^{sell}$, which implies that high and low prices on the wholesale market are not completely passed through to community prices. Moreover, fluctuation in the $SDR_t$ have much less impact on community prices. The advantage is that this attenuation of price volatility means that the time during which the price mechanism has an impact on community prices is much greater than the SDR pricing.

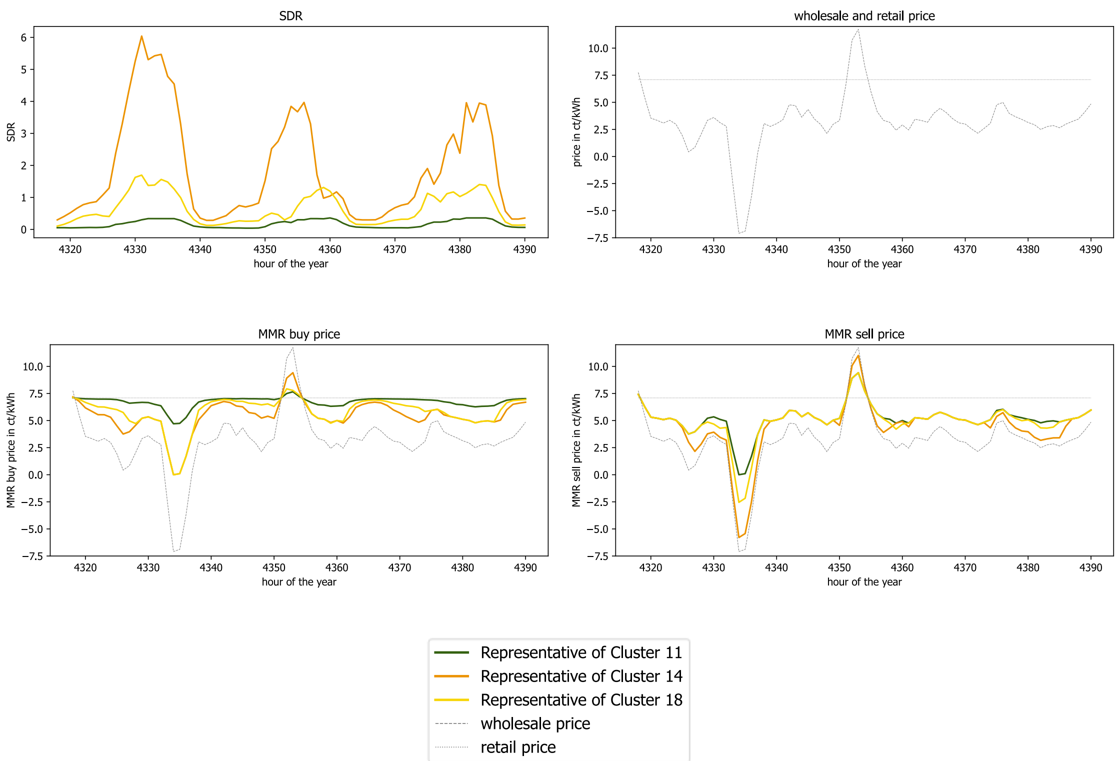


Figure 8-9: Side by side comparison of MMR prices, retail and wholesale prices as well as the supply demand ratio (SDR) on three randomly chosen summer days within three representative municipalities of clusters 11, 14 and 18

Figure 8-10 depicts weighted prices (buy and sell) of MMR pricing in all German municipalities. In 2019, 90 % of MMR sell prices were between 3.54 and 5.34 ct/kWh and 90 % of buy prices between 5.59 and 7.02 ct/kWh. In 2035, 90 % of sell prices are projected to be between 3.50 and 5.04 ct/kWh and buy prices between 5.63 and 6.81 ct/kWh. For a typical household (i.e., 2.500 kWh/a) cost savings by this mechanism are in the range of 1.75 – 37.5 €/a (1-21 %) in 2019 and 7.0 -36.5 €/a (4-21 %) in 2035, compared to a static retail price.

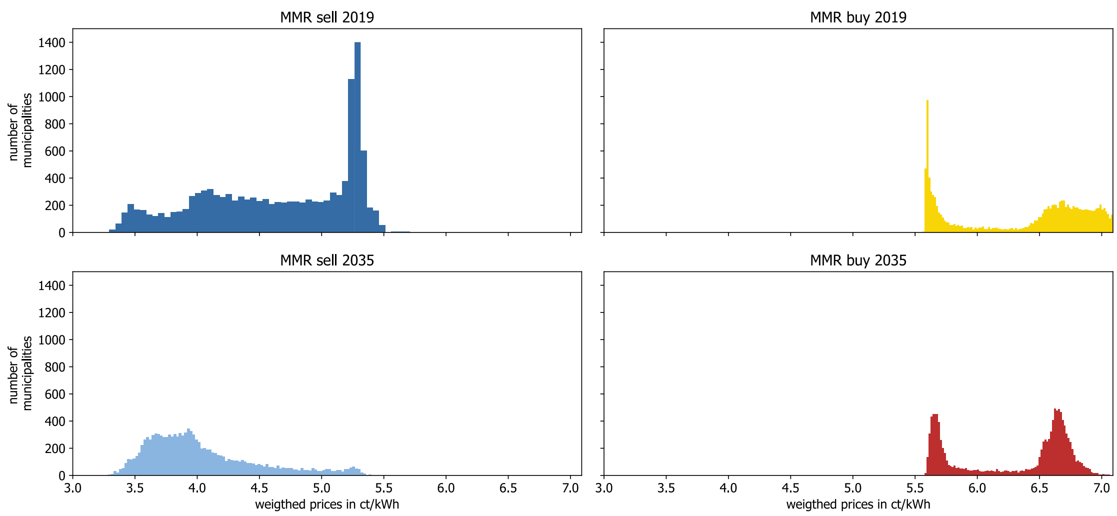


Figure 8-10: Histogram of weighted MMR sell and buy prices in 2019 and 2035

The buy prices have the same characteristics as SDR pricing in both 2019 and 2035 (see Figure 8-4). The explanation for this is equivalent to SDR pricing. Only the level and spread of the prices are different, since MMR pricing allows for smaller price fluctuations as it always lies between $p^{retail}$ and $p_t^{mid}$ or $p_t^{wholesale}$ and $p_t^{mid}$ instead of using their full range between $p_t^{wholesale}$ and $p^{retail}$ (as in SDR pricing and LEM).

However, the sell prices in 2019 and 2035 show a different behavior than SDR pricing. While many municipalities have relatively similar weighted SDR sell prices and are much closer to the lower end of the price levels, MMR is much more distributed, showing a higher variance between municipalities.

Figure 8-11 and Figure 8-12 show that this is not due to the cluster characteristics but due to the design of the pricing mechanism. In MMR, $p_t^{mid}$ as a reference point is defined as $\frac{p_t^{wholesale}+p_t^{retail}}{2}$. If the $SDR_t$ in a municipality is greater than one, $p_t^{sell} \approx p_t^{wholesale}$ and $p^{buy} \approx p_t^{mid}$. If the $SDR_t$ is zero, it is the other way round (i.e., $p_t^{sell} \approx p_t^{mid}$ and $p^{buy} \approx p_t^{retail}$). On average, $p_t^{mid}$ equals 5.46 ct/kWh, which explains the high frequency of municipalities with a $p_t^{sell}$ in this price range in 2019. Since supply is higher in 2035, the MMR sell prices are lower than 2019. These relationships are also evident in the various clusters, depicted in Figure 8-13 and Figure 8-14.

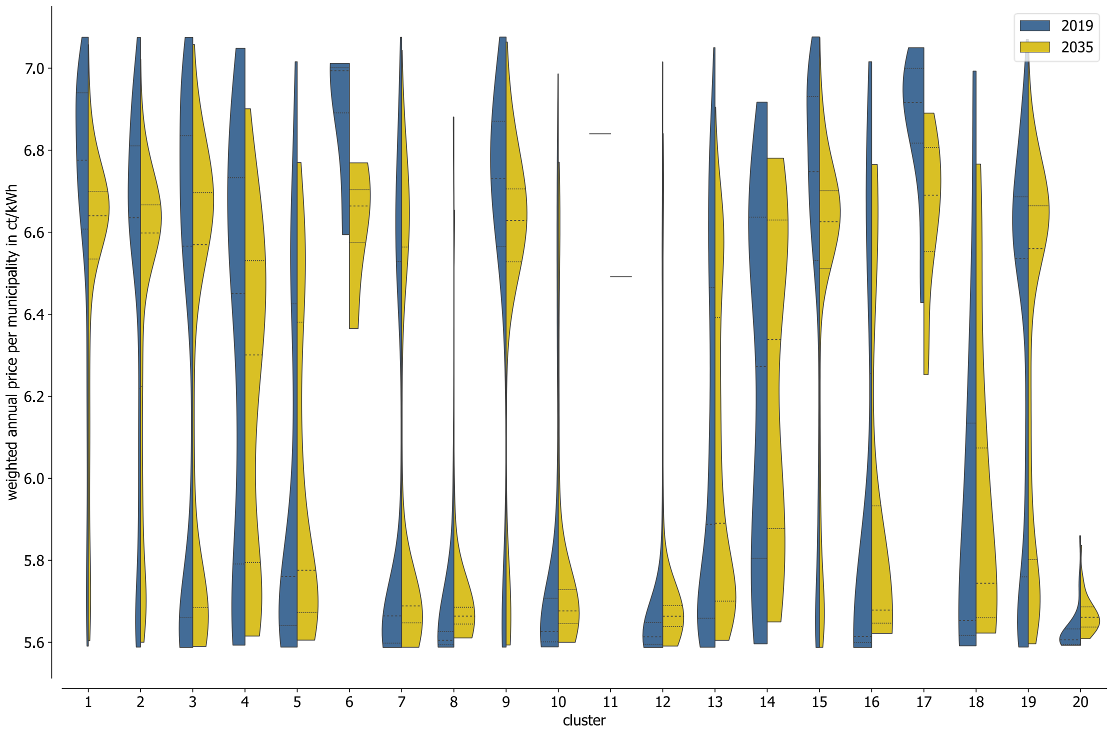


Figure 8-11: Weighted average prices of MMR buy in 2019 and 2035 per cluster

The MMR buy price in Figure 8-11 shows similar behavior as the SDR buy price in Figure 8-5. Urban and suburban clusters (i.e., 1, 6, 11 and 17) and small rural clusters (2,6 and 15) all have low $SDR_t$ values and hence high MMR buy prices. In contrast, clusters 7,8, 10, 12, 16 and 20 have high $SDR_t$ values and hence relatively low prices. Both highest and lowest MMR prices are higher than equivalent SDR prices. The lower SDR buy prices are located at 4.05 ct/kWh while the lower MMR buy prices are generally higher and located around 5.6 ct/kWh. The same goes for the higher MMR buy prices, which are located between 6.5 and 7.09 ct/kWh, while higher SDR buy prices have a higher spread between 5.7 and 7.09 ct/kWh.

The same cannot be observed in the MMR sell prices for 2019 in Figure 8-12.

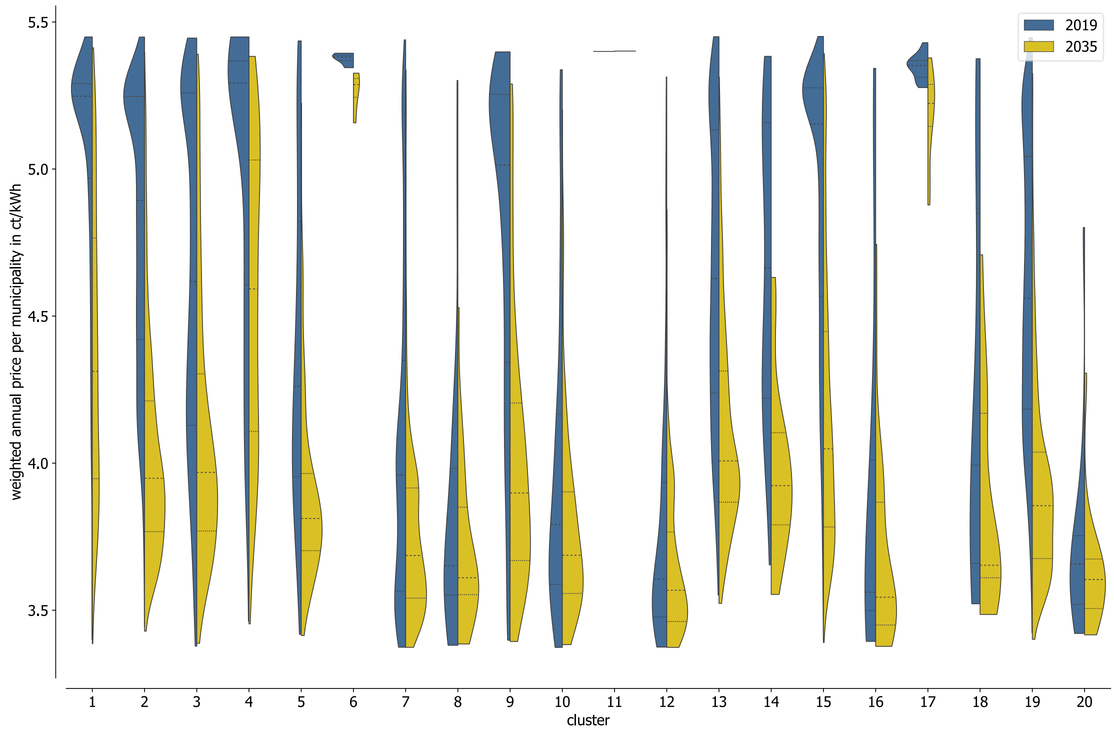


Figure 8-12: Weighted average prices of MMR sell in 2019 and 2035 per cluster

While the overall behavior of MMR sell prices within each cluster is equivalent to SDR sell prices in Figure 8-6, the price niveous is generally more compact in all clusters, i.e., the spreads within the clusters are much lower. In MMR pricing, maximum sell price peaks are reduced due to $p_t^{mid}$ while in SDR pricing, prices often reach $p_t^{wholesale}$ which leads to high peaks and hence overall higher spreads within the clusters. However, similar to the SDR sell price, it can be seen that the price levels in the communities converge in 2035. This is due to the fact that primarily PV is added as a supply and therefore the behavior becomes similar in all communities. If plants above 2 MW were also considered, the differences would be more pronounced.

Clusters 1, 2, 3, 9, and 13 experience a shift from high sell prices in 2019 to low sell prices in 2035. This is attributable to the fact that generation in these municipalities was very low in 2019, which means that the sell prices were high. The addition of PV in 2035 causes the sell prices to drop during the day, as the $SDR_t$ often exceeds one.

Figure 8-13 depicts the average volume weighted MMR prices of demand and supply in 2019 in different municipalities in Germany.

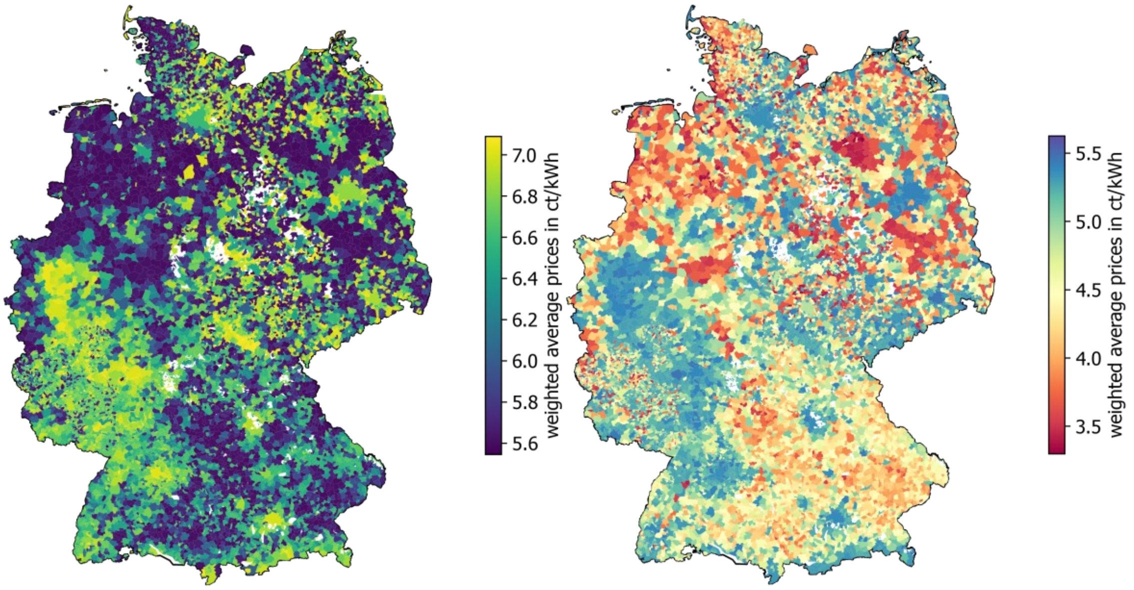


Figure 8-13: Weighted average MMR buy prices (left) and sell prices (right) in 2019

Since the behavior is comparable to the SDR pricing, the prices follow the same patterns. However, the resulting buy and sell prices are lower than the corresponding SDR prices and hence price differences in Germany are smaller. This results in higher costs for electricity demand and lower revenues for the supply, compared to the SDR prices.

Figure 8-8 depicts the average volume weighted MMR prices of demand and supply in 2035 in different municipalities in Germany.

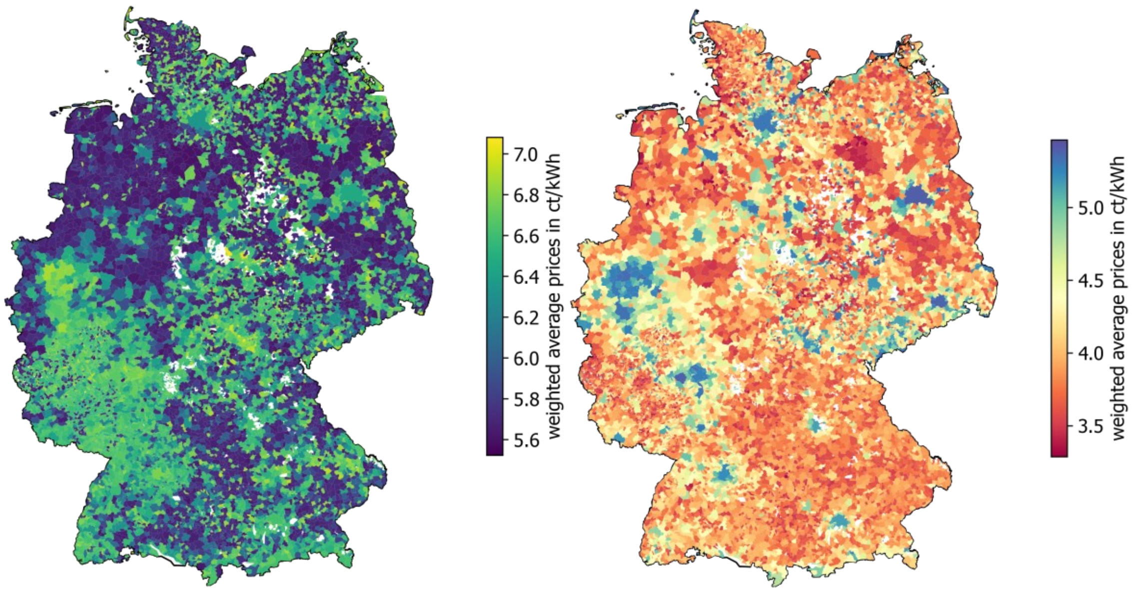


Figure 8-14: Weighted average MMR buy prices (left) and sell prices (right) in 2035

All in all, both price mechanisms share the same relative behavior, depending on the SDR. Price fluctuations and also the level of prices are lower with MMR pricing, where the SDR and market signals are passed on to the community to a lower extent. A key difference is the handling of and sensitivity to negative exchange electricity prices of the SDR pricing. Since these are passed on directly to buy and sell prices in SDR pricing, independent of the $SDR_t$ in the municipality, prices are more often negative here, reducing electricity prices for consumers. This leads to more stable prices of the MMR pricing and a more fair distribution of revenues.

### 8.2.3 LEM Price Analysis

The difference of local energy markets (LEMs) to LES is the more active involvement of supply and demand to determine a uniform price in a double-sided call auction. The price differences in Germany are evaluated and the spreads of the prices analyzed. All pricing mechanisms are compared in section 8.4.

In the following, the resulting uniform prices in a double-sided call auction are outlined. On the local market, only the amount of electricity that is needed (demand) or available (supply) can be traded at any given time. Furthermore, it is not guaranteed that all agents trading on the market will find a trading partner and are considered. This means that the market turnover might be lower than own consumption within the community. Therefore, the market price does not cover the complete demand and supply. For those quantities that cannot be covered by the market, either residual quantities must be procured or surpluses sold on the wholesale market. For better comparability, only the average price for the complete demand and supply in the community is analyzed in this section; not just the one formed on the local energy market. In addition to the LEM price, the surpluses or shortages of electricity, retail and wholesale prices are also included in the analysis. As outlined in section 5.4.3 and 5.6, a high $SDR_t$ leads to $p_t^{buy} \approx p_t^{sell} \approx p_t^{wholesale}$ while a low $SDR_t$ leads to $p_t^{buy} \approx p_t^{sell} \approx p_t^{retail}$. For $SDR_t \geq 18$, the model assumes $p_t^{buy} = p_t^{sell} = p_t^{wholesale}$ to reduce computational cost. If the $SDR_t = 0$, $p_t^{sell} = p_t^{buy} = p_t^{retail}$. Contrary to SDR pricing, and alike MMR pricing, negative wholesale prices are not fully passed on into the community. LEM prices at a balanced $\widetilde{SDR}$ ($SDR_t = 1$) approach the $\frac{p_t^{retail} + p_t^{wholesale}}{2}$ ($=p_t^{mid}$) since zero-intelligence traders place bids as a normal distribution between $p_t^{retail}$ and $p_t^{wholesale}$ on the market. In these times, LEM behaves like MMR pricing. However, while the $p_t^{mid}$ in MMR pricing serves as an upper boundary, LEM prices can easily surpass this boundary in cases of higher $SDR_t$. In cases with no supply ($SDR_t = 0$), $p_t^{sell} = p_t^{buy} = p_t^{retail}$ applies.

Figure 8-15 shows $p_t^{retail}$, $p_t^{wholesale}$ and LEM prices in three different representative municipalities (the same as Figure 8-3 and Figure 8-9), with different supply demand ratios ($SDR_t$). It shows the described behavior of the LEM price. In municipalities with a high $SDR_t$ and high simultaneity, prices reach $p_t^{wholesale}$. Since the agents always place bids towards $p_t^{mid}$, the peaks are only passed through to the $p_t^{sell}$ in cases of very high supply. Otherwise, high price peaks of $p_t^{wholesale}$ are mitigated by this bidding strategy. The same goes for negative prices. While they are passed through to $p_t^{sell}$ and $p_t^{buy}$ at the SDR pricing, peaks are also mitigated in LEMs. Comparable to MMR pricing, the LEM considerably dampens wholesale market prices but has no upper boundary at $p_t^{mid}$. In contrast to MMR, the prices are not hard-capped at $p_t^{mid}$, leading to higher sell- and lower buy prices. The impact of price signals through the wholesale market and the influence of the $SDR_t$ are between MMR and SDR pricing.

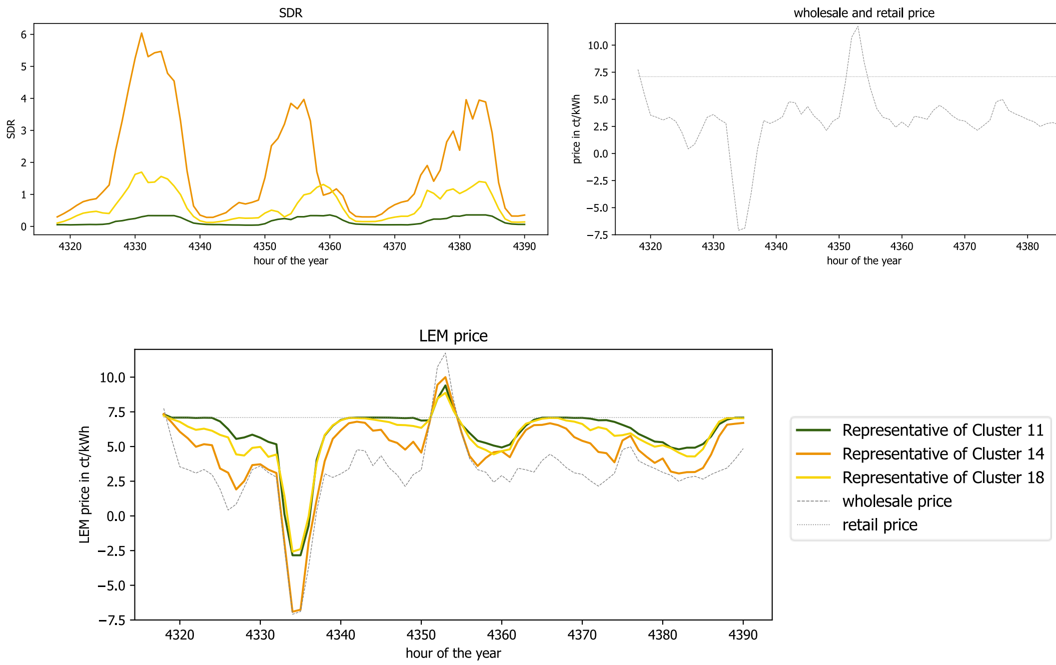


Figure 8-15: Side by side comparison of LEM, retail and wholesale prices as well as the supply demand ratio on three randomly chosen summer days within three representative municipalities of clusters 11, 14 and 18

Figure 8-16 shows a histogram of weighted prices in all German municipalities. LEM prices are weighted by supply and demand. For $p_t^{sell}$ in 2019 and 2035, the weighted prices are like a middle ground between SDR and MMR pricing. In 2019, 90 % of buy prices ranged between 4.22 and 7.05 ct/kWh. Sell prices were in the range of 3.51 and 6.87 ct/kWh. In 2035, 90 % of buy prices range between 4.26 and 6.71 ct/kWh while sell prices are at 3.48 to 5.22 ct/kWh. For a typical household (i.e., 2.500 kWh/a) cost savings by this mechanism are in the range between 1 – 71.75 €/a (1-40 %) in 2019 and 9.5 -70.75 €/a (5-40 %) in 2035, compared to a static retail price.

Sell prices often reach closer to $p_t^{retail}$ without the upper boundary of $p_t^{mid}$, limiting MMR sell prices. Since wholesale prices are not passed through to buy and sell prices directly (as in SDR pricing), the LEM sell prices are generally higher than SDR sell prices and higher than MMR sell prices. LEM sell prices are hence more advantageous in most municipalities over SDR and MMR sell prices. For buy prices, the price level is between MMR and SDR buy. Since SDR pricing passes negative prices through to consumers, it provides lower overall prices. MMR on the other hand is limited by $p_t^{mid}$. This leads to MMR buy prices being generally higher than both SDR und LEM buy prices.

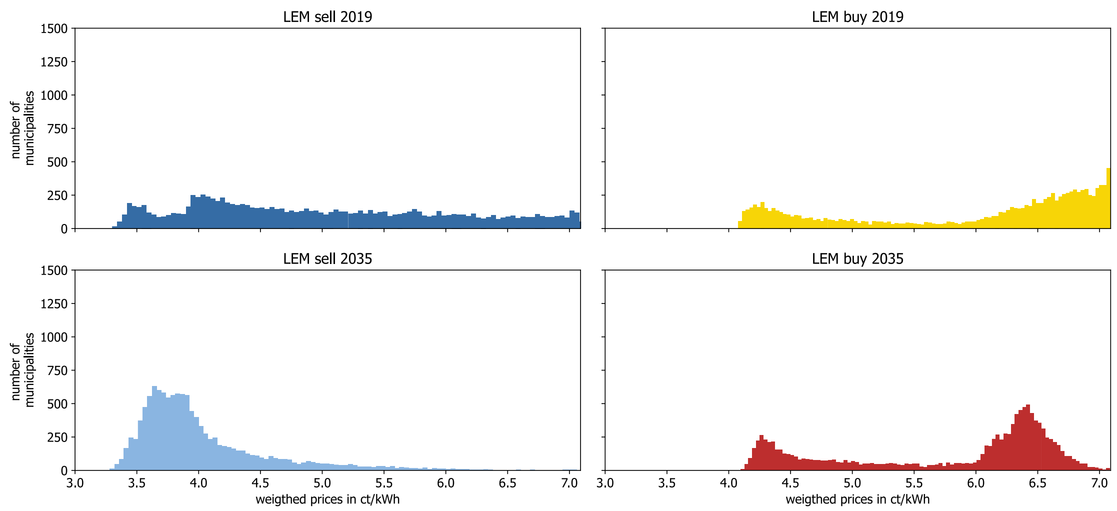


Figure 8-16: Histogram of weighted LEM prices in 2019 and 2035

Figure 8-17 and Figure 8-18 show prices per clusters, weighted by supply and demand. Again, the patterns from the other price mechanisms can be seen.

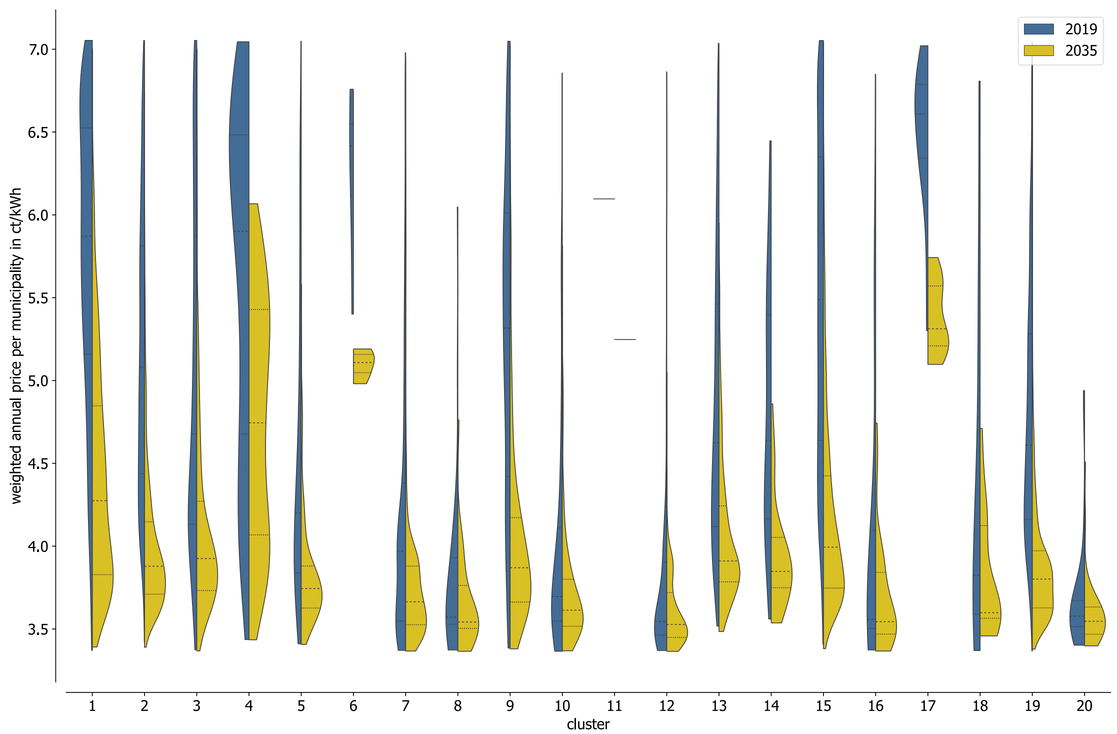


Figure 8-17: Uniform LEM prices weighted by supply in 2019 and 2035 per cluster

Sell prices are particularly high in urban and suburban clusters with low $\widetilde{SDR}$ (i.e., 6, 11, 17), while buy prices are close to $p_t^{retail}$. In clusters with high $\widetilde{SDR}$ (i.e., 7, 8, 10, 12, 20) the sell and buy prices approach the wholesale prices. Prices have a larger spread in these clusters than in MMR pricing, but a smaller spread than in SDR pricing. In Figure 8-17, it also becomes apparent that the LEM represents the middle ground between MMR and SDR pricing.

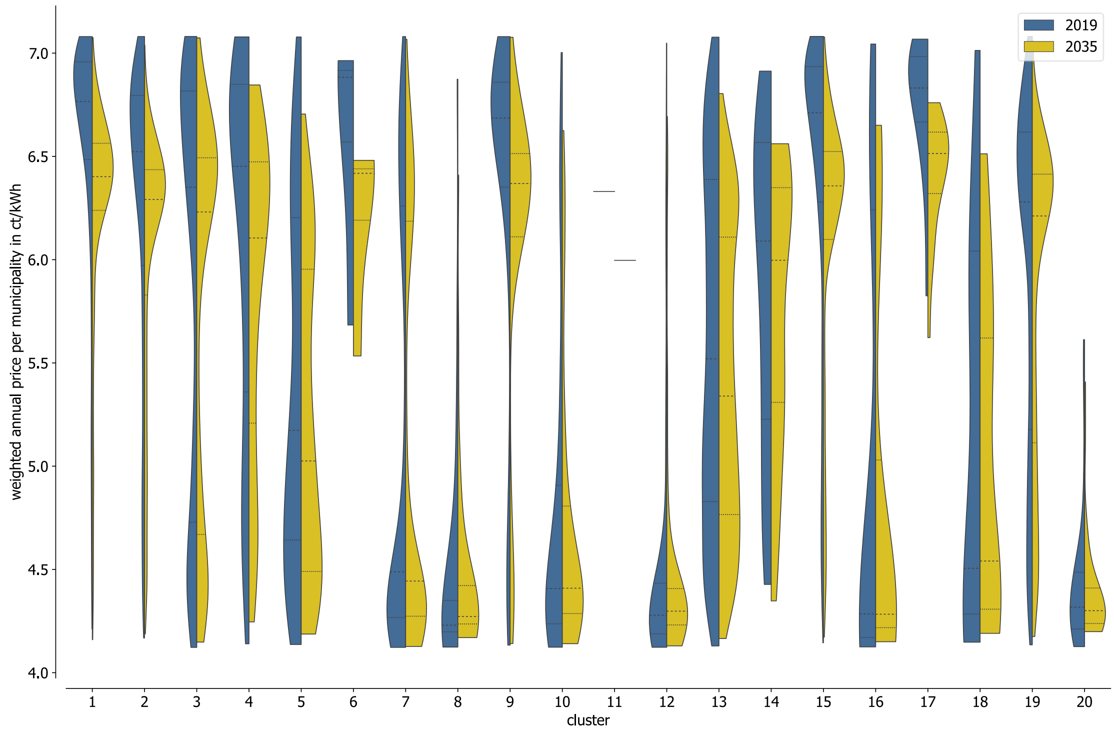


Figure 8-18: Uniform LEM prices weighted by demand in 2019 and 2035 per cluster

Since the regional distribution of LEM buy and sell prices is equivalent to MMR and SDR pricing, the corresponding maps can be found in Figure 14-26 and Figure 14-27 in the appendix.

All in all, the prices reflect the fluctuation of local supply and demand as well as price fluctuation of the wholesale price. Compared to the status quo (7.09 ct/kWh for consumers and the respective weighted wholesale prices for producers), all price mechanisms are better. However, the pricing mechanisms differ greatly in terms of which stakeholder benefits most at which point in time.

### 8.2.4 Price Stability and Flexibility Incentives

The incentive for flexibility (i.e., battery storage) can be evaluated by analyzing the intra-day spread of buy and sell prices within each community and day $t$: $spead_t = max({p_t}^{sell}) - min({p_t}^{buy})$

If $spead_t > 0$, a flexibility provider can buy electricty in $t$ and sell it for a higher price. The higher $spead_t$, the higher the incentive to provide flexibility. If $spead_t < 0$, the buy price is always higher than the sell price, resulting in no incentives to provide flexibility. This consideration only takes into account flexibility providers that can both generate and consume electricity (i.e., batteries or bidirectional BEV).

Figure 8-19, Figure 8-20 and Figure 8-21 depict the daily price spreads in the clusters of different pricing mechanisms. It becomes clear that the spreads in each pricing mechanism hardly differ among the clusters and that the difference between 2019 and 2035 is also often small.

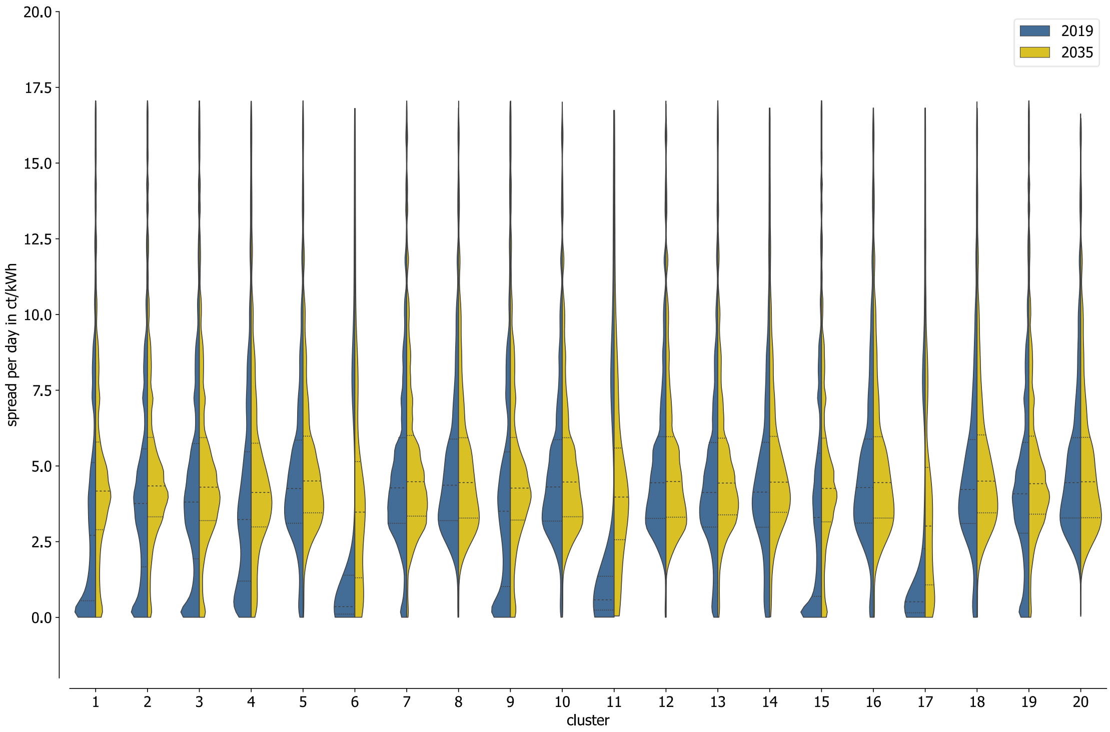


Figure 8-19: Comparison of intra-day price spreads in 2019 and 2035 of the SDR per day, grouped per cluster

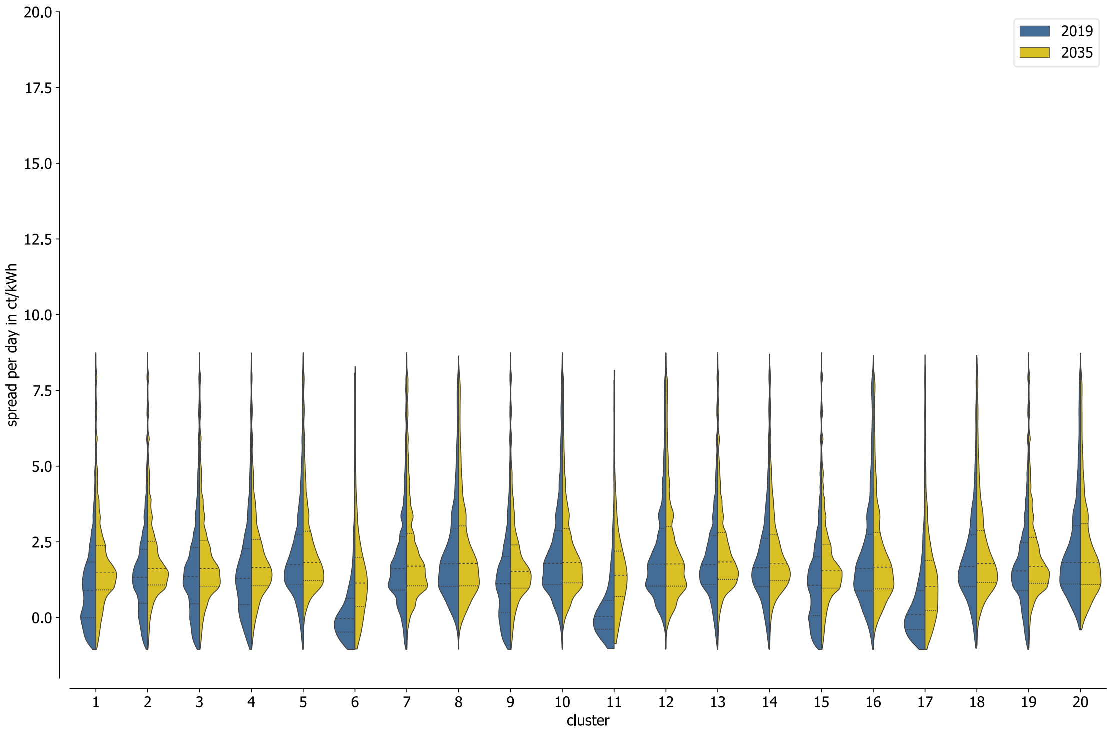


Figure 8-20: Comparison of intra-day price spreads in 2019 and 2035 of the MMR per day, grouped per cluster

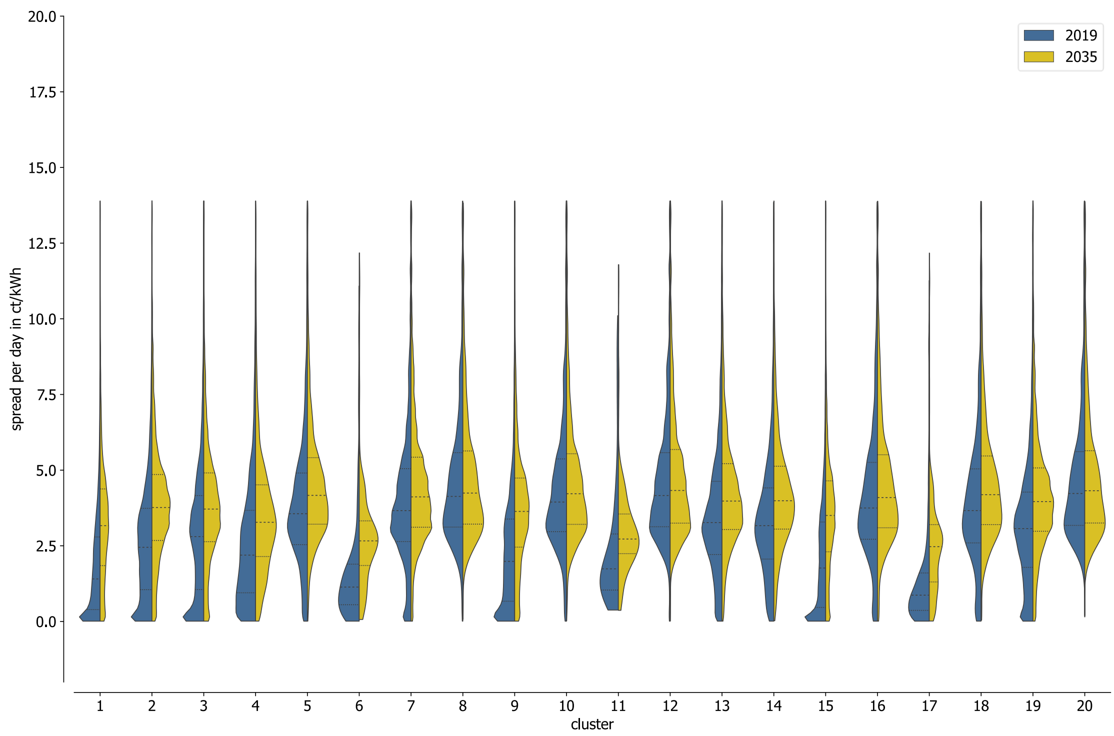


Figure 8-21: Comparison of intra-day price spreads in 2019 and 2035 in LEM per day, grouped per cluster

In all figures, three different "shapes" of spreads can be identified. Clusters 6, 11 and 17 are the clusters with large cities. Since their $\widetilde{SDR}$ is the lowest of all clusters, $p_t^{buy}$ is almost constantly close or equal to $p^{retail}$, and vice versa, the $p_t{}^{sell}$ also almost constantly reaches $p^{retail}$, i.e., $p_t{}^{sell} \approx p^{retail} \approx p_t^{buy}$ for the SDR pricing. This leads to low or even negative spreads (only MMR pricing) if $max(p_t{}^{sell}) \leq min(p_t{}^{buy})$. In 2019, the low $SDR_t$ did not change much during the day. In 2035 however, due to rooftop PV installations with high simultaneity, the $SDR_t$ peaks during noon leads to an increased daily spread compared to 2019. MMR pricing shows the same behavior. However, due to the reference point of $p_t{}^{mid}$, price niveous and spreads are lower than in SDR pricing.

MMR pricing is the only mechanism with negative price spreads. These occur when $p_t^{buy} < p_t^{sell}$ throughout the day. Then electricity can never be bought cheaper than sold. This is only the case with MMR pricing, since the boundary of $p_t^{mid}$ ensures that even in cases with no supply or oversupply either $p_t^{buy}$ or $p_t^{sell}$ is limited. On days with low $SDR_t$, the buy price corresponds to the retail price, the sell price to $p_t^{mid}$, which is lower. LEM does not have this upper boundary of $p_t{}^{mid}$ and hence lies in between SDR and MMR pricing.

Clusters 1, 2, 3, 4, 9 and 15 show low spreads around 0 ct/kWh (or negative, in the case of MMR pricing) per day in 2019. Low (and negative) spreads appear in days with no or very low supply ($p_t{}^{sell} \approx p^{retail} \approx p_t^{buy}$). All clusters with this behavior have in common that there are very low or no installed RE capacities in 2019. This accumulation of low (and negative) spreads disappears in 2035 due to the increasing RE generation and hence increasing $SDR_t$. This leads to all municipalities having $SDR_t > 0$ during each day, leading to $p_t{}^{sell} \neq p^{retail}$ and hence to a positive spread.

Clusters 5, 7, 8, 10, 12, 13, 14, 16, 18, 19 and 20 all show a comparable behavior of price spreads in 2019 and 2035. In these clusters, the supply and hence the $SDR_t$ was already high in 2019. Since the spreads are relatively similar despite the different generation structures in the clusters, they are mainly caused by the exogenous wholesale price.

All in all, the prices and spreads in SDR pricing are higher than in MMR pricing. The incentives to provide flexibility or to invest in new flexibility options are therefore higher in SDR pricing than in MMR pricing. LEM spreads are in between these two mechanisms. The spreads are mainly influenced by the wholesale price and less by the $SDR$ in the communities, since the spreads in the clusters are often very similar.

High spreads are an advantage for the provision of flexibility. Even though demand response flexibility was not deeply analyzed in this section, the qualitative behavior of the three pricing mechanisms is the same. SDR pricing provides the highest incentives and price volatility, followed by LEM and MMR prices. However, high price fluctuations are also a disadvantage, especially for consumers with little or no flexibility. High costs can arise e.g., if more energy-intensive household appliances, electric cars or heat pumps are consuming power during times of price peaks.

## 8.3 Use Case: Regional Direct Marketing

The RDM potential is derived by a linear optimization, maximizing the electricity that can be supplied by plants ≤ 2 MW and consumed within 4.5 km in the same time step. Figure 8-22 depicts the resulting electricity, multiplied by 2.05 ct/kWh electricity tax (see § 9 StromStG) per municipality, normalized on the demand. Thus, the resulting values correspond to the case where RDM revenues are fully allocated to consumers.

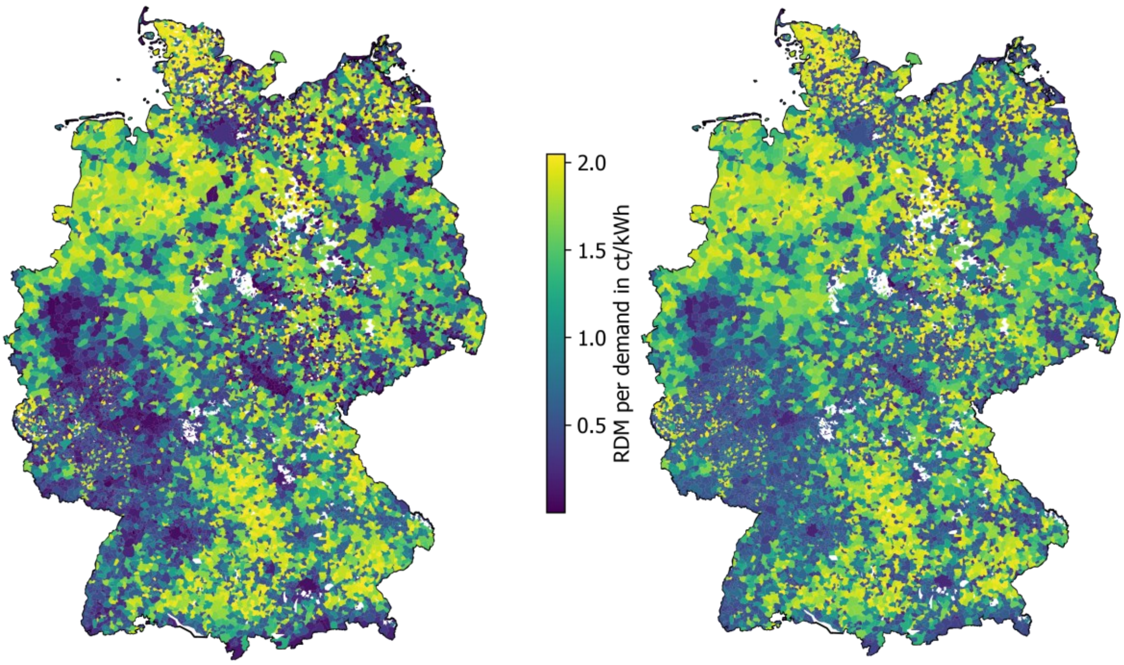


Figure 8-22: Mean annual RDM potentials normalized on the demand in Germany in ct/kWh (left = 2019, right = 2035)

The results show high potential for rural areas in the north-west and south-east. In these areas, either PV (South-East) or older wind turbines lead to a high oversupply. Low consumption due to low population density results in high potentials (from to consumption perspective), and vice versa, only a small fraction of the overall supply can be used in RDM, due to the high oversupply.

In small municipalities (with diameters < 4.5 km), the distance restrictions do not reduce the RDM potential. Hence, it can be assumed that the own consumption within the municipality, which is the minimum of supply and demand (not to be confused with prosumers' own consumption), is eligible for an RDM. In large rural municipalities, the distance restrictions limit the regional direct marketing potential. The more balanced supply and demand are within communities and the smaller their size, the higher the RDM potential.

In urban areas (i.e., cities like Berlin, Munich, Hamburg or the Rhine-Ruhr metropolitan region), small-scale renewables ≤ 2 MW are comprised predominantly of rooftop PV systems. With the high consumption due to high population density, this results in a big undersupply and hence small supply demand ratios. Hence, all renewable electricity can be consumed locally, adding to the RDM potential. From the supply perspective, the full 2.05 ct/kWh can be earned with each supplied kilowatt-hour. From a demand perspective (as displayed in Figure 8-22), the effect is almost negligible.

Looking at the differences between 2019 and 2035, it is clear that there is only slightly more RDM potential overall in 2035, although a lot of wind and PV systems are added in the scenario used. This is where the restriction of 2 MW comes into effect. Modern ground mounted PV and wind turbines often exceed the limit of 2 MW. Hence, the added installations are for the most part not included in the RDM potential. Thus, since rooftop PV almost exclusively increases the RDM potential and these are mainly added in regions with high population density (and high consumption) and are foremost used to increase the own consumption of the owner (prosumer), the potentials in 2035 are only slightly higher than in 2019. In comparison, additional electric vehicles increase consumption only slightly, so that even in communities with a lot of oversupply, hardly any major changes can be seen.

Figure 8-23 depicts the RDM potential, normalized on the supply in ct/kWh. A value of 2.05 ct/kWh implies that all supply can be consumed within 4.5 km at the same time. The lower this value, the less the supplied electricity can be consumed within this time frame and distance.

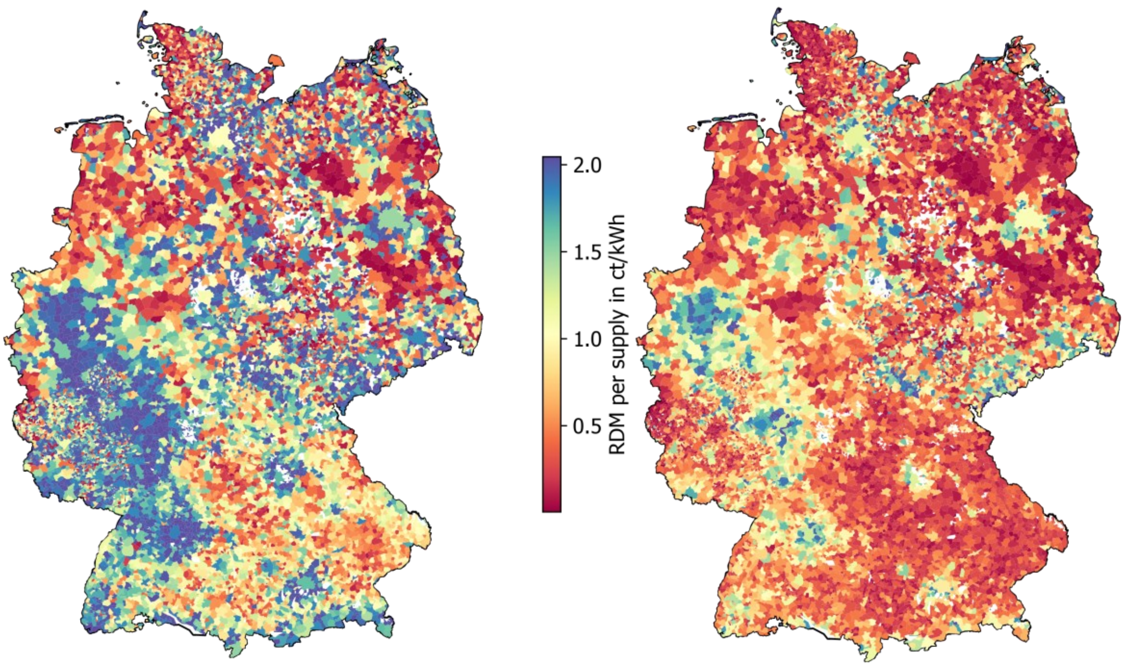


Figure 8-23: Mean annual RDM potentials normalized on the supply in Germany in ct/kWh (left = 2019, right = 2035)

The maps show that in 2019, almost all local supply could be consumed at the same time within the range of 4.5 km in most urban and suburban municipalities with a low $SDR$. In municipalities with oversupply and large municipalities this was not the case. Oversupply could not be consumed locally and was hence limited by the low demand. In large municipalities (e.g., in North-Eastern Germany), especially with a lot of wind capacities which are usually not built in close proximity to residential areas, the 4.5 km distance and the oversupply became a limitation.

As in 2035, mainly PV capacities in the range of ≤ 2 MW are projected to increase, supply will increase as well. Three aspects play together, limiting the RDM potential for the supply. On the one hand, PV plants will be located close to or in residential areas, so the proximity limitation is not a factor. On the other hand, rooftop PV leads to increasing self-consumption of households due to a higher number of prosumers. High self-consumption in prosumer households reduces the RDM potential, as less electricity is needed from other community members. The additional PV systems also lead to strong simultaneities, so that much of the additional generation cannot be consumed locally.

The clusters (see section Figure 14-25 in the appendix) reflect the earlier interpretation. For urban and suburban municipalities (clusters 1, 4, 6, 11, 17) with high populations, high consumption and small RE supply, almost no RDM potential is available. However, since these municipalities have the most rooftops available for rooftop PV, the overall increase to 2035 will be relatively high. This can be seen in cluster 4 (densely populated cities) with high rooftop PV-potentials

Rural municipalities with low populations and very low renewables (clusters 2, 3, 9 and 15) also have only small RDM potential. In contrast, small municipalities with average or high RE supply and relatively low consumption have high RDM potentials (see clusters 7, 8, 10, 12, 16, 20) since they have an almost constant oversupply. From a supply perspective, this is disadvantageous since the oversupply cannot be marketed locally. Consumers hence profit from it. The distance restriction does not affect the potential in these small municipalities. Since they already have a high potential, additional renewables do not have a visible effect in 2035. By contrast, larger municipalities cannot harvest their full potential. Especially in big municipalities with wind as the main source of electricity, the distances between wind turbines as well as their size limits the potential. Considering existing distance limits for wind turbines ("10 H"), the potential of regional direct marketing for new wind turbines is not only restricted by their size but also by the distance to the next consumers. Especially in windy regions, additional wind power is not applicable for RDM due to the capacity restrictions. Hence, even though in the scenario many new wind turbines are installed by 2035, the RDM potential does not increase much (i.e., in clusters 3, 8, 10, 12, 18, 20).

Cluster 14 is comprised of southern hydropower regions. The spread of the RDM potential within these municipalities highly depends on the number of small hydropower plants. In areas with many smaller rivers, the RDM potential is higher than in areas with a few large hydropower plants, due to the size restriction of 2 MW. This also explains the spread in cluster 13. In cluster 5, the resulting spread is caused by ground-mounted PVs. As with hydropower, some of these plants exceed the 2 MW mark, thus excluding them from RDM. In cluster 4, the spread depends on the different population densities within the municipalities. In those with more one- and two-family homes, rooftop PV generates more supply, resulting in a higher RDM potential. In more densely populated municipalities within this cluster, multi-family homes produce much lower supply since the electricity is consumed by the households in the respective buildings.

In conclusion, small municipalities with high $SDR$s are advantageous from a consumer perspective. All electricity can be supplied within proximity in small municipalities with low $SDR$s. From a supply perspective, this leads to the highest efficiency since almost 100 % can be used for RDM. As with the introduced pricing mechanisms, a balanced $SDR$s also leads to balanced RDM potentials. This is advantageous for both supply and demand.

## 8.4 Comparison and Synergies of Use Cases

In this section, the pricing mechanisms are compared and assessed from different stakeholder perspectives. Subsequently, use cases are combined and assessed from an overall energy-economic perspective.

### 8.4.1 Comparison of Revenues with the Status Quo

Evaluating the business cases for the various stakeholders goes beyond the scope of this dissertation. However, a brief assessment of the theoretical potential of the use cases for energy service providers (ESPs) is conducted in the following.

Since the price mechanisms all provide benefits to both consumers and producers, the ESP suffers financial disadvantages since their former revenue sources are allocated differently through the pricing mechanisms. On the one hand, compared to today, the ESP can only sell electricity to consumers who are not supplied within the community. On the other hand, the processes for managing the community are more costly than selling a commodity product. The resulting additional costs with lower revenues are a major reason for the lack of economic viability of energy communities today.

In the reference case, an ESP sells the generation of RE on the wholesale market for a fee (which is disregarded in this work for reasons of simplicity). The demand of consumers is covered by the ESP with electricity bought on wholesale markets (usually procured as futures). In this section, the assumption is made that the ESP procures electricity on intra-day markets.

An estimation of whether energy communities in Germany are viable with the presented price mechanisms for the ESP shall be conducted in this section. Since all price mechanisms are at least equal or better for both demand and supply (prices are always lower than the reference values, see section 8.2), the pricing mechanisms only allocate the revenues differently than in the status quo. The ESP is hence losing money. Therefore, it is necessary that additional monetary incentives are created to cover these losses and the additional workload (due to new tasks). In the following, the question of whether the existing legislation in § 9 StromStG (= RDM) is sufficient to cover the losses of the ESP induced by the pricing mechanisms, is answered.

**Evaluation Method**

For the comparison of the pricing mechanisms to the status quo, the following method is applied for every pricing mechanism in 2019 and 2035. The comparison of the differences in costs ($C_{demand,m}$) of the demand and revenues of the supply ($R_{supply,m}$) is made per municipality $m$ by

$$C_{demand,m} = \sum_{t=1}^{8760} demand_{m,t} * p_{m,t}^{buy}$$

$$R_{supply,m} = \sum_{t=1}^{8760} supply_{m,t} * p_{m,t}^{sell}$$

Cost only includes electricity costs on wholesale markets. Electricity within the community is shared for the price of the respective pricing mechanism (MMR pricing, SDR pricing or via LEM) resulting in:

$$internal_{m,t} = demand_{m,t} * p_{m,t}^{buy} - supply_{m,t} * p_{m,t}^{sell}$$

Oversupply is sold and undersupply bought at the wholesale market for $p_t^{wholesale}$ by the ESP, resulting in:

$$external_t = (demand_{m,t} - supply_{m,t}) * p_t^{wholesale}$$

The delta of $internal_{m,t}$ (internal cost or revenues among supply and demand in each community) and $external_{m,t}$ (external cost or revenues by selling or buying residual loads on wholesale markets) is the total revenues in the energy community for the ESP:

$$revenues_{m,t} = internal_{m,t} - external_{m,t}.$$

The reference to this system is the case with $p_t^{buy} = p_t^{retail}$ and $p_t^{sell} = p_t^{wholesale}$. In all pricing mechanisms, this leads to $revenues_{SQ,t} = demand_{m,t} * (p^{retail} - p_t^{wholesale})$.

The delta in revenues is to be compared to the losses of the ESP. The assumption is made that if the resulting revenues fall short of the status quo (i.e., selling electricity as a commodity product) the potential inside a community is low.

$$R_{ESP,m} = \sum_{t=1}^{8760} revenues_{m,t}$$

As the price analysis shows that both supply and demand benefit from the price mechanisms, it is certain that the ESP loses revenue. Therefore, the next step is to analyze whether the additional revenues from RDM are sufficient to cover the losses. For this, the annual RDM revenues per municipality are added to the delta of the revenues of the ESP with the pricing mechanisms with $R_{ESPtotal,m} = R_{ESP,m} + R_{RDM,m}$ and $R_{RDM,m} = \sum_{t=1}^{8760} RDM_{m,t} * 2.05\ ct/kWh$.

**Results**

A comparison of revenues among supply and ESP and the comparison of costs of demand is provided in Table 8-1.

Table 8-1: Difference of cost and revenues, compared to the status quo in percent (positive values imply cost reductions or increases in revenue)

| Year | Perspective | MMR pricing | SDR pricing | LEM pricing |
|---|---|---|---|---|
| 2019 | demand | 10.38 % | 21.18 % | 16.03 % |
| | supply | 30.78 % | 15.36 % | 41.15 % |
| | ESP | -49.10 % | -53.16 % | -62.83 % |
| 2035 | demand | 11.19 % | 22.85 % | 18.75 % |
| | supply | 14.53 % | 3.03 % | 14.37 % |
| | ESP | -54.27 % | -57.63 % | -68.23 % |

The results in Table 8-1 reflect the evaluations and comparisons in the previous sections. All mechanisms are advantageous for both supply and demand over the status quo, since electricity within the community is sold between $p_t^{wholesale}$ and $p^{retail}$, depending on the $SDR_t$. This is better for both sides, but comes with financial disadvantages for the ESP.

From a demand perspective, SDR pricing is advantageous in 2019 and 2035, since $p_t^{buy}$ often reflects $p_t^{wholesale}$. The MMR pricing only affects about half the cost of the SDR, since it only reflects $p_t^{mid}$ in times where the SDR price is $p_t^{wholesale}$. LEM pricing is not capped at $p_t^{mid}$, as is MMR pricing, but does not as quickly reflect $p_t^{wholesale}$ in times with high SDR (as does SDR pricing). Therefore, LEM pricing is right in between these two mechanisms. This is reflected by overall reductions in annual electricity costs for demand.

From a supply perspective, the maximum possible improvement of revenues over the status quo is to receive the full retail price instead of the $p_t^{wholesale}$ (status quo). This corresponds to an improvement of approx. 43 %. Hence, SDR pricing is the least viable for suppliers, leading to almost no additional revenues in cases with high SDR and high simultaneity, since the time in which the pricing mechanisms effects community prices is relatively limited and reaches $p_t^{wholesale}$ quickly. Hence, SDR pricing is the worst in both 2019 and 2035. In 2019, LEM pricing is advantageous in 67.8 % of municipalities over MMR pricing (in 32.2 % of municipalities) since it is not capped at $p_t^{mid}$ and sell prices can reach $p^{retail}$. This only affects municipalities with a low $\widetilde{SDR}$. Since many municipalities have a low $\widetilde{SDR}$ in 2019, this was often the case, leading to LEM being the best pricing mechanism in most municipalities. However, in 2035 the most advantageous pricing mechanism shifts to MMR in 74.0 % of the municipalities over LEM (26.0 %) from the supply perspective, even though they are relatively even in all municipalities in Table 8-1. This shows that with MMR the benefits are better distributed while the higher benefits of LEM affect only a minority (i.e., 26 %) of municipalities. While in 2019, $p_t^{mid}$ often serves as an upper boundary for MMR prices, it also serves as attenuator for low prices if the $SDR_t$ is high. That is, sell prices in LEM approach $p_t^{wholesale}$ quicker than in MMR pricing, which is advantageous in times with high simultaneity and high $SDR_t$. The upper boundary of $p_t^{mid}$ is seldom reached and has hence less impact on the overall MMR sell prices.

From an ESP perspective, the status quo is the optimum. Instead of consolidating supply and demand in the community, all demand is supplied by the ESP at the retail price, leaving $p^{retail} - p_t^{wholesale}$ for cost, risk, and margin. Energy communities, however, lead to a consolidation of electricity within the municipality. Hence, two factors lead to considerable losses of ESP revenues:

- own consumption within the community reduces sales volumes,
- internal pricing mechanisms reduce the prices of the electricity sold to consumers.

The higher the own consumption within the EC, the smaller the amount of electricity the ESP can sell to consumers, since it is already supplied by local RE. Because the $p^{retail}$ was set at 7.09 ct/kWh, which includes an average wholesale price as well as cost, risk, and margin of the ESP, $p_t^{buy} > p_t^{wholesale}$ is disadvantageous for the ESP. Since this is always the case when the $SDR_t \neq 0$, this occurs very frequently in 2019. Since the $\widetilde{SDR}$ rises in 2035, this occurs more frequently, coming with greater financial disadvantages. Simplified, the best mechanism for ESP is therefore the one that ensures the lowest possible sell- and the highest possible buy prices. The evaluations in previous sections as well as Table 8-1 identify the MMR pricing as the "least worst" pricing mechanism for the ESP, as prices are on average the closest to the status quo. LEM prices on the other hand are much more distributed with high sell and low buy prices (see Figure 8-16). SDR pricing lies in the middle from this perspective.

It should be mentioned here that LEMs are (theoretically) possible in a completely decentralized manner (e.g., via a Blockchain), without an ESP (see section 4.3.2). The resulting losses for the ESP are therefore not necessarily critical in this context. Nevertheless, many administrative barriers must be overcome today, for which a service provider is advantageous. Moreover, this section has disregarded the additional expenses incurred to overcome bureaucratic barriers and additional responsibilities of the use cases, which further reduce cost-effectiveness. Whether additional costs can be covered by the revenues is not analyzed in greater depth in this work and should be addressed in further research.

## 8.4.2 Economic Assessment of Synergies

In this section, the synergies of RDM and pricing mechanisms is to be assessed.

**Combining Pricing Mechanisms and RDM Revenues**

One way to limit the financial disadvantages of the ESP from energy communities arises from the combination of the pricing mechanisms with the RDM potential. The assumption is that the RDM revenues within a community are given to the ESP[5] to compensate for the losses. The losses however are relatively high compared to the status quo, ranging from 49.1 to 62.8 % in 2019 (depending on the price mechanism), and from 54.3 to 68.2 % in 2035 (details see Table 8-1).

Figure 8-24 depicts the losses of ESP, compared to the status quo per municipality and year. For reasons of comparison, the losses are normalized to the demand. As elaborated in section 5.5, the reference value for revenues of the ESP is 2.75 ct/kWh.

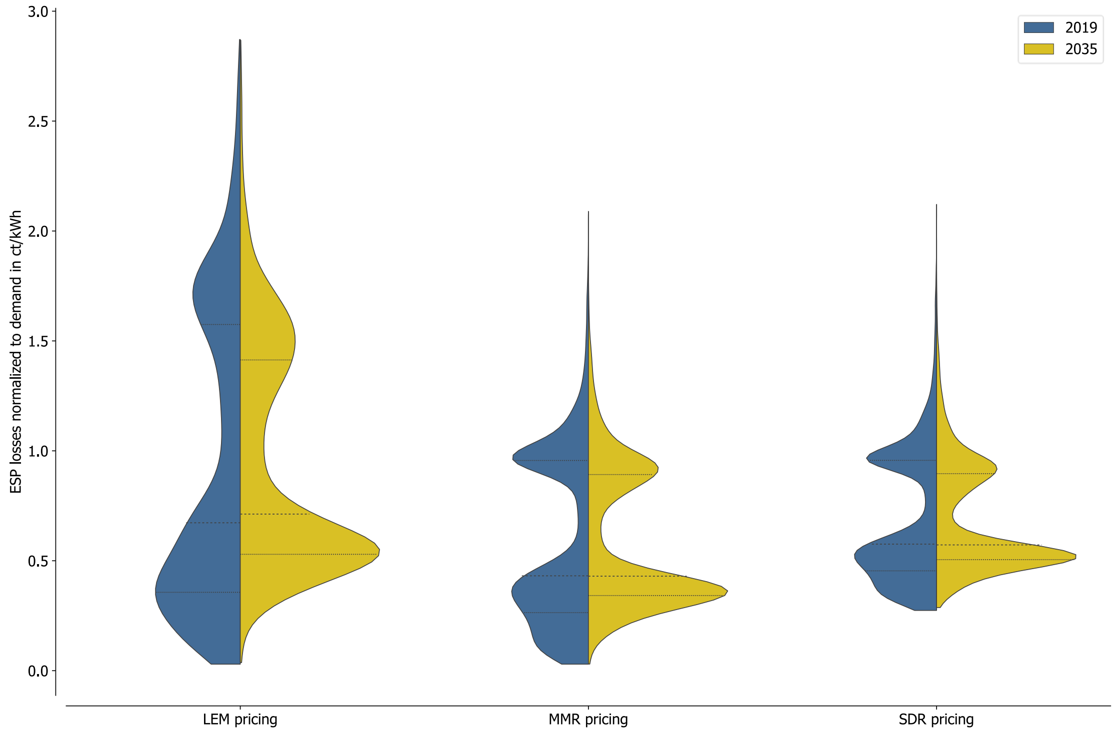


Figure 8-24: Losses, normalized on the demand of the ESP in ct/kWh per pricing mechanism and year, after RDM revenues have been added

Figure 14-28, in the appendix shows the same value without the consideration of RDM. Figure 8-24 shows that the high losses of ESP can be reduced to a low, one-digit loss per kilowatt-hour, if revenues of RDM are considered. If the ESP receives RDM revenues to reduce the losses induced by the pricing mechanisms, the average losses are more than halved to -18.91 % from -49.1 % in MMR pricing (2035: -20.16 %), to -22.97 % from -53.16 % in SDR pricing (2035: -23.52 %) and to -32.64 % from -62.83 % in LEM (2035: -34.13 %). Hence, RDM potentials are not sufficient to cover the entire losses, yet compensate for a large part of them.

Below, it shall be examined whether these losses of the ESP can be mitigated by means of a monthly participation fee for either consumers only or consumers and RE producers.

[5] In § 9 StromStG, the RDM revenues are intended for RE operators.

Only in these cases would all stakeholders theoretically be willing to voluntarily participate in such a community. The question is whether it is possible for all stakeholders to benefit from a community with a flexible pricing mechanism and a static base fee compared to the status quo, using the potential of regional direct marketing.

**Covering Losses of the ESP by a Monthly Fee**

In this case, a monthly fixed subscription fee is determined to cover the losses of the ESP. This is done by dividing annual losses of the ESP by the number of consumer and prosumer households within a community. The benefits from lower annual electricity costs of consumers, as analyzed in section 8.2, are compared to this fee.

Previous analysis shows that supply is better off in all pricing mechanisms. With a monthly fee for consumers, which corresponds to the losses of the ESP, the ESP does not book any profits or losses compared to the status quo. Hence, the decisive factor of whether an energy community can be worthwhile or at least not costly for all stakeholders, is determined by the feasibility of consumers only. If communities are still feasible for consumers, even if they have to pay a monthly fee to cover the losses of the ESP (after utilizing revenues of RDM), a price mechanism is deemed worthwhile for all stakeholders. A monthly fee for consumers is appropriate because they do not actively contribute to the energy community either (unlike generators, prosumers, and flexibility). If they are minimally better off or in the same position as before, they have no direct disadvantage in participating. Through flexible consumption behavior incentivized by the dynamic price (i.e., through active participation in the community), however, they can generate an individual economic advantage.

In Figure 14-28, in the appendix, the monthly fees per household with and without consideration and with consideration of RDM revenues are depicted. The fees without RDM are under 20 € per household and month, not considering RDM revenues. In 2035, the fees per municipality are primarily under 10 € per household and municipality.

The fees, considering RDM potentials as well as the share of municipalities, where participation in LES is still viable despite a monthly fee, are depicted in Table 8-2.

Table 8-2: Average monthly fees, considering RDM revenues and share of municipalities in which the pricing is still viable for consumers

| Pricing Mechanism | Year | Average monthly fee per consumer in € | Feasibility for consumers in percent |
|---|---|---|---|
| LEM | 2019 | 3.59 | 52.78 |
| LEM | 2035 | 3.18 | 87.57 |
| SDR pricing | 2019 | 2.59 | 91.31 |
| SDR pricing | 2035 | 2.28 | 97.14 |
| MMR pricing | 2019 | 2.13 | 90.95 |
| MMR pricing | 2035 | 1.94 | 95.24 |

The "feasibility for consumers in percent" shows the ratio of municipalities in which the average consumer still profits off a price mechanism, even though only the consumers have to pay a monthly fee.

Table 8-2 and Figure 14-29 in the appendix show considerably reduced fees due to the consideration of RDM revenues to cover the losses of the ESP. Accordingly, SDR and MMR pricing mechanisms are still feasible for consumers, even though they are charged with a monthly fee. Since with SDR pricing consumers profit the most, a monthly fee still leaves them with an advantage over the status quo. With LEMs, suppliers gain the highest profits over the other two mechanisms while buy prices are in between SDR and MMR pricing. Since this results in the highest losses for the ESP in a LEM, participation in about half of the municipalities is no longer feasible for consumers after the subtraction of the monthly fee. In MMR pricing, advantages are lower for both supply and demand resulting in the lowest losses of the ESP and hence the lowest monthly fee. Hence, this mechanism is still feasible, even after the consideration of the monthly fee. The higher the supply in a community, the more consumers benefit from it, at the cost of the suppliers. The losses for the ESP also increase as a result, but not as much. Hence, MMR and SDR pricing are viable in more than 90 % of municipalities in 2035, if the losses of the ESP are allocated among consumers. Price mechanisms are uneconomical only in those municipalities where there is hardly any supply, and consumers have no advantage. Figure 14-30 in the appendix shows that in 2019 53.7 % of municipalities (in 2035 89.3 %), all three pricing mechanisms are viable, after a monthly fee is charged for consumers. In 2019, in 36.5 % two pricing mechanisms are viable per municipality (in 2035 9.4 %). This implies that all stakeholders are either equal or better off than in the status quo if RDM potentials are exhausted and consumers participate via a monthly fee. Then, the choice of pricing mechanism is relatively free and depends on what incentives are to be set for whom and what local circumstances are to be taken into account.

The use of RDM revenues of 2.05 ct/kWh for electricity generated and consumed simultaneously within 4.5 km can therefore ensure that community members are financially equal or better off on average than today, disregarding additional costs. However, the remaining economic benefits are very small. Participants in the energy community can generate economic benefits by using the variable price to their advantage.

**Economic Viability**

As shown in prior sections, the average monetary benefit for consumers to participate in energy communities is relatively small in Germany, since the price of electricity makes only about 23.3 % of the price of household electricity. If the revenues from regional direct marketing are then used to ensure the economic feasibility of the ESP, the economic benefit remains only very slight, yet is still positive in many cases.

Comparing the costs for a smart meter (i.e., 30 €/a for a consumer with 2,500 kWh/a) with the cost savings of consumers, depicted in Figure 8-25, the model is no longer economical on its own. Additional costs, e.g. due to administrative barriers, required software, and services, further decrease its economic viability. However, the EC also offers new commercialization opportunities, e.g. for ancillary services, which in turn can generate additional revenues.

Figure 8-25 shows that especially in clusters with balanced and high $SDR$ (i.e., clusters 5, 7, 8, 10, 12, 13, 14, 16, 18 and 20), annual average cost savings of more than 10 € are realistic for consumers on average, even with the monthly fee. In municipalities with low supply, the feasibility is low. These cost savings do not require any active contribution. They increase for those consumers and prosumers who actively adjust their consumption behavior to the prices. Prosumers and RE generators are always better off than consumers because they also actively contribute to the community.

If there are no additional costs, e.g. for smart meters (as is often the case, for example, when a complete package of storage, inverter and PV is purchased or a smart meter is already installed) and the pricing mechanisms SDR and MMR are used (which hardly involve any bureaucratic hurdles), this is already feasible today. In these cases, prosumers can respond to price signals or sell their flexibility to generate additional revenue. The calculation shows that many requirements of stakeholders can already be met with the existing possibilities and energy communities are on the brink of economic viability. If regulatory barriers are lowered and incentives are added in the future, such as the reduction of disproportionate costs, charges, taxes or levies, the price mechanisms presented provide a good basis for implementing energy communities for all stakeholders involved.

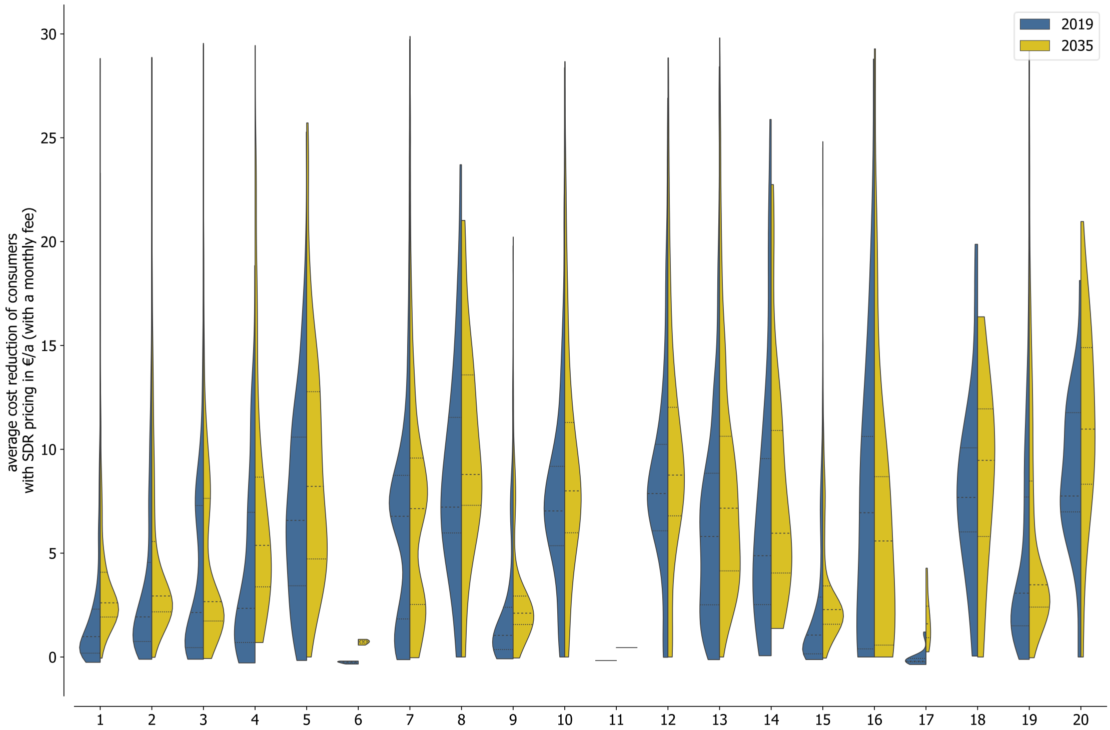


Figure 8-25: Average annual cost reductions of consumers in different clusters for participating in energy communities with SDR pricing and a monthly fee to cover the losses of the ESP after utilizing RDM revenues

### 8.4.3 Labeling Framework and Allocation Methods

The potential of regional direct marketing was calculated using the allocation method presented in section 5.4.1. In section 5.5, two case studies showed that the allocation method is both working as it intended and is sufficiently scalable, since it requires on average only 0.95 s per time step. Even in communities with 100.000 participants, the optimization time per time step does not exceed 10 s per time step. The scalability of the allocation method is therefore given. A bigger challenge is the ZKP. The scalability is not yet given in this order of magnitude, but is developing fast [76].

Thus, the labeling framework and the allocation method can be used in energy communities in addition to all pricing mechanisms. This allows the maximization of the RDM potential (as shown in section 8.3) or the implementation of further use cases, if regulatory changes allow it (as shown in section 5.5).

## 8.5 Qualitative Potential Assessment

In sections 3.2 and 3.3, technical, infrastructural and stakeholder requirements were introduced which are the basis for the labeling framework as well as the subsequent use cases. In section 4.3, value propositions of the use cases were described which satisfied most of the value requirements. However, as stated in section 4.5, some value propositions can only be evaluated after a simulation. These are discussed, based on the results in section 8, in the following.

In the following, the requirements from Table 3-2 in section 3.4 are discussed, based on the quantitative assessments of the pricing mechanisms in this work.

**1) High and stable long-term revenues**

From an RE supply perspective, all three pricing mechanisms offer better sell prices than in the wholesale market. However, the magnitude of these benefits is highly dependent on how much the RE contributes to simultaneity in the community and how strongly a pricing mechanism responds to it. SDR pricing is most responsive to local $SDR_t$. RE supply with high simultaneity (i.e., wind and PV) in the community, which quickly increases $SDR_t$ as a result, does not benefit much from this mechanism. Here, LEMs are fundamentally better. However, the more the supply and simultaneity increases, the less often $p_t^{mid}$ comes into effect as an upper boundary in MMR pricing. For communities with very high generation and simultaneity, revenues of LEM and MMR pricing are identical for the supply.

The situation is different for those RE and flexibility providers that operate contrary to the simultaneity of renewables. They can take advantage of the high prices (close to $p^{retail}$) during periods of low PV and wind and can greatly increase their revenues as a result. Therefore, from their perspective, SDR is the best mechanism.

Long term revenues were analyzed by simulating the 2035 expansion of renewables. Pricing mechanisms show that due to higher simultaneity and increased PV capacities, revenues in general are reduced. Possible average revenues decrease by about 80 % in SDR pricing, 65 % in LEMs and 53 % with MMR pricing. Therefore, MMR is the mechanism that guarantees the most stable and least fluctuating prices on average in the long run.

**2) Reduced electricity costs and long-term price security**

From the consumer's point of view, the opposite is true of the producers. SDR pricing best passes on the exchange electricity prices to consumers, which allows savings in the range of 21.18 % per year. Due to the limitation via $p_t^{mid}$ in MMR pricing, the possible cost savings are only about half. LEM pricing is in between with 16.03 % cost savings. In terms of long-term price stability, all three price mechanisms are relatively similar. There are only minor changes from 2019 to 2035.

One challenge, however, is short-term price stability. Exchange electricity prices are passed on to consumers in an attenuated form, nevertheless, strong fluctuations occur during the day.

Compared to the static $p^{retail}$ (status quo), this has advantages for those consumers who can respond flexibly to these price signals. However, vulnerable or poor households in particular often lack these capabilities. This can create risks that costs will also rise if, for example, large electricity consumers in the household are switched on at times when prices are very high. Another disadvantage arises for these households due to the proposed monthly fee. Even though it is low, the cost savings due to the pricing mechanisms in energy communities (especially due to the small share of electricity prices in the household electricity price) are not very high, especially for low annual consumption. However, the monthly price affects all households equally, instead of basing costs on consumption and thus also on cost benefits.

In addition, developments in electricity and gas markets in 2022, due to the Covid-19 pandemic and geopolitical conflicts, show that rising electricity prices are being passed on directly to consumers through all three mechanisms. As a result, short-term procurement on the electricity markets becomes uneconomical, and thus all price mechanisms cause social problems in times of such events.

**3) Integration of energy communities into wholesale markets**

By design, all three mechanisms are incorporated into Wholesale Markets. At the same time, generation and consumption in the community are reflected in the local price.

**4) Reflection of local demand and supply in the price to incentivize flexibility**

All three price mechanisms manage to combine local signals caused by supply and demand as well as prices from wholesale markets. In particular, SDR pricing passes on the price signals from the wholesale market directly to the community in the event of high SDR or negative prices. The incentives for providing flexibility are thus very high.

This creates a fundamental conflict of objectives. The higher the incentives for flexibility or the construction of new, demand-oriented RE plants (i.e., with base-load or flexible capabilities), the lower the revenues for existing suppliers and the lower the cost reductions for consumers. Again, LEMs offer a middle ground between SDR and MMR pricing, balancing both goals.

**5) Providing clearly defined, transparent, non-discriminatory and verifiable pricing mechanism**

By design, all three are clearly defined, transparent, non-discriminatory and verifiable pricing mechanisms. Although SDR and MMR pricings are determined by the ESP, the labeling framework allows transparency to be established through ZKP and ensures the correctness of the price.

However, a challenge arises with LEMs in small communities. As there are often only a few suppliers eligible for supply-side offers, this can lead to a concentration of market power. Therefore, especially in small communities with few large RE suppliers, there is a risk for market manipulation [222].

All in all, the price mechanisms fundamentally fulfill all requirements. However, due to their differences, they offer opportunities to specifically steer the energy transition based on local conditions and common interests of the energy community.

## 8.6 Preliminary Summary

In this section, the resulting supply demand ratios, prices and RDM potentials were assessed, and confirmed that all price mechanisms depend on the SDR in the municipalities, and the resulting prices vary considerably depending on local conditions. This answers **RQ 5: What potentials of regional direct marketing and prices are emerging in German "Energy Communities"?**

The evaluation shows that the pricing mechanisms all respond relatively similarly to changing $SDR_t$ and $p_t^{wholesale}$. While SDR pricing reacts very sensitively to fluctuations in $SDR_t$, this is attenuated for LEM and MMR as both utilize $p_t^{mid}$ (i.e., $\frac{p^{retail}+p_t^{wholesale}}{2}$) as a reference point for the determination of the price. However, while $p_t^{mid}$ is defined as an upper (and lower) boundary in MMR pricing for sell and buy price, it does not serve as a hard boundary in LEMs. In many evaluations, therefore, LEMs (with a double-sided call auction, a uniform price and a naïve trading strategy of agents) are to be viewed from their behavior on exogenous and endogenous parameters between MMR and SDR pricing. When $SDR_t = 0$, the buy prices are equal to the $p^{retail}$ in all three mechanisms. The mechanisms only have a direct effect between $0 < SDR_t < 1$. Outside of this, the retail and the exchange electricity price have the greatest effect on overall prices, costs and revenues.

In general, the more RE supply or less demand in a region, the higher the $\widetilde{SDR}$. This leads to low sell and buy prices alike, reinforced by high simultaneity. In municipalities with high RE installations, this leads to low sell prices and low buy prices. Therefore, existing renewables have only minor advantages in participating in energy communities with SDR pricing over the wholesale market. The economic benefits of participation lie primarily with consumers. In the case of MMR pricing and LEMs, the benefits for producers are greater. As a result, the costs for consumers in these mechanisms are higher than in SDR pricing, yet still better than today's retail price. Regions with high SDRs are most frequently in the rural areas in the south-east of Germany (PV), in the north (wind) and in the north-east (wind and PV). Since it was assumed in this work that only RE plants up to a maximum of 2 MW participate in energy communities, many hydropower and wind plants are excluded from participation due to their high capacities. Additional RE capacities in 2035 increase simultaneity, and the SDR rises even faster above one. As a result, the sell prices in 2035 often correspond to the wholesale prices, providing little added benefit for both renewables and consumers compared to 2019. Only in municipalities that had little self-supply in 2019 does the benefit to consumers become noticeable in 2035.

From the consumer's point of view, the SDR pricing is the best one. When the SDR is high, wholesale electricity prices are passed on directly. From the suppliers' point of view, it is vice versa, as they have hardly any advantages over participation in the wholesale market. In MMR pricing, the monetary advantages for consumers and generators in MMR are limited by $p_t^{mid}$. LEMs converging into SDR pricing in times with high $SDR_t$. Overall, however, all price mechanisms are better for both consumers and producers than their respective status quo. In balanced communities, all mechanisms are valuable for both sides. Compared to a static electricity price for consumers (status quo), all three price mechanisms are variable. SDR pricing reacts most sensitively to the $SDR_t$ and also to prices on the wholesale market. Due to its boundary at $p_t^{mid}$, MMR pricing is the mechanism with the least fluctuations. LEMs lie in between. High fluctuations are on the one hand good as an incentive for flexibility, with the addition of RE that enables taking advantage of low prices and demand response to shift consumption to times when there is a lot of generation. However, fluctuating prices also pose risks, e.g., for (vulnerable) households that lack flexibility and consume a lot of electricity at times when there is little local supply or when prices on the wholesale markets are high.

In addition to the price mechanisms, regional direct marketing (RDM) was also simulated and the potential determined for all German municipalities via the ESM. The potential is highest in small communities with very balanced $\widetilde{SDR}$. The larger a community becomes, the greater the effect of the distance restriction of 4.5 km. For wind energy, the distance restrictions have a stronger impact, as they are often installed far away from residential areas. Overall, in many communities with balanced $\widetilde{SDR}$, a lot of additional revenues can be raised through RDM.

The pricing mechanisms only reallocate existing revenues and costs among the stakeholders involved. Since demand and supply benefit (to varying degrees) from all mechanisms, ESP loses revenue. The question was therefore answered as to whether the additional revenue generated by RDM is sufficient to compensate for the losses incurred by ESP on a regional basis. Although they can be reduced considerably, it is not enough to eliminate them completely. However, it is possible for SDR and MMR pricing in almost all municipalities to pass on the resulting ESP losses to consumers as a monthly fee, as the consumers' profits are relatively high on average, compared to LEMs. Although this reduces their economic benefits, participation is still worthwhile. This results in all stakeholders involved either benefiting from the pricing mechanisms or not making any losses compared to the status quo.

All in all, the pricing mechanisms all meet the requirements from section 3. No clear favorite can be identified, as each mechanism has its strengths and weaknesses depending on local conditions and the perspective (consumer or supplier). This means that high and stable long-term revenues for supply and demand are best given in MMR pricing. However, compared to the status quo (retail price) all mechanisms are less stable. Highest revenues for supply are achieved with LEMs, and lowest costs for demand with SDR pricing, which is the least advantageous for supply. All mechanisms reflect local supply and demand as well as wholesale prices. Even though resulting price spreads serve as incentives for flexibility and additional RE, this has drawbacks. As shown by current geopolitical events, all mechanisms lack long-term price security, as price increases on the wholesale market have immediate effects on consumers and producers. All mechanisms are clearly defined, transparent, non-discriminatory, and verifiable. However, as LEMs are market-based they are vulnerable to market manipulation in small communities.

Finally, it can be stated that the implementation of local energy communities is almost feasible with today's incentives. However, in this analysis, the costs due to administrative barriers were disregarded. According to RED II and IEMD, these should be reduced in the future and further incentives added, e.g., in the form of reduced grid charges, taxes or levies for energy communities. If the administrative barriers are reduced at the same time, energy communities are a promising concept for all stakeholders.

# 9 Summary of Machine Learning in Modeling Processes

In this work, different methods of supervised and unsupervised machine learning were incorporated into a bottom-up energy-economic modeling process. In the following, possible applications within this process are summarized. For reasons of simplicity and transferability, a typical modeling process is depicted in Figure 9-1.

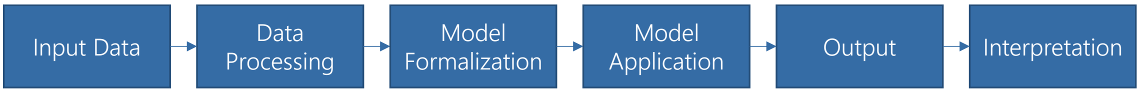


Figure 9-1: Simplified and generic modeling process based on [223]

A typical modeling process, as depicted in Figure 9-1, consists of input-data acquisition and preprocessing (i.e., section 5.1 and 5.2). The formalization of a simulation or optimization model (sections 5.3 and 5.4) as well as its application on the input-data to generate an output (sections 5.5, 7.5 and 7.6). The output is the basis for an interpretation (section 8). In the following, based on the methods, applications, learnings and considerations of this work as well as supporting literature, a summary of machine learning in this process is provided, to summarize **RQ 3** and **RQ 4**. The structure of this section is based on Figure 9-1.

## 9.1 Input Data Processing

Input data and data processing depend on the task at hand, availability and quality of the data. In this step, data is acquired and merged from multiple different sources and interfaces. The acquired data is reviewed, processed and validated. The applications of machine learning in this field are manyfold, as shown in the following.

**Imputation of Missing Data**

A challenge of data processing is to identify and replace missing or incorrect data. While this is necessary for the input of scientific and machine learning models, the latter can be used to improve this process for the former. In order to fill missing values, datapoints can be deleted (list- or case-wise) or imputed [224]. Imputation techniques replace missing or wrong values by predicted values. Simple imputation is achieved e.g., by using the mode, mean or median of available data. While simple to apply, these methods may lead to biased or unrealistic results [224].

Regression imputation methods replace missing values by predictions, generated by (uni- or multivariate) regression models. Available data is utilized to build a regression model which is applied to the missing data. However, instead of stochastic regression, machine learning based regression or classification models can be applied on the data to deal with missing data or to identify potential errors or outliers. Yet, this requires bigger datasets. An alternative is hot-deck imputation (HDI) with unsupervised machine learning. HDI matches the datapoints with missing values, based on their available features, with similar or comparable datapoints e.g., by a clustering for cluster imputation or k-nearest-neighbor algorithms to find the most similar datapoints. Instead of using just a single method of imputation, multiple methods can be combined in an ensemble to improve the results or to quantify uncertainty (details see section 14.4.2 in the appendix).

Since most datasets were already validated and processed after acquisition in [225], this work required no data imputation. Hence, the application of these methods was not necessary. A comprehensive overview of using ML to handle missing data is provided by Tlamelo et al. in [224].

As elaborated, available information on buildings, which could be used to improve the simulation model in section 5.1, is incomplete. Therefore, parallel to this work, a start was made on filling in the missing data using ML. The incomplete datasets on types of buildings, their age, the number of residential units and their electric energy consumption, was completed by using supervised machine learning [226]. The goal was the creation of a nation-wide building dataset which includes each individual building and their relevant attributes [226]. The results achieved an $R^2$ of 0.94 for the data imputation [226]. In further iterations of the simulation framework, this data will be used to improve the model inputs.

**Data Interpretation and Validation**

A part of processing input data is its validation and the gain of a better understanding. While data validation is imperative both for simulation and the training of ML models, machine learning can be applied to simplify data interpretation and validation. As shown in section 6, cluster analysis and the resulting centroids or representatives can be used to verify and interpret both input and output data. Clustering helps with pattern recognition and hence improves the understanding of patterns in big datasets. These patterns, in combination with the domain-knowledge of experts, can simplify the validation process of data or resulting models.

Additionally, as shown in section 7.3, clustering can also be utilized to aggregate time series data (TSA). Validating datasets by investigating only representative datapoints or time steps generated by an unsupervised clustering reduces the complexity. Section 6.6.2 shows a cluster analysis of a big dataset of approximately 12,000 German municipalities, described by 20 clusters. This helps practitioners understand a dataset.

To decrease the computational costs of the clustering process, to reduce the data complexity and to visualize high-dimensional datasets, dimensionality reduction with, for example, principal component analysis, t-SNE or UMAP, can be applied on the dataset. This step can be used in conjunction with the clustering or emulation process, as shown in section 7, to reduce computational costs.

**Input Data Compression**

Clustering and TSA can be used to reduce input data for the simulation framework, as shown in sections 6 and 7.3. This can be used to improve the simulation time considerably. However, the loss of data for simulation also leads to losses in accuracy.

Additionally, based on a simulated sample, classification can improve the modeling process, by excluding simulation parameters which yield irrelevant results.

**Sampling and Outlier detection**

Depending on the task, input data may not be equally relevant, or the population may be too big to consider every member. In many domain-specific appliances, the simulation, investigation or survey of only a selected subset of a population is sufficient. This stratified sampling can be done by dividing the population into subpopulations (strata) and selecting either multiple or single representatives out of each stratum (= cluster). In section 7 and [A3], this approach was used extensively to gain a better understanding of the data and to identify representatives. Additionally, the strata were used for multiple different subsequent sampling methods to choose single (representative) datapoints from the strata.

Via unsupervised learning, k-Means or k-Medoids, for example, can be applied with $k$ as the number of samples, to identify representative datapoints. This can also be applied on already existing clusters, as done in section 7.2. Supervised machine learning can be used via active learning or adaptive sampling to identify samples, as shown in [A3]

This can also be applied the other way around. By unsupervised clustering, (depending on the algorithms) outliers can be detected in order to exclude irrelevant datapoints from a population. Hence, clustering, sampling and outlier detection can reduce the necessary population for a simulation considerably and thus reduce computational cost and complexity. In the case of this dissertation, big urban clusters (i.e., Berlin and Cologne) were excluded from the simulation due to unreasonably high computational costs (see section 7.6).

**Input Feature Engineering**

In addition to this, the resulting clusters can be used for ESM to supply the model with an additional feature. For example, in section 7.6.2, the clusters showed different correlations of input features to the desired output which can improve the output of a regression, if the chosen regression model is capable of processing discrete features. Additionally, the distance of a datapoint to the representative of its cluster may be provided as a feature for regression.

In section 6.4, unsupervised machine learning (i.e., density-based clustering algorithm DBSCAN) was used to determine settlement patches (details see Table 14-5 in the appendix), based on OSM data.

## 9.2 Model Formalization, Implementation and Application

Model formalization includes the qualitative description and full semantic documentation of behavior, structure, and functional relations of input and output [227]. In the next step, the formalized model is implemented and applied on the data [228]. Machine learning can be integrated into this process in various ways, as described in the following.

**Choice of “Level of Detail” and Model Simplification**

As shown in section 8, the correlation (and/or functional relationship) of input features and simulation outputs may vary within a population. Section 8.3 shows different behaviors of pricing mechanisms, spreads or RDM potentials for different clusters. As proposed in section 6.7, Figure 6-9, this can be used as an advantage. For some clusters, a simulation can be simplified, or the clusters excluded from simulation (e.g., due to an expected output, a different functional relationship of in- and output or computational cost). Additionally, depending on the impact of a cluster on the entire population, different levels of detail of the simulation may be appropriate, depending on the use case and desired goals.

In section 8.3, for some small municipalities with high installed capacities of wind power but very low consumption, the regional direct marketing potential equals the demand, since this sufficient generation is present within 4.5 km and consumption is the only limiting factor. If known in advance, different levels of details or models can be applied for different clusters to reduce computational cost. This was assessed in this dissertation. Since three different use cases were simulated, only a few small clusters could have been excluded. However, since this had little impact on computational cost, the approach was not used. Instead, urban clusters 6, 11 and 17 were excluded from the simulation due to high computational costs.

**Emulation, Surrogate and Meta Modeling (ESM)**

A focus of this work was the application of ESM into a scientific modeling process (section 7). The goal of ESM is to create an approximation of a simulation, optimization or any kind of black box model in order to reduce computational cost of the process while maintaining high model accuracy. As shown in section 7, this can speed up the simulation framework significantly. It can improve the overall performance of a simulation model for the initial simulation of a large population, the numerous re-applications of a model, for real-time-applications or for scenario or sensitivity analysis. In this dissertation, the performance increase to generate results for all use cases in all ca. 12,000 municipalities was a factor of 1,874.6. The reapplication of the ESM, compared to the simulation for sensitivity analysis, can be up to 470,912,105.3 times faster than the conventional model.

As shown in the extensive literature review in [A3], ESM can also be utilized to determine in-between results e.g., in fluid dynamics, which can be challenging to solve analytically.

Contrary to computationally expensive, yet known functional relationships in fluid dynamics, the relationship of in- and output within a simulation or optimization model is not always known. This is due to the use of proprietary software, numerical integrators, lookup tables etc. Hence, algebraic models and derivatives are not always available or known [186]. With ESM, algebraic models can be identified by disaggregating more complex processes and identifying a set of surrogate models. A method for this is proposed in [186]. An advantage of this is that the algebraic formulation of a functional relationship leads not only to decreasing computational complexity but also serves as the basis for a sensitivity analysis or further optimization of the process.

**Model Approximation via SimKern ML**

Instead of ESM, unsupervised ML can be utilized to approximate simulation model results. A sample of the simulation parameters is simulated in [229], where "coarse and approximate simulations are used to compute similarity measures, and these similarity measures are then used by the ML algorithm to build a predictive model, called SimKern". In the training process, the similarity between all pairs of simulated samples is measured. In [229], "two samples are given a high similarity score if they behave similarly across a wide range of simulations. To determine the result for a non-simulated datapoint, a similarity to all trained samples is calculated. This is the input for a subsequent predictive model (i.e., regression or classification). According to [229], SimKern outperforms standard ML models for small training sizes. Since the training data proved to be sufficient in [A3], this approach was not pursued further in this work.

## 9.3 Output and Result Interpretation

The interpretation of model outputs is an integral part and can be simplified by ML, as shown in the following.

**Usage of Clusters and Representatives for Result Interpretation**

As shown in section 8, the usage of clusters (=strata) and representatives for result interpretation facilitates the interpretation. To explain characteristics or behavior on representatives or clusters is easier to understand and to process for practitioners, especially if clusters are explained and well distinguishable from each other. Differences between clusters, in turn, show the plausibility of the cluster result.

Representatives resulting from the clustering process can also improve the development of the simulation model. In practice, simulation models are implemented incrementally and with regular reviews and plausibility checks of the simulation results. This is easy and performs well with a small selection of very different, but easy to understand, datapoints.

In terms of result interpretation, the combination of clusters and correlation analysis allows to draw conclusions how certain input features correlate to a result within a cluster. This allows individual statements about correlations to be validated and quantified.

In the context of this work, this approach was often used. During the development process of the simulation framework or the use case modules, simulations were performed for representative communities and the results evaluated. Due to the good description of the clusters in combination with domain knowledge, it was possible to quickly determine when results were incorrect or implausible. The different representatives covered a variety of properties, making it less likely that special cases would be overlooked.

**Result Approximation by Similarity or Cluster Mean**

As shown in section 6.7, clustering can be utilized to approximate simulation results by similarity within the clusters or by the cluster mean. In this process, the results of the representatives are projected onto the other points in the cluster, or their results are used to determine the total potential of the cluster. However, as also shown, this technique requires the use of centroids or datapoints which resemble the mean of a clusters as best as possible. This method is viable if the points in a cluster are very homogeneous or if only very few data points can be simulated. However, this approach is generally inferior to ESM, so it has not been used in this work.

**Sensitivity Analysis**

As already mentioned, ESM can be used to improve the process of sensitivity analysis, since it outperforms the simulation model. Sensitivity analysis can be done by altering certain input features and observing the change in the predicted variable. Alternatively, the feature importance can be derived e.g., by tree-based algorithms. This helps identify those features that have the greatest impact on the simulation. The sensitivity analysis can then be limited to these features or be done qualitatively.

Algebraic ESM make the process of iterative sensitivity analysis completely obsolete, since the result is a mathematical function, describing the functional relationship and hence the importance of input features.

All in all, ML can be used in all parts of modeling processes. As ML libraries become more and more accessible and easier to use, it is therefore advantageous to integrate them into energy-economic modeling processes.

# 10 Discussion and Critical Review

Shortcomings of this dissertation are acknowledged and outlined in the following, structured by the sections. Areas for further research are also identified.

**3) Energy Communities and 4) Use Case Specifications**

In [A1], a brief critical review of the introduced labeling concept and architecture was given, shown in section 4, and gaps and further areas for exploration and testing identified. It can be summarized as follows:

- The modified use case methodology, as used in section 3.1, included only a small portion of the full method, due to reasons of scale and scope. For a more detailed description of the use cases, the application of the full methodology is required.
- This work has focused on the need for a labeling framework as well as pricing mechanisms in energy communities. Implementation proposals for both have been made and their potential analyzed. Other important components of energy communities have been disregarded but should be considered in further works.
- This dissertation did not cover the GOR in detail. The GOR is the current system to label green electricity and was covered extensively in [A1] and [77]. In current legislation, no labeling is possible without this established system. In the project InDEED, we will provide a roadmap on how to improve this system to facilitate the labeling framework, introduced in [A1, 14] and section 4.1.
- The pricing mechanisms in LES forecast an ex-ante price to incentivize flexibility within the community. However, the real price is determined by the actual supply and demand, influenced by flexibility. The interactions of price forecast, actual price and the incentive for flexibility were not part of this work, but should be investigated further.
- As highlighted in section 3, energy communities follow broader goals than just economic benefits. This work identified pricing mechanisms as a key component of ECs and hence focused on the economic benefits as well as possible incentives for flexibility. Subsequent research should investigate the extent to which the prices incentivize and improve GHG emissions, community self-sufficiency, grid loads, peak reductions and other goals.

**5) Simulation Framework**

- Due to missing exchange prices in 2035 (scenario), and to enable better comparability, the same exchange and retail prices were used both in 2019 and 2035. Therefore, no statements can be made about what prices will occur in 2035, but only what prices would have occurred in 2019 under the projected 2035 expansion of renewable energy.
- The validity of the community generation module is hard to assess, since there is no known ground truth at municipal level. Comparing measurement and model data is advised for future use. In this dissertation, the model was only benchmarked with top-down data. However, this data is by itself only modeled but considered valid, since it was already used for official German grid expansion planning (details see [144]).
- The use case module "local energy markets (LEMs)" only depicts a single, relatively simple allocation and pricing model. Additionally, only "zero-intelligence" traders were used to determine a price in the local energy market. Even though this is a standardized approach

yielding good results, the used bidding strategies, allocation and market models should be extended and results be compared.

- The approximation of total simulation time in section 5.6 is very dependent on outliers and the chosen regression model. Alternatively, the underlying code could be assessed in future works to analyze the scaling, using the Bachmann–Landau (big O-) notation.
- The incentive for the use of existing or construction of further flexibility was assessed qualitatively. However, flexibility was not simulated to, i.e., exploit the resulting prices or the possible additional revenues in the community. Flexibility providers affect supply and demand and hence have a direct impact on the pricing. Therefore, feedback of flexibility on prices and vice versa should be assessed in future studies.
- The used scenario (NEB 2035 B) was published in 2021. Due to current geopolitical events, this (and most other scenarios) does not correspond to current political developments. It is therefore recommended to recalculate 2035 with more current scenarios.
- SMEs were neglected in the simulation, since no load profiles were available. This should be integrated when sufficient data on load profiles is available.

**6) Cluster Analysis of German Municipalities**

A detailed discussion about the method in section 6 is provided in [A2].

**7) Emulation-/Surrogate-Modeling**

The method of section 7 was discussed in [A3] in detail. Additionally, the following critical review can be made:

- ESM is often used to (fully or partially) substitute a simulation model. However, this requires a different sampling approach, as outlined in [A3]. The ESM in this thesis does not generalize on any given simulation parameters. In this work, it was trained to achieve the simulation of a known and finite population. Further evaluation should be made to examine if the samples used from two different scenarios are already sufficient to represent any other future scenarios.
- The model accuracy of the ESM was improved by an extensive grid search approach with selected ML algorithms and selected error metrics. Even if the most accurate models were chosen from this process, it is not impossible that an even better accuracy could be achieved by additional features, other (untested) ML models or hyperparameters not included in the grid search.
- The runtimes of individual ESM components were logged and compared with the runtime of the simulation model. The time for the grid search was disregarded, due to its subjectivity. The duration of the grid search depends on the used method, the considered parameters as well as the experience and the demands of the involved persons and is optional. In the future, it could be investigated how a standardized grid search process (i.e., independent of the user by means of a fixed number of parameters or tries) affects the runtime.
- A goal of this dissertation was to show the performance increases using an ESM instead of energy-economic models. To ensure comparability, all computational intensive processes were performed on existing hardware. As this is shared hardware, some of which was also used by other users in parallel, the runtime measurements would have been slightly affected by the server usage. For more robust results, it would be better to do the measurements on separate hardware to avoid these distortions.

**8) Energy-Economic Potential Assessment**

- The assessed potentials focused on the technical potential. Since it is expected that the administrative hurdles will decrease, no costs being incurred today (to participate in the use cases) were analyzed in more detail. In section 8.5, this was qualitatively compared with selected costs (i.e., smart meter). It showed that a detailed analysis of which costs still need to be eliminated or incentives need to be created is absolutely necessary. This thesis provides the data for this.
- The energy communities in this work were considered isolated from each other. However, if many of them emerge, they in turn will have an impact on wholesale prices. In future works, this impact on exchange prices should be quantified.
- A key assumption of this work is the capacity restriction of renewables (≤2 MW), due to §9 StromStG. However, in further research the impact of higher and lower restrictions should be investigated.
- For the pricing mechanisms, a fixed retail price of 7.09 ct/kWh was assumed. This corresponds to the real, average prices paid for household electricity in 2019. Part of this price is the average exchange price and the share of the utility (costs, risk, margin). However, this share of the utility was calculated for electricity as a commodity product. In practice, however, energy communities increase the expenses and risks while lowering sales. This corresponds to higher costs of the utility.
- The ESM generated time series data for all of the approximately 12,000 municipalities in an hourly resolution for three pricing mechanisms for 2019 and 2035. Accounting for supply and demand, resulting buy and sell prices of SDR and MMR, LEM pricing and RDM, this results in $1.68 * 10^9$ datapoints (disregarding auxiliary data for interpretation). Due to reasons of scope, analyses within the individual communities were not performed. The resulting data offers a variety of possibilities for further evaluation or further use. These include:
    - the evaluation of the energy-economic performance of the energy communities by applying the value tapping index, participation willingness index, equality index, power and price flatness index, as defined in [151].
    - the training of reinforcement learning models for trading on local markets.
- Flexibility incentives were evaluated, based on the difference of buy and sell prices per day. However, depending on the type of flexibility, only the variation in buy or sell price might be of relevance. In other words, demand response only sees the buy price and may shift consumption accordingly. These types of flexibility as well as their impact on price volatility should be further assessed.
- The goal of the methodology was to compute results for multiple use cases and all municipalities in two scenarios. Accordingly, the resulting ML models are not suitable for predicting arbitrary input parameters (i.e., other scenarios). Subsequent research should examine to what extent the generated data is already sufficient for the ML models to generalize to all possible input parameters.

# 11 Conclusion and outlook

Energy communities can make an important contribution to the energy transition. The definition of energy communities, their characteristics, components, technical and legal requirements, stakeholder perspectives, and implementation in other EU member states were presented in section 3. Energy communities can be defined as "group of individuals (citizens, companies, public institutions) who voluntarily accept certain rules in order to act together in the energy sector to pursue a common goal". The goals are diverse and can include many others besides economic and environmental. The EU has already initiated the reduction of existing administrative barriers and disproportionate costs, as well as the creation of incentives, to make them economically feasible. Based on this research, the focus of this dissertation was set on pricing mechanisms and a labeling framework with an optimization-based allocation mechanism in energy communities. Pricing mechanisms are an integral component, as they ensure that electricity is exchanged for a fair price within the community. The price mechanisms should reflect prices on wholesale markets as well as demand and supply in the community. Furthermore, they should provide incentives for flexibility, offer better long-term revenues than wholesale markets, reduce costs for electricity consumption, and provide benefits for all involved stakeholders. A labeling framework with an allocation method is required to provide information about the origin and greenhouse-gas emissions of electricity. It is also necessary to match supply and demand to distinguish own consumption in the community from residual electricity. If costs for own consumption in the community are to be reduced or financial incentives are to be created (i.e., reduced grid fees, taxes or levies), it needs to provide the information to third parties, granting these incentives.

**RQ 1: How can use cases of a framework for electricity labeling in the context of "Energy Communities" be developed and described ?**

To develop and describe implementation proposals for energy communities, with a focus on pricing and a labeling framework in Germany, the use case methodology was extended by elements of requirements for engineering in section 3.1. By comparing the requirements of the stakeholders involved and the value propositions of the use cases, it can be ensured that the use cases are developed in a targeted manner and meet all requirements. The use case methodology helps to formalize the use cases and to describe them in a standardized and comparable way.

The foundation of the labeling framework is introduced in section 4 and was laid in [A1] and [14]. It allows energy service providers (ESP) to allocate generation and consumption and provide information about the origin of electricity within a community to the community members. To ensure that this is done in a transparent and tamper-resistant way, to ensure privacy and provide proof of the correctness of both data and processes, zero-knowledge-proofs and blockchain technology are utilized.

Based on the labeling framework and the extended use case methodology, three implementations of energy communities were specified in section 4. Local energy sharing communities (LES) rely on an ESP that determines a price using supply demand ratio (SDR) pricing or mid-market rate (MMR) pricing. Local energy markets (LEMs) do not necessarily require an ESP. Instead, a price is determined via a market-based approach, requiring the stakeholders to actively buy and sell electricity on a local market. The proposed market in this work is a double-sided call auction with a uniform price.

In section 4.4, the requirements of stakeholders towards the labeling framework and pricing mechanism are compared with their value propositions. The labeling framework is capable of fulfilling the set requirements. A qualitative evaluation is sufficient to show its viability. Only that it is capable of delineating different use cases and claims regarding monetary incentives within energy communities needs to be proven by a simulation. In contrast, the requirements for price mechanisms cannot be answered by means of qualitative analysis. Therefore, they have to be simulated and the results evaluated.

**RQ2: How can the potentials of the use cases be modeled and evaluated using a simulation framework?**

To evaluate and compare the properties of the pricing mechanisms and show the viability of the optimization-based allocation method (as part of the labeling framework), a simulation framework was developed in section 5, using existing energy-economic and census data to create a digital representation of German municipalities. It takes into account private households, including rooftop PV, electric vehicles and home storage systems. It also includes all installed renewables. Methods were developed to map future developments (via scenarios). The results of this "community generation module" were tested for plausibility in section 5.3. It can be seen that both the status quo and the scenarios are mapped with a high degree of accuracy. Based on this community generation module, different use case modules were implemented. They determine, for example, SDR and MMR prices (simulation), local energy markets (multi-agent model), as well as RDM potentials, which is an application of the allocation method (optimization).

The allocation method of the labeling framework is validated in two case studies in section 5.5, based on the simulation framework. One goal is to prove that it is capable of allocating different use cases and claims regarding monetary incentives within energy communities. For this purpose, the optimization-based allocation is applied in a sample community. It is shown that both the distance between supply and demand and the costs can be used as a basis for the optimization. These distances or costs are then minimized to achieve a global optimum. The ZKP of the labeling framework make it possible to prove the correctness of the results to external third parties. The two case studies showed that the allocation method is both working as intended and is sufficiently scalable, since it requires on average only 0.95 s per time step. Even in communities with 100.000 participants, the optimization time per time step does not exceed 10 s per time step. The scalability of the ZKP is not yet given in this order of magnitude, but develops fast [76]. Thus, the labeling framework and the allocation method can be used in energy communities in addition to all pricing mechanisms. This allows the implementation of further use cases, if regulatory changes allow it (as shown in section 5.5).

Based on the case studies and further simulations in section 5.6, a challenge becomes apparent that occurs in many bottom-up simulation models. The computational complexity is high due to a high level of detail. As about 12,000 communities are to be calculated, this becomes computationally infeasible. The generation of all municipalities (status quo and a scenario for 2035) would require about 45.9 days. While the simulation of SDR and MMR pricing is computationally feasible, the determination of RDM potentials via a linear optimization model (i.e., the allocation method) would require 4.53 years. The multi-agent model to determine a price in a LEM would require 198 years.

**RQ3: How can clusters and representative regions be determined by unsupervised machine learning methods and applied in the modeling process of German "Energy Communities"?**

For this reason, unsupervised machine learning methods are evaluated in section 6 to reduce the computation time. While they can assist with pattern recognition, outlier detection, information compression, dimensionality reduction and knowledge expansion, the focus is primarily set on the identification of clusters and representative municipalities. For this purpose, a method was developed in [A2] to combine the expertise of domain-experts with the selection of the best cluster result for a specific use case. So-called cluster validation indices (CVI) are used, which are selected specifically for an individual task and weighted using MCDA methods. This allows the best individual result to be selected from a number of cluster results generated with different algorithms and cluster sizes. This method is applied in section 6 and the results are presented and evaluated. The best result includes 20 clusters and was generated using k-Means clustering. It turns out that the clusters can be well described with a few properties and easily distinguished from each other.

The clusters were described from an energy-economic perspective in more detail in section 6.6.2. They were described using data on population, potential of renewable energies, residual load structure, generation, consumption, building and settlement structures and site conditions. They were not created for the use cases in this thesis alone, but can be used universally for a wide variety of cases. This is shown by the evaluation of multiple features and results in section 8. Although not specifically intended for these use cases, the clusters considerably simplify the interpretation of the simulation and ESM results. Furthermore, the clusters and their representatives can be used in many different ways to simplify the energy-economic modeling process. Six ways to incorporate clustering into the modeling process to approximate results for either every municipality individually or all of them collectively were identified. These options include result approximation by cluster mean, result deduction by similarity, cluster pre-selection for the simulation, level of detail assessment, stratified sampling in combination with different forms of regression and time series aggregation to reduce the computational cost of the simulation model. Based on this research, a workflow to incorporate clustering in conventional energy-economical modeling processes is proposed in Figure 6-9. Further research of these options in section 6.7 shows that the cluster representatives are of limited use for simplifying the simulation model. As they do not accurately represent the mean (centroid) of a cluster and not all municipalities within a cluster are the same, extrapolating their results leads to a large error. For this reason, the next step was to investigate to what extent supervised machine learning can be used to generate results for all use cases and to accelerate the simulation.

**RQ4: How can supervised machine learning improve energy-economic modeling processes?**

In [A3], summarized in section 7, emulation-/surrogate- and meta-modeling (ESM) was proposed and tested to substitute parts or the entire simulation model by machine learning.

It was shown that especially when using small training datasets, simple random sampling is not sufficient. Instead, cluster sampling and adaptive sampling provide good results even with small sample sizes. A combination with previously created clusters is also possible. Therefore, in this dissertation, cluster sampling was used to select 10% of the municipalities for training and 1 % for testing of the ESM. Cluster sampling was applied to the clusters from section 6 and clusters with large cities (i.e., clusters 6, 11 and 17) were excluded beforehand (see cluster pre-selection for the simulation in Figure 6-9). However, the sample of 11% of the municipalities still requires a lot of simulation time, especially in the RDM and LEM use cases. To avoid this, it was shown in section 7.3 that a time series aggregation (TSA) can reduce the otherwise 8,670 h per municipality and year to 50 type hours, with only minor losses in the quality of the results. In section 7.6, supervised machine learning methods (ensemble methods) were applied as an ESM on the sampled training data and both performance and accuracy were evaluated. It turns out that this method can accelerate the simulation to determine all of the required data for this work by a factor of 1,874.6. This reduced the runtime from 201.24 years, required by the conventional simulation model, to 39.18 days with the ESM, while retaining high accuracy. All ESMs achieved $R^2$ values between 0.929176 and 0.999965 and low MAE and MSE in the individual municipalities. In computationally expensive and very slow models (i.e., the multi-agent model to determine LEM prices), the runtime can be increased up to a factor of 2346.7. When reapplying the models for sensitivity analysis, the ESM exceeds conventional models by a factor of 161.7 and 163.6 for LES prices, 26,684.8 to 51,721.2 for RDMs and 2,765,392.5

to 470,912,105.3 for LEMs. This shows one of the major strengths of the ESM over conventional models.

**RQ5: What potentials of regional direct marketing and prices are emerging in German "Energy Communities"?**

Section 8 provides an energy-economic evaluation of these results. The focus is on a quantitative evaluation of the value propositions of the pricing mechanisms in terms of electricity costs for consumers, additional revenues for RE supply, flexibility incentives, etc. The results are summarized in Figure 11-1 qualitatively, based on the model results, summarized in Table 14-7 in the appendix.

| | MMR pricing | LEM double-sided call auction with uniorm price | SDR pricing | Status Quo retail/wholesale price |
|---|---|---|---|---|
| Consumer Savings | ★☆☆ | ★★☆ | ★★★ | ☆☆☆ |
| Added Revenue RE | ★★★ | ★★☆ | ★☆☆ | ☆☆☆ |
| Added Revenue ESP | ☆☆☆ | ☆☆☆ | ☆☆☆ | ★★★ |
| Flexibility Incentives | ★☆☆ | ★★☆ | ★★★ | ★★★ Supply<br>☆☆☆ Demand |
| Consideration of Local Supply & Demand | ★☆☆ | ★★☆ | ★★★ | ☆☆☆ |
| Long-Term Price Stability | | | | ✓ Demand |
| Risko for Market Manipulation | | ✓ | | |

Figure 11-1: Summary and qualitative comparison of the analyzed pricing mechanisms to the respective status quo (i.e., retail price for demand or wholesale price for the supply)

The pricing mechanisms all reflect wholesale prices and local supply and demand. Therefore, they manage to represent both the incentives from the wholesale market and the community in the price. The situation of the community is defined by the available supply and demand, summarized in the supply demand ratio ($SDR_t$).

However, depending on the mechanism, the benefits from the resulting prices are distributed differently among stakeholders. Whereas with SDR pricing only consumers or producers benefit in the case of a high $SDR_t$, this is not the case with MMR pricing. MMR pricing uses the average of retail and exchange electricity prices ($p_t^{mid}$) as the upper and lower boundary, respectively. As a result, the potential profits for supply or reduced costs for consumers do not fluctuate as much and resulting benefits are considerably lower, however more fairly shared than those of SDR pricing. Since on LEMs agents bid prices that are between the wholesale and retail price, this price behaves similarly to MMR pricing. Likewise, spreads, maximum revenues and costs are attenuated compared to SDR pricing. However, unlike MMR pricing, $p_t^{mid}$ is not extremely high or low within the LEM range. Therefore it exceeds MMR pricing at very high or low $SDR_t$. LEM prices behave thus like a middle ground between the other two.

The mechanisms provide varying degrees of incentives. While the SDR offers particularly strong incentives for flexibility and new RE that balance out the $SDR$, this is much less the case with MMR pricing. On the other hand, long-term price stability of MMR pricing is better. Moreover, revenues and costs are distributed more evenly.

While both supply and demand gain benefits from all price mechanisms (compared to the status) quo, the ESP loses revenues. With sufficient regulatory adjustments, this would not be problematic, as LEMs are possible even without an ESP. In the case of LES, however, ESPs are an integral part. Therefore, the revenues from regional direct marketing were included in the calculation.

Today, this is the only possibility to get a tax exemption for electricity that is generated and consumed simultaneously within 4.5 km. It can be seen that these revenues could be used to reduce the ESP losses substantially. The remaining losses could be paid as a monthly basic fee by consumers. Using this approach, the feasibility for SDR and MMR pricing is low, yet given in almost all communities. Considering additional costs, such as installing smart meters, the price mechanisms in combination with RDM are not yet quite sufficient to make energy communities economically viable everywhere. All in all, all implementation proposals fulfil the requirements by the stakeholders if the SDR is balanced or high in a municipality. This the case especially in rural areas with high supply in the south, north-east and west of Germany. Vice versa, energy communities are less advantageous for consumers but provide high benefits for renewables in urban and suburban areas with low generation and high consumption.

Incentives to provide flexibility or to invest in new renewables contrast with price stability. The SDR in particular offers large fluctuations here and hence provides good incentives yet low price stability. MMRs provide lower incentives for flexibility but higher price stability. LEMs, unlike SDRs and MMRs, are not applicable in small municipalities because of the risk of market manipulation by individual plants.

Section 9 summarized the possible applications of machine learning, as used or considered in this thesis (summarizing RQ 3 and RQ 4). In a typical modeling process, machine learning can be utilized along the entire process. It can be used in input data processing for the imputation of missing data, for data interpretation and validation, input data compression, sampling and outlier detection, and input feature engineering. In model formalization, implementation and application to choose the appropriate "level of detail", for model simplification, Emulation, Surrogate and Meta Modeling (ESM) or model approximation via SimKern ML. Especially the usage of clusters and representatives for result interpretation proved viable, but also the result approximation by similarity or cluster mean and sensitivity analysis can help to improve the energy-economic modeling process.

All in all, the energy-economic evaluation shows that energy communities need both a labeling framework and a pricing mechanism. It was shown that the proposed implementations of these components meet the stakeholder requirements. The pricing mechanisms presented have other strengths and weaknesses, allowing for deliberate regional incentives, i.e., to provide more stable prices or to incentivize flexibility and demand-oriented expansion of renewables.

It was further elaborated that revenues of regional direct marketing (§ 9 StromStG) is sufficient for all stakeholders involved to be in an equal or better position than today. This assumes that no disproportionate costs are incurred and administrative barriers are lowered, which the EU wants to achieve by RED II and IEMD. The proposed optimization-based allocation method of the labeling framework can be used to ensure an optimal usage of available incentives and cost reductions. This was shown by two case studies in section 5.5 and application of the allocation on the RDM potential. The labeling framework provides high-resolution information on the origin of electricity and GHG emissions, simplifies proof to external third parties and ensures privacy.

By using available flexibility, all involved stakeholders can generate additional revenues. Since not only the financial incentive is important for energy communities (especially for local energy sharing communities), the community can also be optimized with respect to other goals (e.g., minimal GHG emissions) through the ESP. The extent to which different goals are in line should be analyzed in the future.

This dissertation provides the basis for a practical test, already extending the ongoing proof-of-concept of the labeling framework. Regulatory and administrative barriers, however, still hamper their economic realization. In further projects, it should be evaluated which electricity price components and disproportionate costs could be lowered to improve economic viability. The provided implementation proposals and methods as well as the simulation framework of this work are the basis for this evaluation.

The use of machine learning in energy-economic modeling processes shows great potential. Supervised and unsupervised ML can be used at all points of the process. The presented methodology should be applied to other bottom-up models and results be compared. In particular, sensitivity analysis should be investigated in more detail, since the results of this work show that the re-application of the ESM brings huge advantages compared to conventional models. In general, this method should be used in the energy sector if a simulation for a known population would take too long and conventional options to accelerate the simulation model have been exhausted. Especially if quick assessments (i.e., real-time simulations or sensitivity analysis) are necessary, or a huge population has to be simulated with a high level of detail, the advantages of the method in this dissertation prevail.

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# 14 Appendix

In this section, additional information, data and figures are provided.

## 14.1 Use Cases

In this section, additional information about the use cases is provided.

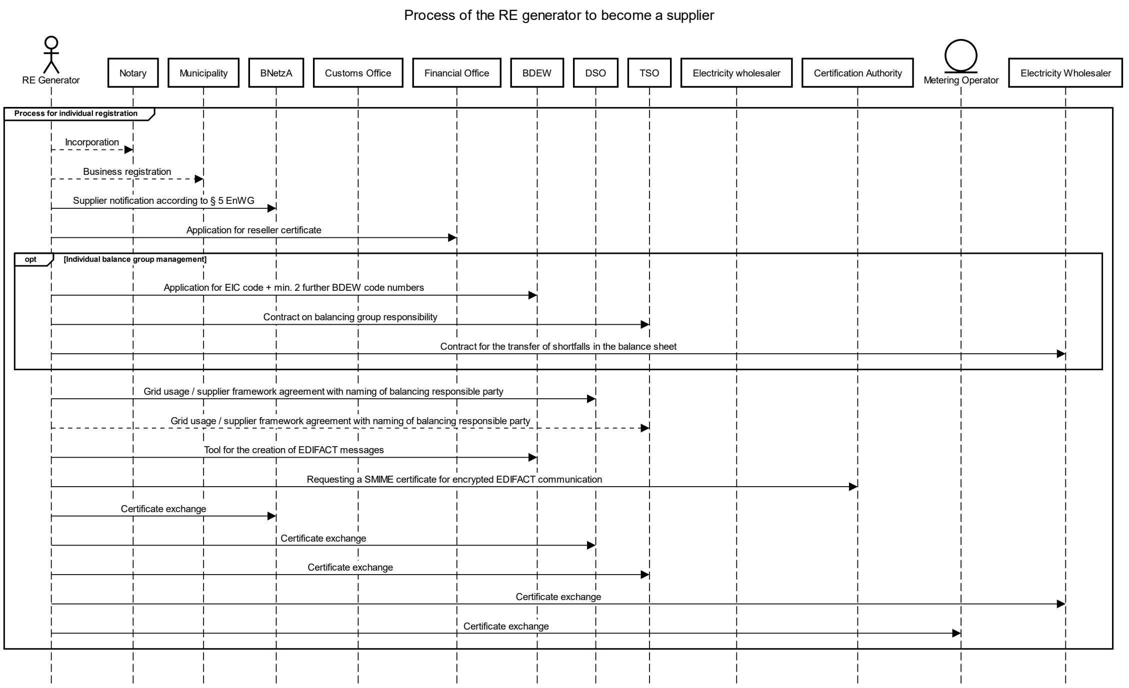



Figure 14-1: The German process for a prosumer to follow to become a supplier and sell their electricity to consumers (or peers) without a utility as intermediary, based on [230, 231, 232, 233, 234, 235, 236, 237, 238, 239, 240]

Figure 14-1 includes costs for incorporation (notary costs and fee at municipality), application for EIC codes [235], tools for EDIFACT communication, certificates, etc.

## 14.2 Simulation Framework

In this section, additional information on the simulation framework is given.

### 14.2.1 Case Study

Table 14-1: Description of the energy community in the case study

| Characteristic | Value |
|---|---|
| Total annual RE supply | 227.02 MWh |
| Total annual demand | 191.38 MWh |
| Hours with surplus/hours with shortfalls | 5174 / 3586 |
| minimum/median/mean/maximum SDR | 0.27 / 1.11 / 1.42 / 10.57 |

Figure 14-2 depicts costs for different use cases in energy communities, as assumed for the case studies in section 5.5. These values do not reflect real regulatory specifications and only serve the purpose of showing the viability of the labeling framework.

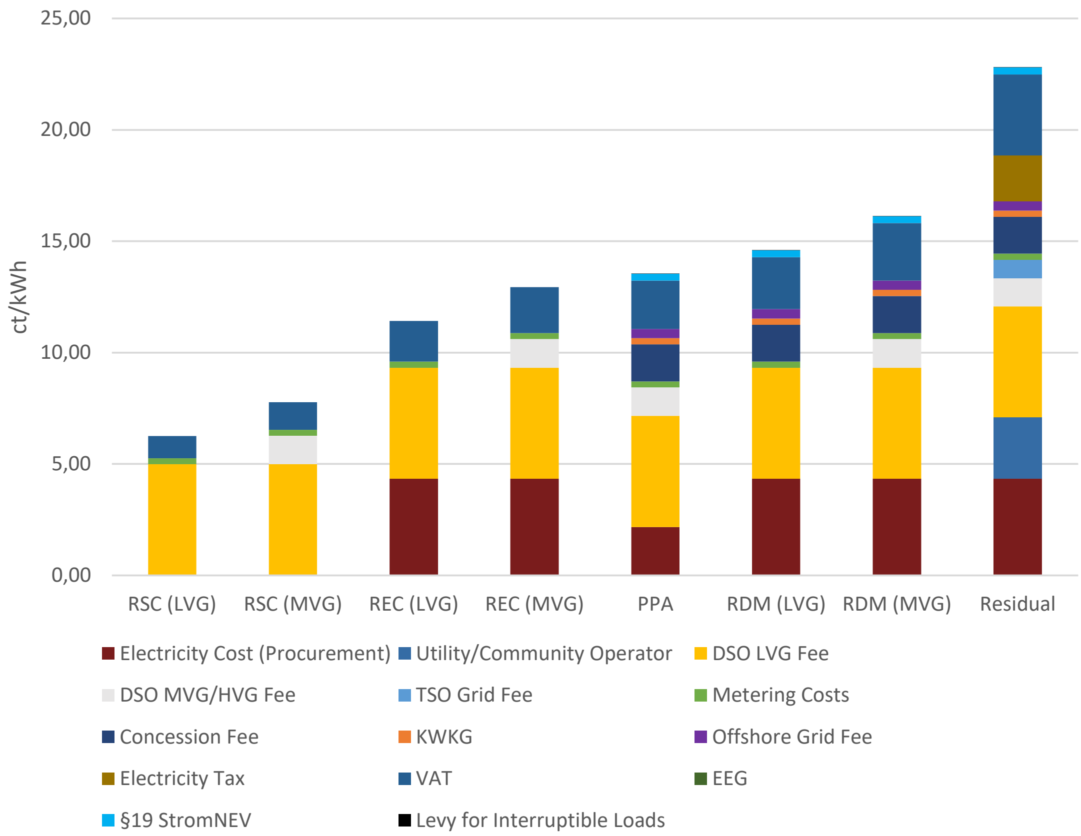



Figure 14-2: Costs of different use cases, as assumed for this case study

The VAT (19 %) is based on all resulting price components and hence increases with higher costs.

Since the EEG was discontinued in 2022, the EEG was exempt in this case, resulting in electricity costs of 22,8 ct/kWh (Residual).

### 14.2.2 Scenario

The used scenario in this work is provided in [144] and visualized in the following.

Table 14-2: Scenario data from [144] as used in the simulation framework to map future developments (NEP 2035 B)

| Installierte Leistung [GW] | | | | | |
|---|---|---|---|---|---|
| **Energieträger** | **Referenz 2019** | **A 2035** | **B 2035** | **C 2035** | **B 2040** |
| **Kernenergie** | 8,1 | 0,0 | 0,0 | 0,0 | 0,0 |
| **Braunkohle** | 20,9 | 7,8 | 0,0 | 0,0 | 0,0 |
| **Steinkohle** | 22,6 | 0,0 | 0,0 | 0,0 | 0,0 |
| **Erdgas** | 30,0 | 38,1 | 42,4 | 46,7 | 42,4 |
| **Öl** | 4,4 | 1,3 | 1,3 | 1,3 | 1,1 |
| **Pumpspeicher** | 9,8 | 10,2 | 10,2 | 10,2 | 10,2 |
| **sonstige konventionelle Erzeugung*** | 4,3 | 3,8 | 3,8 | 3,8 | 3,7 |
| **Summe konventionelle Erzeugung** | **100,1** | **61,2** | **57,7** | **62,0** | **57,4** |
| **Windenergie onshore** | 53,3 | 81,5 | 86,8 | 90,9 | 88,8 |
| **Windenergie offshore** | 7,5 | 28,0 | 30,0 | 34,0 | 40,0 |
| **Photovoltaik** | 49,0 | 110,2 | 117,8 | 120,1 | 125,8 |
| **Biomasse** | 8,3 | 6,8 | 7,5 | 8,7 | 8,2 |
| **Speicherwasser und Laufwasser** | 4,8 | 5,6 | 5,6 | 5,6 | 5,6 |
| **sonstige regenerative Erzeugung*** | 1,3 | 1,3 | 1,3 | 1,3 | 1,3 |
| **Summe regenerative Erzeugung** | **124,2** | **233,4** | **249,0** | **260,6** | **269,7** |
| **Summe Erzeugung** | **224,3** | **294,6** | **306,7** | **322,6** | **327,1** |
| **Stromverbrauch [TWh]** | | | | | |
| **Nettostromverbrauch zzgl. Verteilnetzverluste**** | 524,3*** | 603,4 | 621,5 | 651,5 | 653,2 |
| **Treiber Sektorenkopplung** | | | | | |
| **Haushaltswärmepumpen [Anzahl in Mio.]** | 1,0 | 3,0 | 5,0 | 7,0 | 6,5 |
| **Elektromobilität [Anzahl in Mio.]** | 0,2 | 9,1 | 12,1 | 15,1 | 14,1 |
| **Power-to-Heat (Fernwärme/Industrie) [GW]** | 0,8*** | 4,0 | 6,0 | 8,0 | 7,0 |
| **Power-to-Gas [GW]** | <0,1*** | 3,5 | 5,5 | 8,5 | 10,5 |
| **Weitere Speicher und nachfrageseitige Flexibilitäten [GW]** | | | | | |
| **PV-Batteriespeicher** | 0,6 | 11,0 | 14,1 | 16,8 | 14,9 |
| **Großbatteriespeicher** | 0,4 | 3,6 | 3,8 | 3,8 | 3,8 |
| **DSM (Industrie und GHD)** | 1,5*** | 4,0 | 5,0 | 8,0 | 7,0 |
| **Klimaschutz** | | | | | |
| **$CO_2$-Limit (Mio. t $CO_2$)** | – | 120,0 | 120,0 | 120,0 | 60,0 |

## 14.2.3 Runtime Optimization

### Regional Direct Marketing

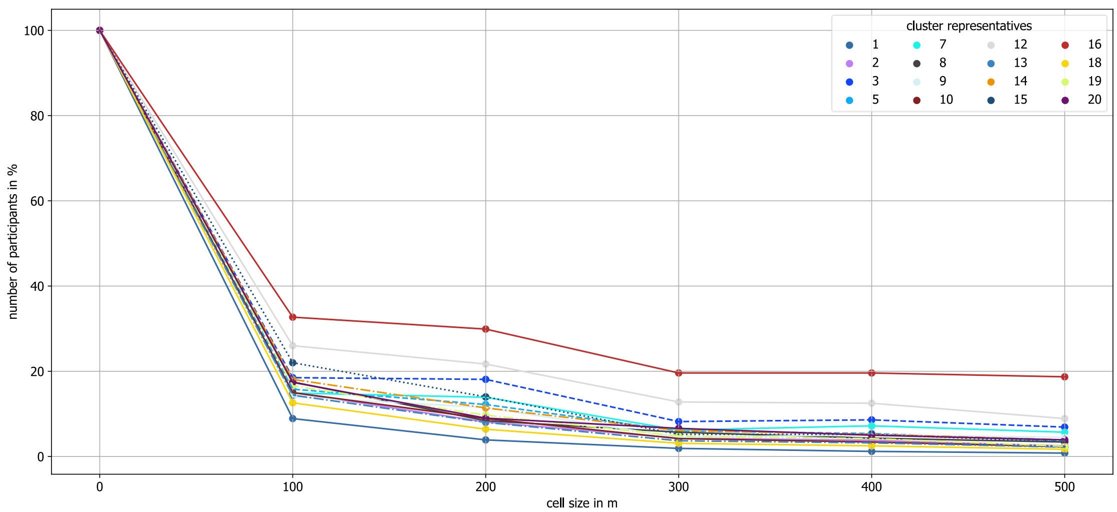



Figure 14-3: Reduction of participants if supply and demand are aggregated in different grid sizes (i.e., 100x100, 200x200 ...)

**Local Energy Markets**

Figure 14-4 (left) shows the average prices in all time steps for consumers and producers in the simulated 1,323 municipalities. The average price includes the price and turnover on the local energy market as well as the amount of residual load/surplus and exchange price.

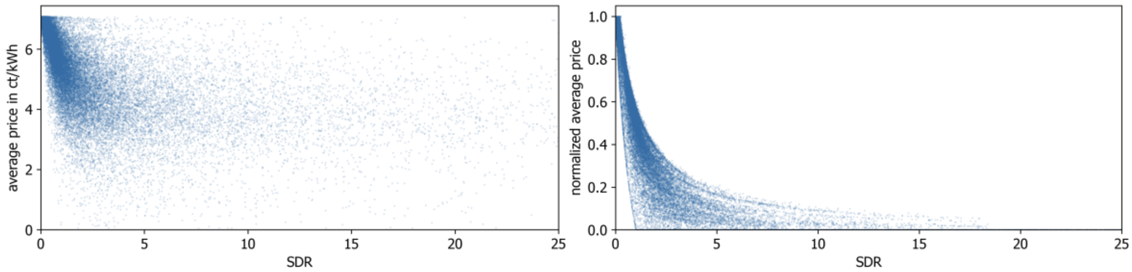



Figure 14-4: Behavior of the modeled price within municipalities based on the SDR. Average prices in each modeled time step (left) and normalized average time steps (right)

It also shows a rapid decrease in price with an increasing $SDR_t$, starting from the retail price. The normalized price is a min-max normalization with retail and wholesale prices as upper and lower bound. A value of 1 resembles the retail price as average price in the municipality; a value of 0 the exchange price. The prices show a high (non-linear) correlation to the $SDR_t$ within each municipality. They approach the exchange electricity price as the SDR increases. At an $SDR_t$ of 18 or higher (18 times more supply than demand), the price within the community lies within a 5% deviation from the exchange price. To reduce simulation time, an $SDR_t \geq 18$ in a time step is not modeled; instead the exchange price used as a uniform price of the market.

## 14.3 Clustering

In this section, additional data and information for the clustering process is provided.

### 14.3.1 General Cluster Notation

The notation used in this work is described in the following, based on [169]

Table 14-3: Notation for the clustering process

| Abbreviation | Explanation |
|---|---|
| $D$ | Set of $n$ datapoints with $D = x_1, \ldots, x_n$ and $x_1, \ldots, x_n$ in Euclidean space |
| $C$ | Set of clusters or strata with $C = \{C_1, \ldots, C_K\}$ with $C_j \in D$ and $j = 1, \ldots, K$ |
| $c_j$ | Centroid of a Cluster $C_j$ |
| $cr_j$ | Cluster representative of a Cluster $C_j$ (e.g. medoid, centroid or closest point to centroid) |
| $n_j$ | Number of datapoints or objects in $C_j$ or a population $P$ |
| $P$ | Population of size $N$ |
| $S$ | Sample of $n_j$ objects from $P$ or $C_j$ |

Table 14-4: CVI from [A2], based on [169]

| Name | Abbreviation | Usage |
|---|---|---|
| average within-cluster distance | $I_{avg_{wc}}$ | Measure of similarity of objects/points in a cluster. The higher the index, the smaller the average within-cluster distance. |
| p-separation-index | $I_{p-sep}$ | Measures separation between clusters. Instead of minimum/maximum distance (prone to outliers) this can be calculated by a mean of a portion (p) between two clusters. The higher the index, the better the between-cluster separation. |
| Representation by centroids | $I_{centroid}$ | Measure of how well a cluster is represented by its centroid. The higher the index, the better the representation. |
| Representation of dissimilarity structure by clustering | $I_{Pearson}$ | Measure of the dissimilarity structure denoted by the Pearson correlation between pairwise dissimilarities (e.g., Euclidean distances) and "clustering induced dissimilarity" (matching cluster). For increasing dissimilarity, objects/points should not be assigned to the same cluster. Hence for higher indices, pairwise dissimilarity correlates stronger to clustering dissimilarity. |
| within-cluster gaps | $I_{widestgap}$ | Measure of the connectivity of a cluster. The higher the index, the smaller the within-cluster gaps. The higher the index, the lower the within-cluster gaps. |
| Entropy | $I_{Entropy}$ | Measure for assessing the uniform size of clusters. |
| Parsimony | $I_{Parsimony}$ | Measure to express the preference for a lower number of clusters |
| Density modes and valleys | $I_{densdec}$ | Measure to quantify the density drop from cluster-mode to the edges of a cluster and the density-valleys between clusters |
| Uniform within-cluster density | $I_{cvdens}$ | Measure to quantify the within-cluster density levels. For higher indices, density is more uniform within the cluster. |

### 14.3.2 Dataset and Preprocessing

Table 14-5: Dataset (Features) for the clustering

| Name | Explanation and Source |
|---|---|
| Area | The area of the municipalities is calculated using the geometries from [181]. |
| Building types | The number of different building types results from the census [126]. These are also assigned using the official municipality keys. A distinction is made between total buildings, detached houses, semi-detached houses, terraced houses and other building types. |
| Settlement area | The basis are polygons from OpenStreetMap data (filter: landuse='residential') [241]. |
| Settlement patches | Settlement patches are contiguous, dense settlement areas. The settlement patches originate from OSM polygons and were added as follows:<br>The centers of the OSM buildings were clustered using DBSCAN (max. 150 m spacing, min. 5 buildings per cluster). The points of each cluster were converted to a polygon (synthetic settlement patch) using st_concavehull (param_pctconvex = 0.8). The resulting dataset has a settlement area of about 29,000 km² for Germany, whereas the OSM polygons alone have a settlement area of 25,000 km².<br>From these polygons, their number per municipality, average area as well as the smallest distances to the next patch were derived. |
| Wind turbines<br>(WT) | The data for the status quo comes from the MaStR [132] Data for the scenario was taken from the network development plans (NEP 2019 Scenario B) [242].<br>Data was categorized according to the following logic:<br>Hub height < 120 and power < 1 MW.<br>→ old WT<br>Hub height < 120 and power >= 1<br>→ strong wind turbine<br>Hub height >= 120 and power >= 1<br>→ low wind turbine<br>Power < 1 → old WTG<br>Power > 2.5 → strong wind turbine<br>Power <= 2.5 → low wind turbine |
| PV | The data for the status quo comes from the MaStR [132] Data for the scenario was taken from the network development plans (NEP 2019 Scenario B) [242] These are separated into ground-mounted and rooftop PV. |
| PV full load hours | PV full load hours are taken from [243] and were transferred from NUTS-3 level to municipality level. |
| WT full load hours | The wind turbine full load hours are taken from [123] and are regionalized as PV full load hours. |
| Wind speeds | The geometries of municipalities were intersected with those of the COSMO-EU 7.5 km grid. Wind speeds at 100 m height were extracted from the corresponding COSMO-EU cell [123]. |
| PV potential | The potential is divided into rooftop PB according to [244] or NEPv2019 [242] and groundmounted PV according to NEP v2019 [242]. |
| Population | The census data sets are assigned via the official municipality key (ags, id_ags) and originate from the 2011 census [126]. |
| Hydropower<br>(number & power) | The data are taken from [142] and [245]. They include run-of-river and storage hydropower plants with natural inflow. No pumped storage. |

| | |
|---|---|
| Biomass (number & power) | The data are taken from the MaStR [132]. |
| PV and wind load profiles | The installed capacity was multiplied by the respective normalized load profiles available at NUTS-3 level [123, 243]. |
| Number of households & electricity consumption by household size | The data comes from the 2011 census [126] |
| Household loads | The household sizes from the 2011 census were each offset with the corresponding standard load profiles H0 (including type days and seasons) [246]. |
| Hydropower load profile | Electricity from hydropower for 2019 was distributed to the municipalities based on installed capacity (run-of-river and storage hydropower only). The same normalized load profile was used for all municipalities. |
| Biomass load profile | Electricity from biomass for 2019 was distributed to the municipalities based on the installed capacity. The load profiles are originally available at NUTS-3 level and are therefore identical for all municipalities in the same NUTS-3 region. [142, 247]. |
| Self-sufficiency | Balance-sheet self-sufficiency divides the total energy supplied by generation through the total energy demand of consumers[183]. |
| Self-consumption rate | "The self-consumption rate is the quotient of the energy used directly on site [...] and the total energy" that is "supplied by the producers" [183] |
| Degree of self-sufficiency | "The degree of self-sufficiency relates the self-generated and simultaneously self-used energy to the total energy consumption." [248] |
| RE generation | The sum of the load profiles for PV, wind (onshore), hydro and biomass per municipality was calculated. |
| Share of old buildings | From the 2011 census [126], the building age classes before 1919 to 1978 were set in relation to the total building stock per municipality |
| Residual load | Difference of the generation value per time step minus the consumption value. |

**Correlation Analysis and Feature Selection**

In most machine learning workflows, feature selection is an important process, which aims at removing irrelevant and/or redundant features from the data set, enhancing computing times due to the reduced size of the dataset. According to [249], these methods can be divided into three main groups. Filter approaches aim at selecting relevant features by intrinsic properties of the data itself. They are fast and easily scalable, as opposed to so-called wrapper methods. These already include a specific clustering algorithm in order to find the best feature subset, which makes them very computationally expensive. In order to utilize the advantages of the other approaches, hybrid methods include a filter stage to reduce the number of features processed in the following wrapper stage, which has a positive effect on the computational effort [249].

Filter methods can further be divided into univariate and multivariate filters. While the former derive feature importance by analyzing features in isolation, the latter include inter-dependence between two or more features [250]. Thus, univariate filters are able to identify relevant features but are unable to find correlated features. Some basic univariate filter methods include the removal of constant and quasi-constant features, where constant features are those where every sample has the same value, while quasi-constant features have the same value for a certain (user-defined) share of observations (threshold). Applied to the data used for this work neither constant nor quasi-constant features (threshold = 90 %) could be identified.

Correlation filter methods are multivariate filter methods that facilitate the identification redundant features by analyzing their dependency on each other. Pearson's correlation coefficient quantifies the linear dependency between two variables x and y as formulated in 14-1:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad 14\text{-}1$$

$r_{xy}$ Pearson's Correlation Coefficient for variables *x* and *y*

This is a parametric test, which carries some assumptions about the data (e. g. normality). Thus, the coefficient is easily misinterpreted if any of those are violated [251].

Another widely used method is Spearman's rank correlation coefficient – a non-parametric measures dependency between two variables not by the values themselves but their rank in the sorted feature vector [252]: The Spearman's rank correlation coefficient is shown in 14-2.

$$\rho_{xy} = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2 - 1)} \quad 14\text{-}2$$

$\rho_{xy}$ Pearson's Correlation Coefficient for variables *x* and *y*

$d_i$ difference between $rank_{x,i}$ and $rank_{y,i}$

As opposed to Pearson's, the rank-based nature of Spearman's Correlation Coefficient makes robust against outliers [251].

Kendall's rank Correlation Coefficient is another non-parametric test that quantifies the strength of the relationship between two variables based on the degree of concordance of their ranks [253]:

$$\tau_{x,y} = \frac{(P - Q)}{\sqrt{(P + Q + T)(P + Q + U)}} \quad 14\text{-}3$$

$\tau_{xy}$ Kendall's rank Correlation Coefficient for variables *x* and *y*

P number of concordant pairs

Q number of discordant pairs

T number of ties only in *x*

U number of ties only in *y*

All three correlation coefficients take values in the range between -1 and 1, where 1 indicates a perfect positive correlation and -1 can be interpreted as a perfect negative correlation. No association between the two variables can be assumed, if the coefficient equals to 0.

The 57 features of the dataset have been analyzed for pairwise inter-dependencies based on these measures. The result showed highly correlated features within the dataset. For example, the annual energy consumption correlates to the settlement area, since more settlement area implies more inhabitants and hence more energy consumption. The selection process, to exclude highly correlated data, is shown in Figure 14-5.

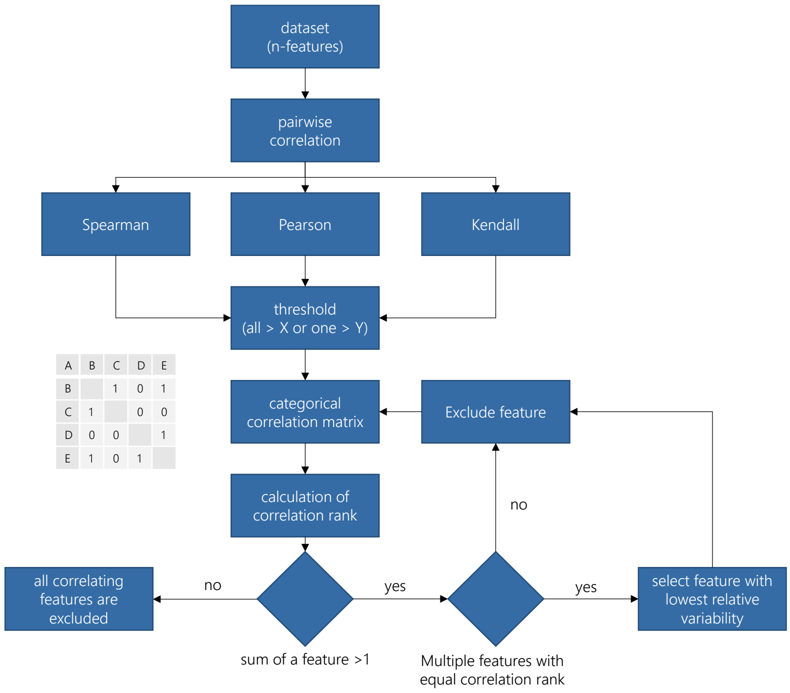



Figure 14-5: Applied feature selection process to remove pairwise correlated features

Figure 14-5 shows the process of feature selection. Pairwise (linear) feature correlation is calculated for the entire dataset including all three methods (Spearman, Pearson, Kendall). A threshold (here: one > +/-0.9) was set above which two features are considered highly correlating. If the threshold is exceeded by one correlation algorithm for a pair of features, the corresponding value is set to one in the correlation matrix. The sum for every column within this matrix expresses the correlation rank of each feature. In an iterative process, features with the highest correlation are excluded from the dataset until no feature has a rank > 1. The resulting dataset includes only features that are not highly correlated, according to the set threshold of 0.9.

The dataset, initially consisting of 57 features, was reduced to 32 features (56 %) due to this process. This decreases the computational costs of the clustering process.

### Scaling

Machine learning algorithms use measures of distance to determine the similarity of two datapoints (= n-dimensional vectors) $a$ and $b$. A distance metric is a function that "associates to any pair of vectors a real positive number" [254] The chosen distance metric is highly dependent on the predominant datatypes in the features. The methodology in chapter 6.3 may apply for different data-types (e. g. binary, categorical, continuous, ordinal) and therefore requires different distance-metrics.

Distance measures include Manhattan (integer feature space), Kullback-Leibler (probability distribution), Hamming distance (binary feature space) or Minkowski Distance (distance between two objects e. g. images) [254].

This work will only consider continuous numeric features within n-dimensional Euclidean space. Hence, Euclidean distance is the measure of choice in this work due to continuous feature space in the dataset. The Euclidean distance is shown in formula 6-1 for two n-dimensional vectors $a = a_1, \dots, a_n$ and $b = b_1, \dots, b_n$.

$$EUD_{(p,q)} = \sqrt{\sum_{n=1}^{N} (a_i - b_i)^2} \qquad 14\text{-}4$$

Since the calculation of the distance depends on the relative size of the included features, those that are very large would dominate. Therefore, all features must be scaled so that they all lie in e. g. in the range between 0 and 1, for example. For the given dataset, the Scikit-Learn Standard Scaler was applied to remove the mean and scale to unit variance [215, 255].

### 14.3.3 Cluster Validation Indices

In the following, CVIs are shown for exemplary data and for the municipality dataset, as used in section 6.

**Exemplary Data**

In the following, the normalized cluster validation indices, as proposed in [169] are compared, utilizing the depicted standard scikit-learn datasets from [215] in Figure 14-6 with the ground truth as reference.

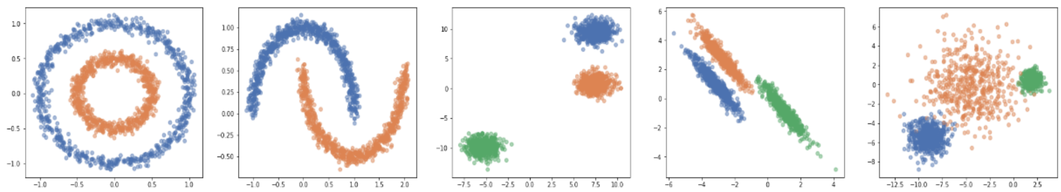


Figure 14-6: Toy datasets with different properties from scikit-learn from A (left) to E (right)

Table 14-6: Resulting sCVI on the toy datasets from A (left) to E (right)

| Indices | A | B | C | D | E |
|---|---|---|---|---|---|
| $I_{withindis}$ | 0.563 | 0.695 | 0.932 | 0.865 | 0.853 |
| $I_{p\text{-}sep}$ | 0.144 | 0.157 | 0.267 | 0.081 | 0.108 |
| $I_{centroid}$ | 0.663 | 0.764 | 0.953 | 0.906 | 0.896 |
| $I_{cp2cent}$ | 0.602 | 0.763 | 0.953 | 0.906 | 0.896 |
| $I_{Pearsonr}$ | 0.550 | 0.719 | 0.902 | 0.798 | 0.869 |
| $I_{widestgap}$ | 0.905 | 0.948 | 0.945 | 0.880 | 0.823 |
| $I_{densdec}$ | 0.980 | 0.968 | 0.975 | 0.979 | 0.989 |
| $I_{cvdens}$ | 0.977 | 0.967 | 0.955 | 0.941 | 0.954 |

The results for $I_{centroid}$ show a relatively low value for A and B. Due to its circle and moon shape, a centroid is relatively distant to all points of its cluster. The result for $I_{cp2cent}$ is lower for A, since there are no points close to a centroid. With dense clusters in C to D, the real datapoints are close to the centroid so the values are identical to $I_{centroid}$. This shows the value of the new index in these types of datasets yet also shows a high correlation of these two indices. It should be avoided to use both at the same time. With $I_{Pearson\Gamma}$, a high value can be identified from C to E. This indicates a strong correlation of large distances with cluster dissimilarities. In A & B this correlation is much lower since large pairwise distances do not necessarily indicate different cluster affiliation. The $I_{p-sep}$ shows relatively low values in D and E due to close proximity and overlapping of different clusters. With decreasing proximity of clusters (from C, A to B), these values increase. $I_{withindis}$ shows a very low average within-cluster distance in C, D and E. In contrast, due to their elongated shape, A and B show a much higher $I_{withindis}$. $I_{widestgap}$ denotes the widest within-cluster gap. Since all clusters in these examples are well connected and relatively dense, the values are generally high with a minimum in E, due to its lower density.

$I_{densdec}$ is an indicator for the density drop from the mode (i.e. density maximum) to "outskirts" of the cluster. As no clusters in these exemplary datasets show increasing densities towards their edges or density valleys within clusters, $I_{densdec}$ is high in all cases A-E. The coefficient of variation $I_{cvdens}$ gives implications about the uniformity of clusters [169]. Again, all clusters have rather uniform densities, leading to high values.

### CVI on Municipality Dataset

In the following figures, the single cluster validation indices (after calibration) are shown. These CVIs are used in conjunction with the weights, introduced in section 6.5. The mathematical formulation of the CVI was introduced in [169]. A detailed explanation for each CVI (as used in the captions) was already provided in [A2].

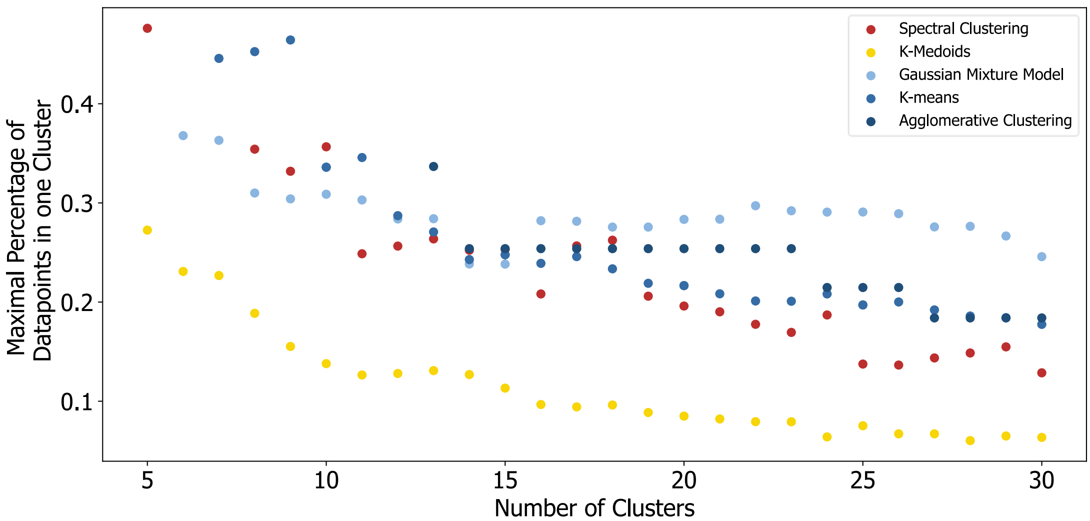



Figure 14-7: Maximum cluster size for different numbers of clusters and algorithms for all remaining clusterings, with a maximum cluster size of < 50 %

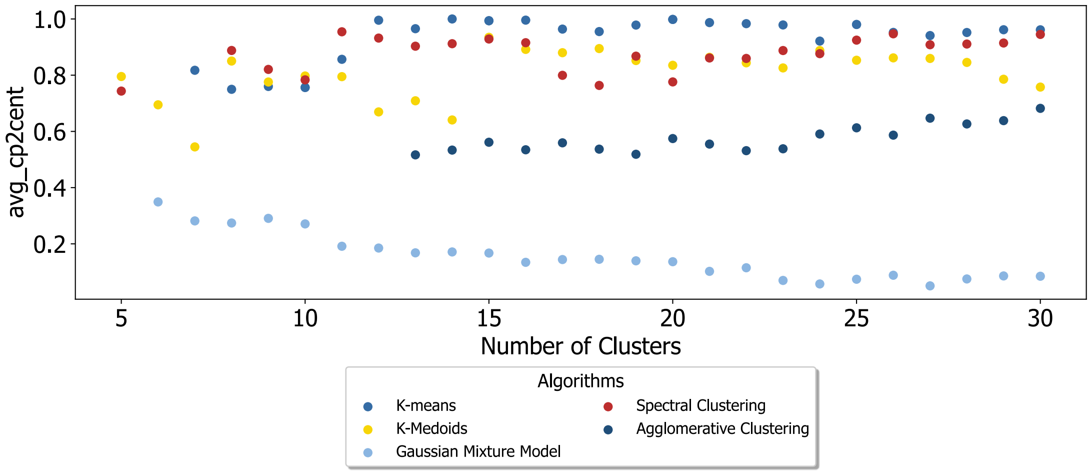



Figure 14-8: The average point to the "closest point to the centroid" (cp2cent) is a measure of the representation of a cluster by its centroid

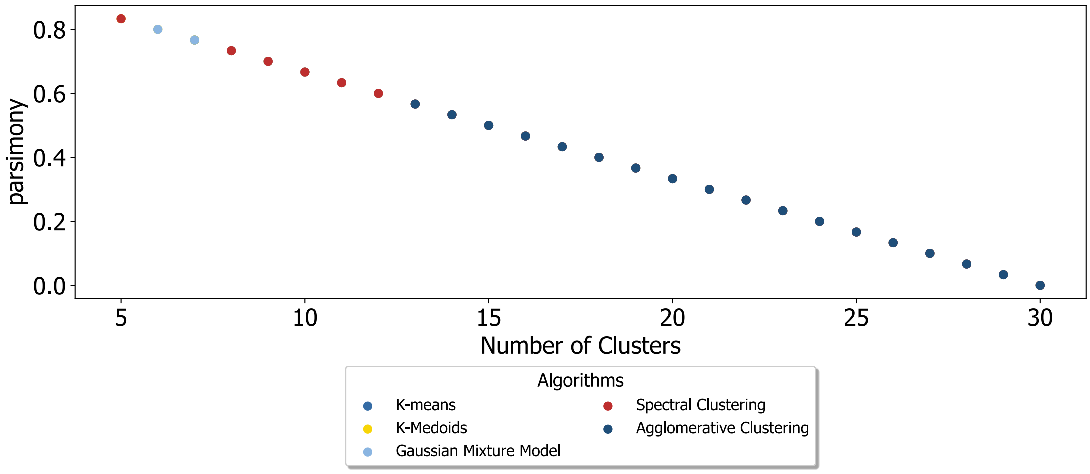



Figure 14-9: Parsimony shows a linear tendency towards a lower number of clusters (maximum here: 30) [169]

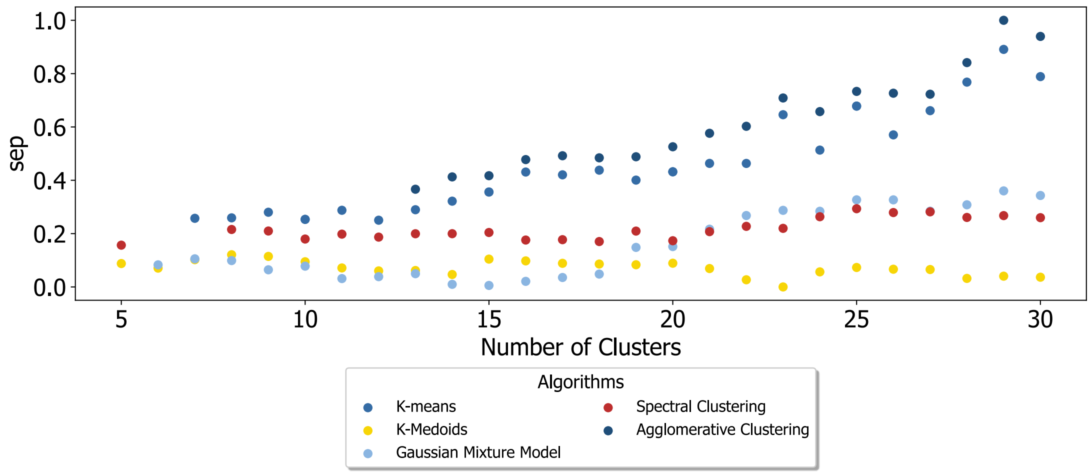



Figure 14-10: P-separation index for cluster sizes in the range of 5 to 30 for five different clustering algorithms. This quantifies the separation between clusters. Instead of minimum/maximum distance (prone to outliers) utilizes the mean of a portion (p) between two clusters (here: 10 %) [169]

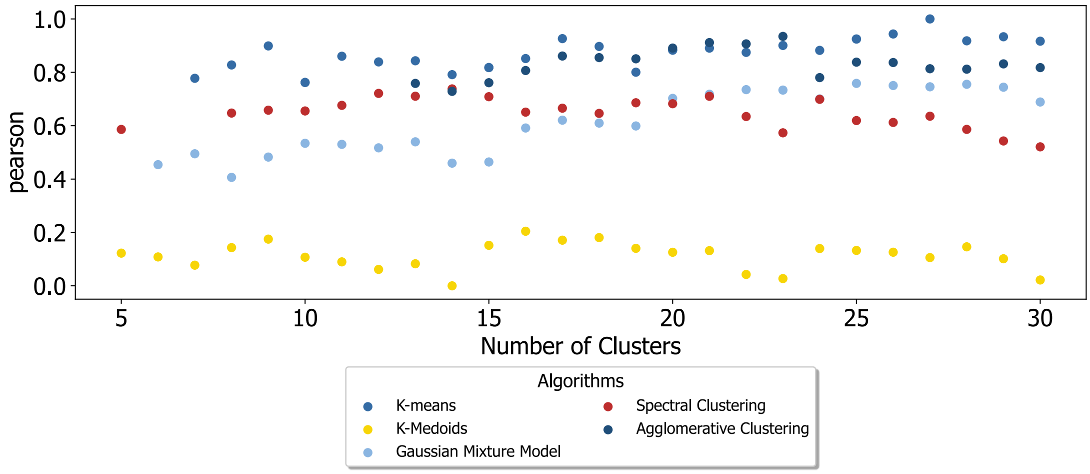



Figure 14-11: Representation of dissimilarity structure via the sample Pearson correlation [169]

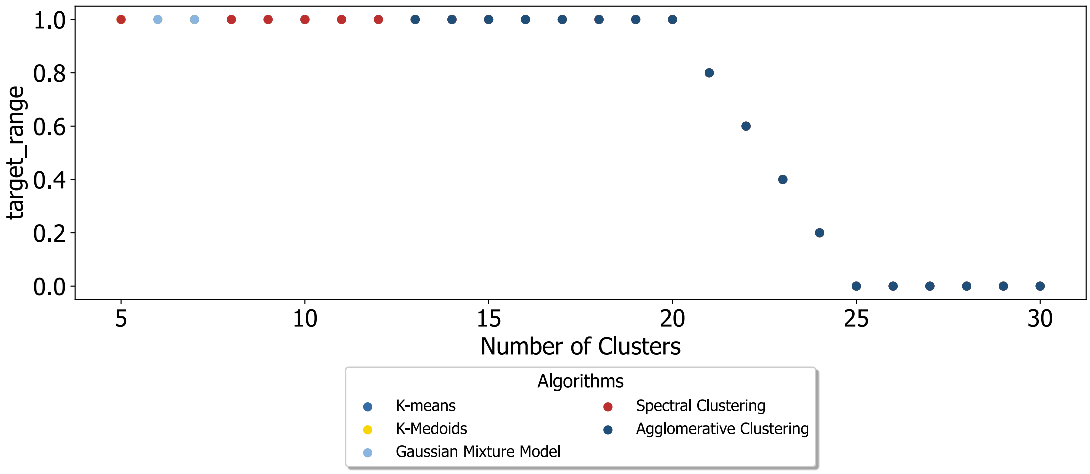



Figure 14-12: The target range penalizes clusterings above a given threshold (here: 20) down to a non-acceptable threshold (here: 25)

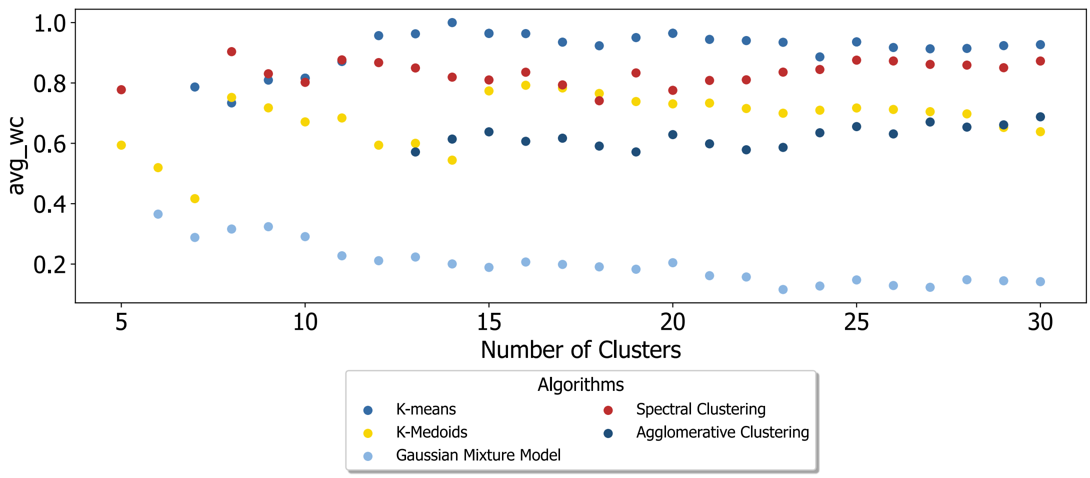



Figure 14-13: Within-cluster gaps are a measure of similarity of objects/points within a cluster [169]

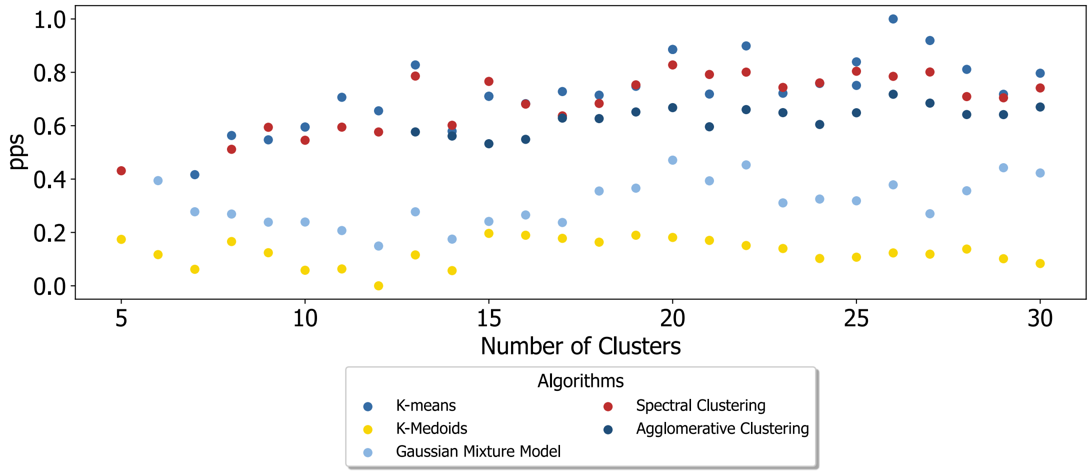



Figure 14-14: Predictive power score for cluster sizes in the range of 5 to 30 for five different clustering algorithms. This is a measure of how describable clusters are by a low number of features (introduced in [A2]

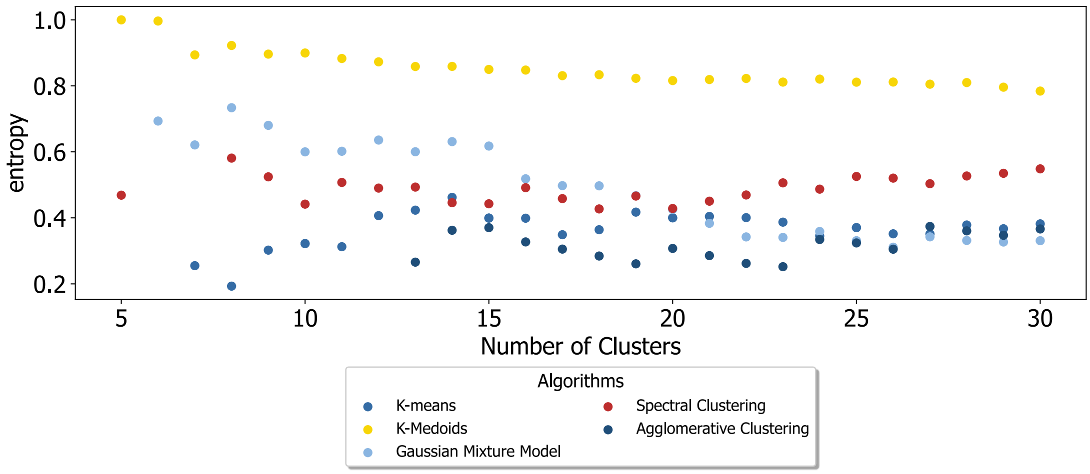



Figure 14-15: Entropy indicates a tendency towards a uniformity of cluster sizes [169]

### 14.3.4 Energy-Economical Clustering Results

In this section, additional energy-economic data and visualizations are depicted.

**Cluster Comparison**

The following radar plots illustrate a comparison of the resulting 20 clusters with standardized features for the following categories:

- Building structure
- Settlement Structure
- Consumption
- Generation
- Renewable Energy Potential
- Structure of Residual Load

### Cluster Profiles

Figure 14-16 shows the ranks of the cluster features of the municipalities. The higher the rank, the higher the features of a certain cluster compared to the others. The ranks within each feature always correspond to the cluster number.

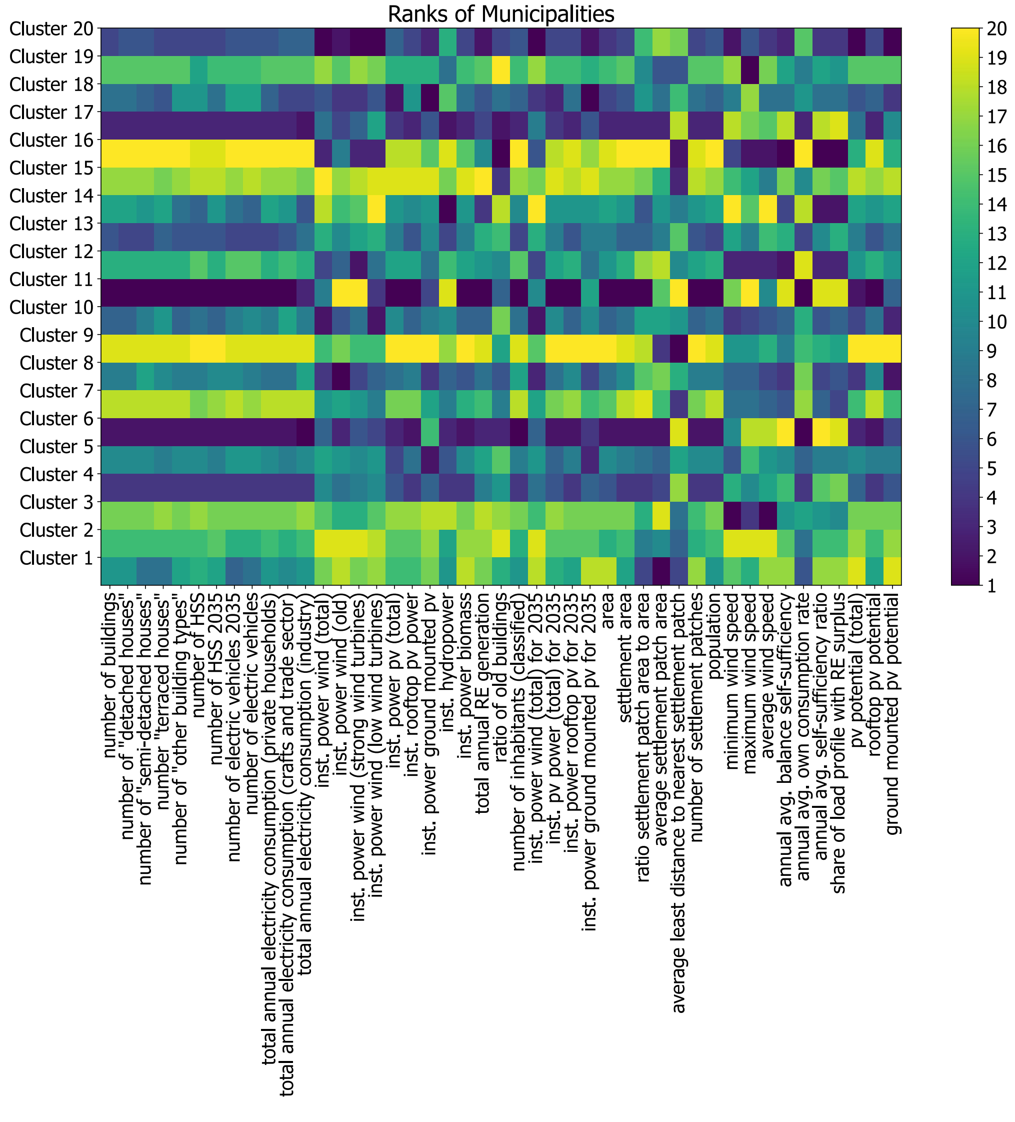
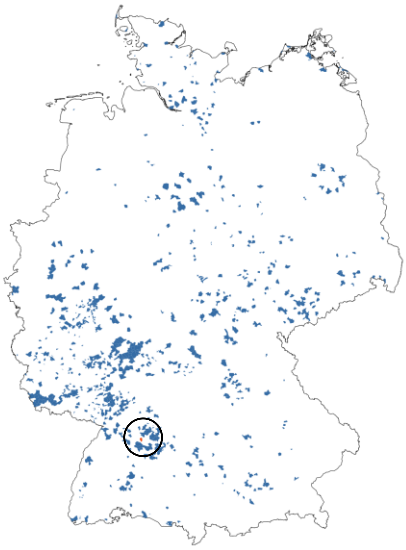
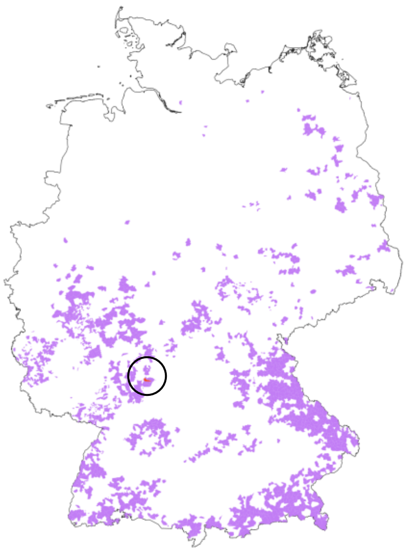
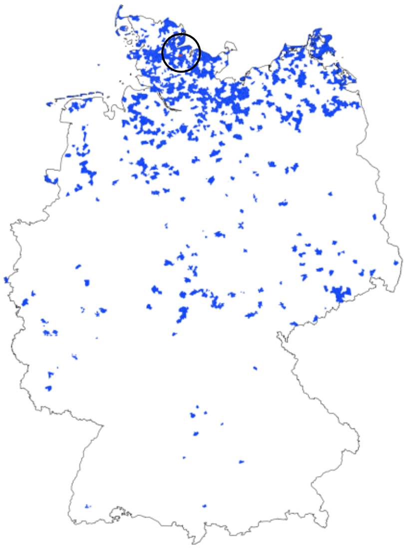


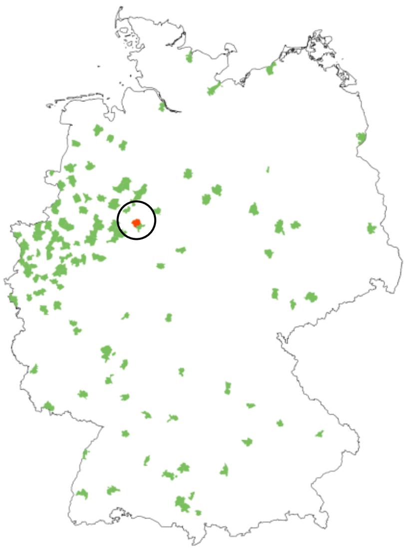

Figure 14-16: Ranks from 1 (biggest) to 20 (smallest) of the mean features of all 20 clusters

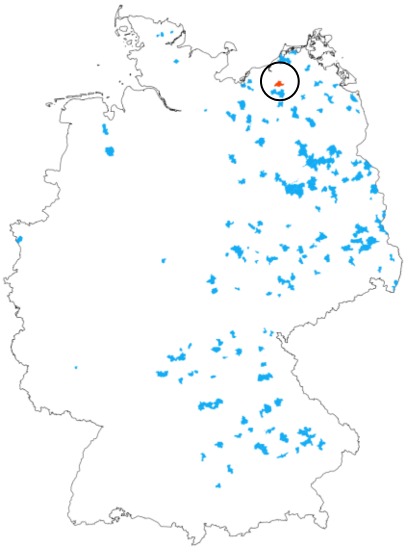
In the following, clusters are described and visualized on maps. The cluster profiles include a description of the typical municipality e.g., the population of each municipality (25th and 75th quantile) as well as information about individual key characteristics. For each cluster, the importance of the entire cluster is highlighted, summarizing both cluster characteristics and number of municipalities in the cluster.

<table>
<tr><th>Cluster</th><th>1</th><th>Representative</th><th>Gerlingen (metropolitan area of Stuttgart)</th></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td>
<ul>
<li>number/percentage of municipalities in cluster:<br>957 / 8.0 %</li>
<li>suburbs of middle and south-west Germany with 5th highest population density and 2,500 – 13,500 inhabitants</li>
<li>7th highest potential for electric vehicles</li>
<li>8th in number of “terraced” and “semi-detached” houses</li>
<li>2nd lowest PV potential</li>
<li>3rd smallest mean area with high population density</li>
<li>3rd lowest wind potential and 5th lowest wind installations today</li>
<li>3rd lowest biomass installments</li>
</ul>
</td></tr>
<tr><td>Description of the entire cluster</td><td colspan="3">The entire cluster accounts for 12.7 % of the German population with 13.1 % of all buildings while only generating 3.1 % of renewable energy. Today, only 6.6 % of Germany’s PV capacity is installed in these areas but the potential accounts for 11.2 %. The municipalities include high shares of Germany’s annual electricity consumption of private households (12.6 %), crafts and trade sector (11.7 %) as well as industry (11.3 %).</td></tr>
</table>

<table>
<tr><th>Cluster</th><th>2</th><th>Representative</th><th>Weilbach (West of Würzburg, Bavaria)</th></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td>
<ul>
<li>number/percentage of municipalities in cluster:<br>1,913 / 15.9 %</li>
<li>middle and south-east Germany</li>
<li>municipalities with 1,000 – 5,000 inhabitants</li>
<li>2nd lowest installed wind and 2nd lowest wind speeds</li>
<li>4th lowest biomass capacities</li>
<li>4th lowest total RE generation, low PV potential</li>
<li>5th least PV installments</li>
</ul>
</td></tr>
<tr><td>Description of the entire cluster</td><td colspan="3">While the entire cluster accounts for 15.9 % of municipalities and 12.7 % of Germany’s area, only 4.9 % of renewable electricity is generated predominantly by rooftop PV (12.7 %). These municipalities account for 10.1 % of the total rooftop PV potential.</td></tr>
</table>

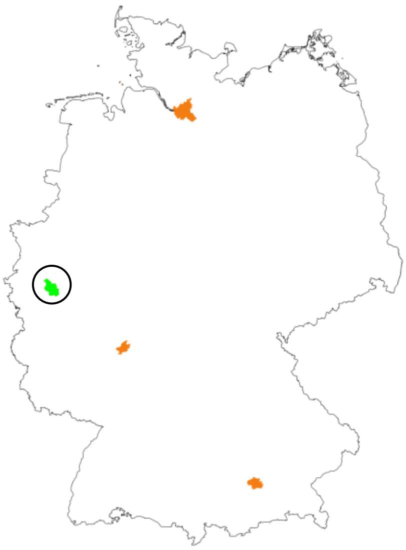
<table>
<tr><th>Cluster</th><th>3</th><th>Representative</th><th>Krummwisch (West of Kiel)</th></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td><ul>
<li>number/percentage of municipalities in cluster: 1,230 / 10.3 %</li>
<li>small municipalities in the north of Germany</li>
<li>municipalities with 500 – 2,000 inhabitants</li>
<li>1st highest average and minimum wind speeds but low installation in wind (15th)</li>
<li>4th least potential and installation in PV</li>
<li>3rd lowest RE generation (3rd lowest hydropower, ground mounted PV)</li>
<li>Low overall energy consumption in all sectors</li>
<li>5th lowest number of buildings, EVs and HSS</li>
</ul></td></tr>
<tr><td>Description of the entire cluster</td><td colspan="3">The 1,230 municipalities account for only 6.9 % of the entire German area but only 2.6 % of its population and 3.6 % of its buildings. The cluster holds great potential for wind energy due to high average wind speeds.</td></tr>
</table>

<table>
<tr><th>Cluster</th><th>4</th><th>Representative</th><th>Detmold (east of Bielefeld)</th></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td><ul>
<li>number/percentage of municipalities in cluster: 132 / 1.1 %</li>
<li>densely populated cities (4th highest population and population density) with 38,000 – 117,000 inhabitants in western Germany</li>
<li>4th highest population, number of buildings, number of settlement patches, number of EVs, inst. rooftop PV power and potential 2035</li>
<li>4th highest hydropower, biomass capacities, rooftop PV, electric vehicles and HSS</li>
<li>4th highest consumption and own consumption rate</li>
<li>5th lowest RE surplus</li>
</ul></td></tr>
<tr><td>Description of the entire cluster</td><td colspan="3">These densely populated cities account for 15.3 % of the German population, 12.9 % of buildings and 8.7 % of German inst. rooftop PV power. Additionally, 4.7 % of German power of biomass plants is located in these areas.</td></tr>
</table>

<table>
<tr><th>Cluster</th><th>5</th><th>Representative</th><th>Laage (south of Rostock)</th></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td>

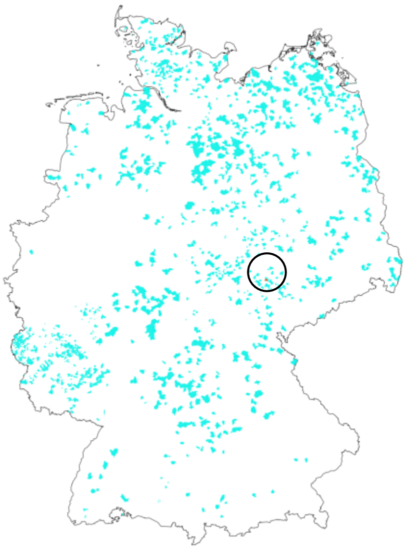
- number/percentage of municipalities in cluster: 174 / 1.5 %
- southern and eastern Germany
- municipalities with 3,500 – 13,500 inhabitants
- 2nd highest installed PV ground mounted and 3rd highest potential for 2035. 5th highest installed PV and 8th installed rooftop PV
- 6th in hydropower
- 7th in annual avg. own consumption rate

</td></tr>
<tr><td colspan="3">Description of the entire cluster</td><td>This cluster accounts for 1.5 % of the municipalities but for 3. 6 % of the total area. 25.8 % of German ground mounted PV capacities are allocated in these areas. This contributes to 9.9 % of the overall installed PV capacities.</td></tr>
</table>

<table>
<tr><th>Cluster</th><th>6</th><th>Representative</th><th>Cologne</th></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td>

- number/percentage of municipalities in cluster: 4 / 0.0 %
- 2nd biggest cities (except Berlin) with 921.500 – 1.438.000 inhabitants
- 2nd most buildings, settlement density, highest number of buildings and 3rd highest old-building ratio
- 2nd highest number of EV installments, 3rd in installed PV capacities, 2nd highest PV potential and 3rd inst. PV capacities in 2035
- 3rd in hydropower, 2nd in biomass, 3rd in total annual RE generation with highest own consumption rate but 2nd lowest surplus and least self-sufficiency
- 2nd highest consumption (private households and crafts and trade sector), highest annual industrial electricity consumption

</td></tr>
<tr><td colspan="3">Description of the entire cluster</td><td>These four biggest cities (except Berlin) only represent 0.5 % of the German area. 5.9 % of Germans live in these areas. The cities contribute to 18.5 % of German electricity consumption in the crafts and trade sector.</td></tr>
</table>

<table>
<tr><td>Cluster</td><td>7</td><td>Representative</td><td>Löbitz (south-west of Leipzig)</td></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td>

- number/percentage of municipalities in cluster: 1,543 / 12.8 %
- middle and north-eastern Germany
- municipalities with 500 – 1,500 inhabitants and $2^{nd}$ least population density
- $7^{th}$ in average wind speeds $9^{th}$ hydropower and $11^{th}$ in installed wind capacities
- $5^{th}$ least inst. PV and PV potential
- Low settlement density, $3^{rd}$ lowest number of buildings and population. Among lowest number of EVs ($4^{th}$)
- $3^{rd}$ least consumption and $4^{th}$ own consumption rate
- $11^{th}$ in installed wind capacities with average hydropower and biomass capacities
- Due to very low consumption, the municipality has the $5^{th}$ highest share of RE-surplus

</td></tr>
<tr><td colspan="2">Description of the entire cluster</td><td colspan="2">The 1,543 municipalities, even though representing 8.6 % of German area only accommodate 2.2 % of the population. Due to high wind yields, 23.0 % percent of German wind capacities are installed in these areas, 10.6 % of biomass and 8.2 % of hydropower and 9.6 % of ground mounted PV capacities. The municipalities contribute 15.5 % of German renewable energy and characterized by high shares of share of load profiles with RE surplus.</td></tr>
</table>

<table>
<tr><td>Cluster</td><td>8</td><td>Representative</td><td>Anröchte (east of Dortmund)</td></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td>

- number/percentage of municipalities in cluster: 32 / 0.3 %
- northern German municipalities with 1,500 – 9,000 inhabitants
- Highest installed old wind turbines, high inst. wind capacity ($4^{th}$) and $3^{rd}$ highest wind potential.
- $4^{th}$ installed ground mounted PV and $2^{nd}$ highest ground mounted PV potential but only $8^{th}$ in currently installed PV capacity
- $4^{th}$ highest wind installations and $3^{rd}$ highest wind potential in 2035
- among highest self-sufficiency ($4^{th}$ ratio with high RE surplus ($6^{th}$) and $4^{th}$ highest annual avg. balance self-sufficiency rate (20 times more generation than consumption)

</td></tr>
<tr><td colspan="2">Description of the entire cluster</td><td colspan="2">These 32 municipalities cover 0.8 % of German area and 0.5 % of its population. Since they are located predominantly in the northern part of Germany, they contribute to 2.4 % of total installed wind capacities and 1.7 % of total annual renewable energy generation.</td></tr>
</table>

| Cluster | 9 | Representative | Henschtal (at Ramstein, Rhineland-Palatinate) |
|---|---|---|---|
|  | | | **Description of the typical municipality**<br>• number/percentage of municipalities in cluster: 305 / 2.5 %<br>• municipalities with 500 – 1,000 inhabitants, low settlement-density, $2^{nd}$ lowest number of buildings $2^{nd}$ smallest population, $2^{nd}$ least EV and lowest area<br>• Lowest PV installations and potential<br>• Both wind speeds and installed wind capacities are relatively low<br>• $2^{nd}$ lowest RE generation<br>• $2^{nd}$ least total annual electricity consumption<br>• $4^{th}$ least hydro power capacities, least biomass |
| **Description of the entire cluster** | | | These small municipalities cover only 0.8% of German area and only 0.2 % of its population. From an energy-economic perspective, these areas show neither relevant installed capacities nor potentials to install additional RE. |

| Cluster | 10 | Representative | Weener (East Frisia) |
|---|---|---|---|
|  | | | **Description of the typical municipality**<br>• number/percentage of municipalities in cluster: 191 / 1.6 %<br>• middle and north-western German municipalities with 3,000 – 15,500 inhabitants<br>• $2^{nd}$ highest in inst. wind power (predominantly low wind turbines)<br>• $2^{nd}$ highest inst. wind potential due to relatively high wind speeds ($6^{th}$ in average wind speed)<br>• $5^{th}$ in PV potential and $3^{rd}$ in ground mounted PV potential and ground mounted PV<br>• $5^{th}$ least old buildings |
| **Description of the entire cluster** | | | While only accounting for 1.6 % of all municipalities, due to their size, they cover 5.1% of German area and 3.0 % of its population. Due to high wind speeds, 19.1 % of German installed wind capacities are located in these areas. The cluster contributes 6.4% of installed biomass capacity and 11.6 % of German renewable generation. |

<table>
<tr><th>Cluster</th><th>11</th><th>Representative</th><th>Berlin</th></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td>

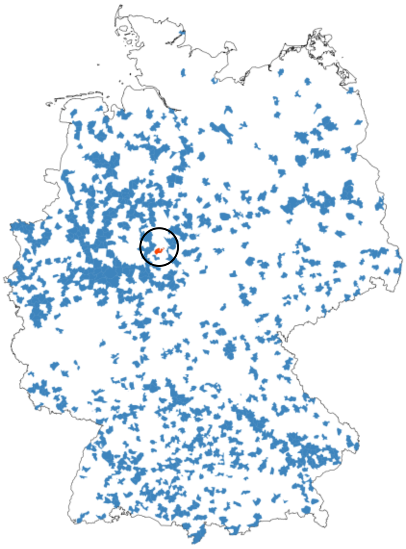
- number/percentage of municipalities in cluster: 1 / 0.0 %
- Biggest area, highest settlement-density, number of buildings, population (4,000,000), area, number of EV
- Largest PV rooftop PV and third largest total potential
- 2[nd] lowest hydropower, 1[st] in biomass
- Highest absolute RE generation
- Highest consumption, and consumption rate
- Lowest self-sufficiency ratio
- 2[nd] lowest RE surplus

</td></tr>
<tr><td>Description of the entire cluster</td><td colspan="3">4.1 % of Germans live in the municipality of Berlin, even though the area only covers 0.3 % of Germany. 1.7 % of buildings are located in Germany's capital city but account for 8.2 % of the German annual energy consumption of the crafts and trade sector.</td></tr>
</table>

<table>
<tr><th>Cluster</th><th>12</th><th>Representative</th><th>Gilten (north of Hannover)</th></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td>

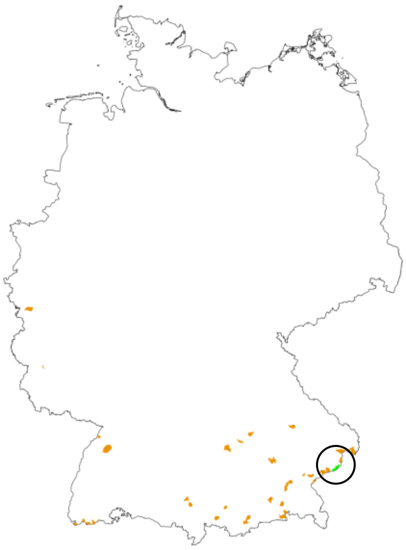
- number/percentage of municipalities in cluster: 273 / 2,3 %
- municipalities with 1,000 – 4,500 inhabitants in northern Germany
- 5[th] highest inst. wind power and 2[nd] in strong wind turbines
- 3[rd] highest average, maximum and minimum wind speeds
- 3[rd] in self-sufficiency and high RE-surplus
- 6[th] least electric vehicles and HSS
- 2[nd] highest annual avg. balance self-sufficiency ratio (24 times more generation than consumption)

</td></tr>
<tr><td colspan="2">Description of the entire cluster</td><td colspan="2">The cluster is located in the north of Germany and has high wind speeds. The 273 municipalities contribute to 19.5 % of German wind power and 10.9 % of total annual renewable electricity.</td></tr>
</table>

<table>
<tr><td>Cluster</td><td>13</td><td>Representative</td><td>Hofgeismar (Hessen, near Kassel)</td></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td>

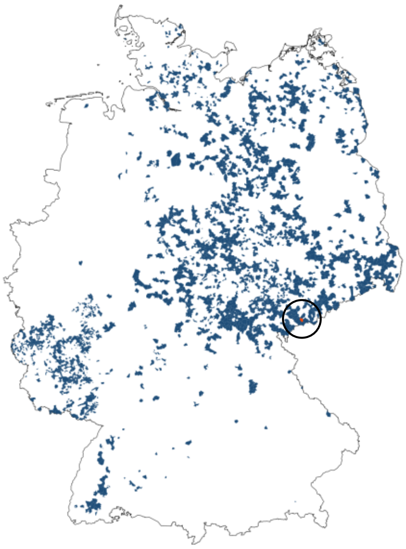
- number/percentage of municipalities in cluster: 876 / 7.3 %
- distributed in Germany
- municipalities with 8,000 – 22,000 inhabitants
- 5th highest population 6th in number of buildings, HSS and installed rooftop PV
- 5th in hydropower
- 6th in stalled rooftop PV and potential
- 5th highest own consumption rate

</td></tr>
<tr><td colspan="2">Description of the entire cluster</td><td colspan="2">Even though, they represent only 7.3 % of German municipalities, they cover 20.6 % of its area and 18.9 % of its population. It is thereby the cluster with the biggest area. Due to the high number of buildings (21.1 %) the municipalities contribute to 21.8% to the installed PV capacities in Germany and even 25.9 % of its rooftop PV. Hydropower (15.0 %) and biomass (23.7 %) capacities are high with high consumption (private households 18.5 %, crafts and trade sector 15.2 and industry 21.9 %).</td></tr>
</table>

<table>
<tr><td>Cluster</td><td>14</td><td>Representative</td><td>Bad Füssing (Inn)</td></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td>

- number/percentage of municipalities in cluster: 36 / 0.3 %
- South-East Germany (Bavaria)
- Municipalities with 3,000 – 10,000 inhabitants
- Most inst. Hydropower
- lowest average wind speeds, 3rd least installed wind power with lowest potential for 2035
- 4th highest RE generation
- 2nd highest RE surplus und 5th highest self-sufficiency ratio

</td></tr>
<tr><td colspan="3">Description of the entire cluster</td><td>These 36 small municipalities are located along German rivers in the south and hence cover 39.2 % of German hydropower capacity. This leads to a contribution of 3.8 % of the total annual RE generation</td></tr>
</table>

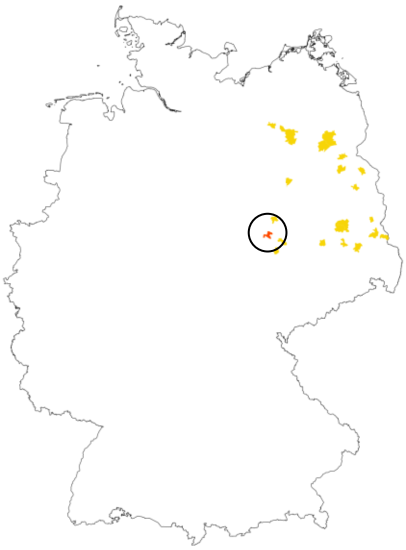
<table>
<tr><th>Cluster</th><th>15</th><th>Representative</th><th>Sosa (Erzgebirgskreis)</th></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td><ul><li>number/percentage of municipalities in cluster:<br>2,598 / 21.7 %</li><li>predominantly in middle and eastern Germany</li><li>municipalities with 500 – 2,000 inhabitants</li><li>4th smallest area, population, number of buildings and a high ratio of old buildings</li><li>lowest RE generation (least wind capacities, 2nd lowest biomass and PV, 5th lowest hydropower)</li><li>low potential for further renewables (2nd least PV, 5th wind)</li><li>Least annual RE generation</li></ul></td></tr>
<tr><td>Description of the entire cluster</td><td colspan="3">These 2,598 municipalities cover 13.5 % of German area (2nd biggest cluster) but only 5 % of its population and 6.7 % of its buildings. In terms of renewable generation, this cluster is at the lower end with only 0.8 %installed wind, 5.3 % installed PV and 4.1 % biomass capacity.</td></tr>
</table>

<table>
<tr><th>Cluster</th><th>16</th><th>Representative</th><th>Sprakebüll (Schleswig-Holstein)</th></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td><ul><li>number/percentage of municipalities in cluster:<br>44 / 0.4 %</li><li>Northern Germany</li><li>municipalities with 200 - 500 inhabitants, with lowest population, population density, lowest number of buildings and 2nd least area</li><li>Highest ratio of old buildings, highest share of RE surplus</li><li>2nd highest average and max. wind speeds and 3rd highest inst. wind capacity</li><li>Lowest electricity consumption, electric vehicles</li><li>3rd lowest inst. PV power and potential</li><li>highest self-sufficiency ratio and balanced self-sufficiency ratio (173 times more generation than consumption)</li></ul></td></tr>
<tr><td>Description of the entire cluster</td><td colspan="3">3.5 % of German wind capacities are located in these 44 small, northern municipalities due to high wind speeds. The municipalities cover 1.7 % of German annual renewable generation.</td></tr>
</table>

<table>
<tr><td>Cluster</td><td>17</td><td>Representative</td><td>Dresden</td></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td>

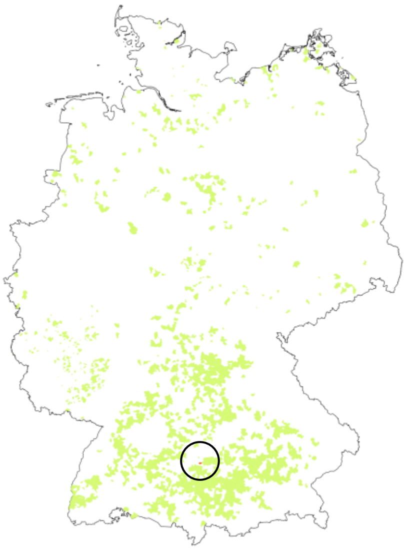
- number/percentage of municipalities in cluster:<br>19 / 0.2 %
- Middle West Germany
- Municipalities with 290.000 – 528.000 inhabitants, 3$^{rd}$ highest population density
- Second in hydropower and 3$^{rd}$ in biomass
- 3$^{rd}$ in population, area number of buildings and old building ratio, and number of EVs
- 3$^{rd}$ highest inst. PV power, rooftop installations and potential
- 2$^{nd}$ highest industrial electricity consumption and ratio of old buildings
- 3$^{rd}$ highest electricity consumption and among highest consumption rate
- 5$^{th}$ in RE generation but 2$^{nd}$ least share of RE surplus

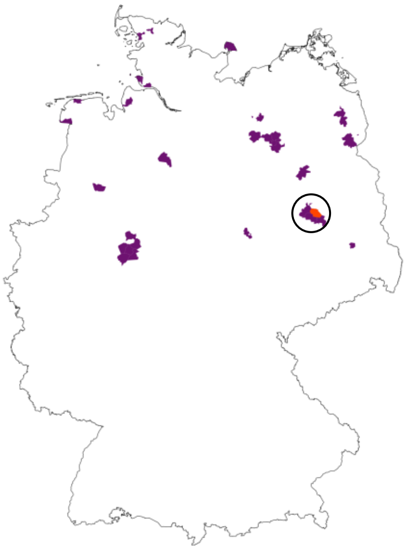
</td></tr>
<tr><td colspan="3">Description of the entire cluster</td><td>9.6 % of Germans live in these 19 cities. Especially high is the annual electricity consumption of the industry (12.1 ) and crafts and trade sectors (15.0 %)</td></tr>
</table>

<table>
<tr><td>Cluster</td><td>18</td><td>Representative</td><td>Köthen (Anhalt)</td></tr>
<tr><td colspan="3" rowspan="2"></td><td>Description of the typical municipality</td></tr>
<tr><td>

- number/percentage of municipalities in cluster:<br>21 / 0,2 %
- East Germany
- Municipalities with 4,000 – 17,000 inhabitants
- Highest installed capacities of ground mounted PV (2$^{nd}$ highest total PV), 3$^{rd}$ highest PV potential, and 4$^{th}$ highest wind potential
- 5$^{th}$ highest area and energy consumption
- 6$^{th}$ highest total renewable electricity generation
- 6$^{th}$ least hydropower

</td></tr>
<tr><td>Description of the entire cluster</td><td colspan="3">The special characteristic of these municipalities is their high share of ground mounted PV installments (12.1 % of the capacity).</td></tr>
</table>

<table>
<tr><th>Cluster</th><th>19</th><th>Representative</th><th>Rettenbach (near Günzburg)</th></tr>
<tr><td colspan="3">Map</td><td>Description of the typical municipality</td></tr>
<tr><td colspan="3"></td><td><ul><li>number/percentage of municipalities in cluster: 1,621 / 13.5 %</li><li>predominantly in the south of Germany</li><li>municipalities with 1,500 – 4,500 inhabitants</li><li>relatively densely populated</li><li>8th most installed hydropower capacities and 14th in biomass</li><li>13th in installed PV capacities and 6th lowest PV potential</li><li>lowest ratio of old buildings</li><li>3rd lowest installed wind capacities</li></ul></td></tr>
<tr><td>Description of the entire cluster</td><td colspan="3">These 1,621 municipalities cover 10.2 % of German area and are among the highest total PV (12.2 %), rooftop PV (13.4 %) and ground mounted PV capacities (9.4 %). Additionally, 10.3 % of German hydropower and 9.1 % of installed biomass capacities are located here.</td></tr>
</table>

<table>
<tr><th>Cluster</th><th>20</th><th>Representative</th><th>Jüterbog (south of Berlin)</th></tr>
<tr><td colspan="2">Map</td><td colspan="2">Description of the typical municipality</td></tr>
<tr><td colspan="2"></td><td colspan="2"><ul><li>number/percentage of municipalities in cluster: 33 / 0,3 %</li><li>big northern municipalities (4th largest) with 4.500 – 19,500 inhabitants</li><li>Highest total annual RE generation with many ground mounted PV plants (3rd), highest overall PV potential</li><li>most installed wind power, highest wind potential in Germany with highest potentials for 2035</li><li>2nd highest RE generation</li><li>5th highest number of buildings and HSS</li><li>3rd highest annual avg. balance self-sufficiency (23 times more generation than consumption)</li></ul></td></tr>
<tr><td>Description of the entire cluster</td><td colspan="3">These 33 municipalities in the north are characterized by their high share of installed wind capacities (9.5 %). This leads to them contributing 5.3 % of German renewable electricity.</td></tr>
</table>

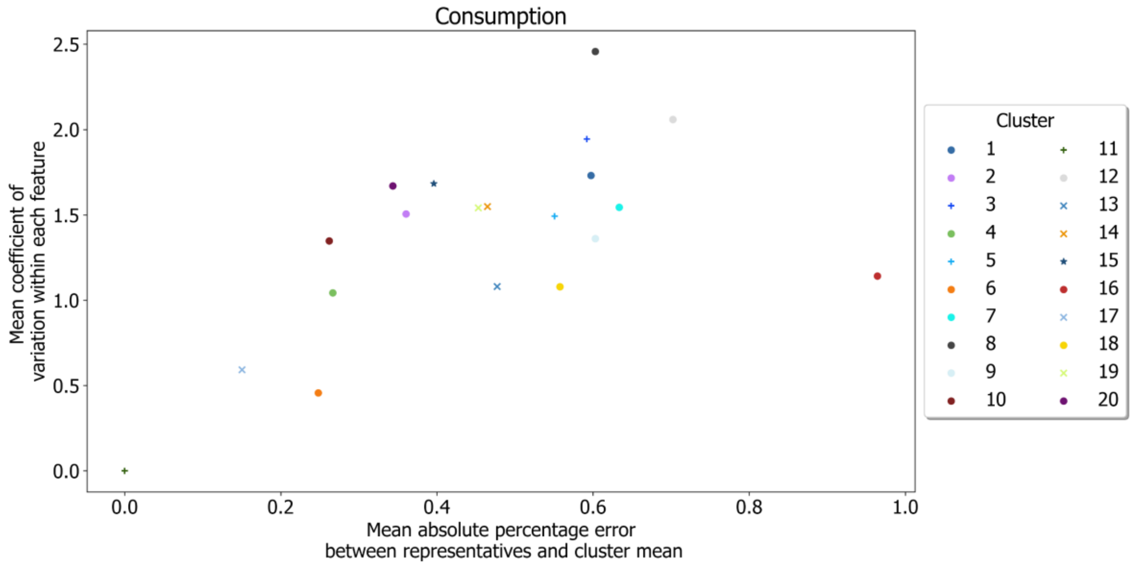



Figure 14-17: Mean coefficient of variation and mean absolute percentage error of all clusters and their representatives within the category “consumption”.

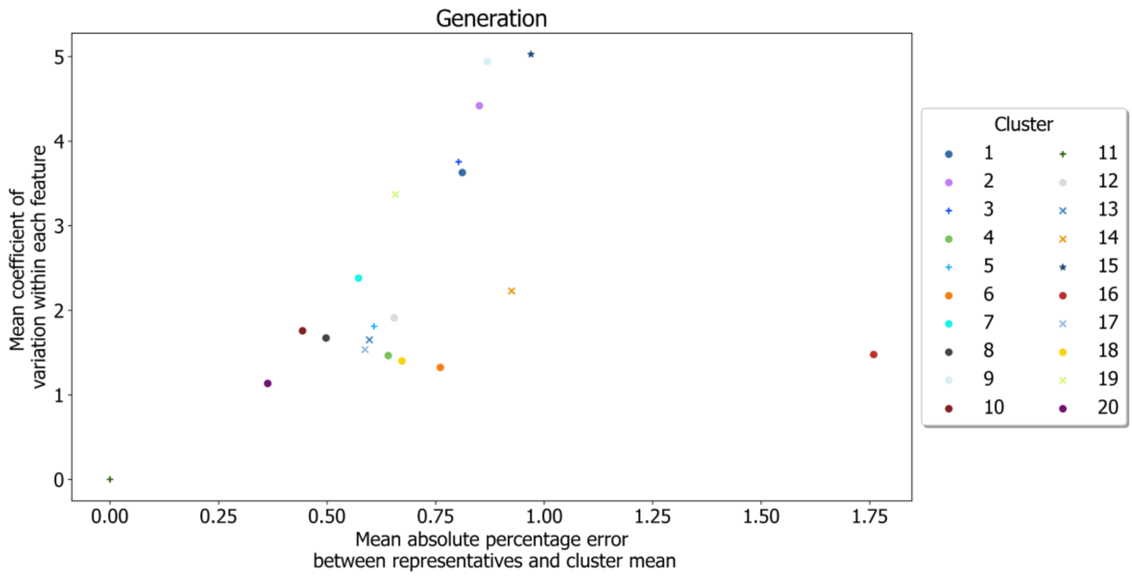



Figure 14-18: Mean coefficient of variation and mean absolute percentage error of all clusters and their representatives within the category “generation”.

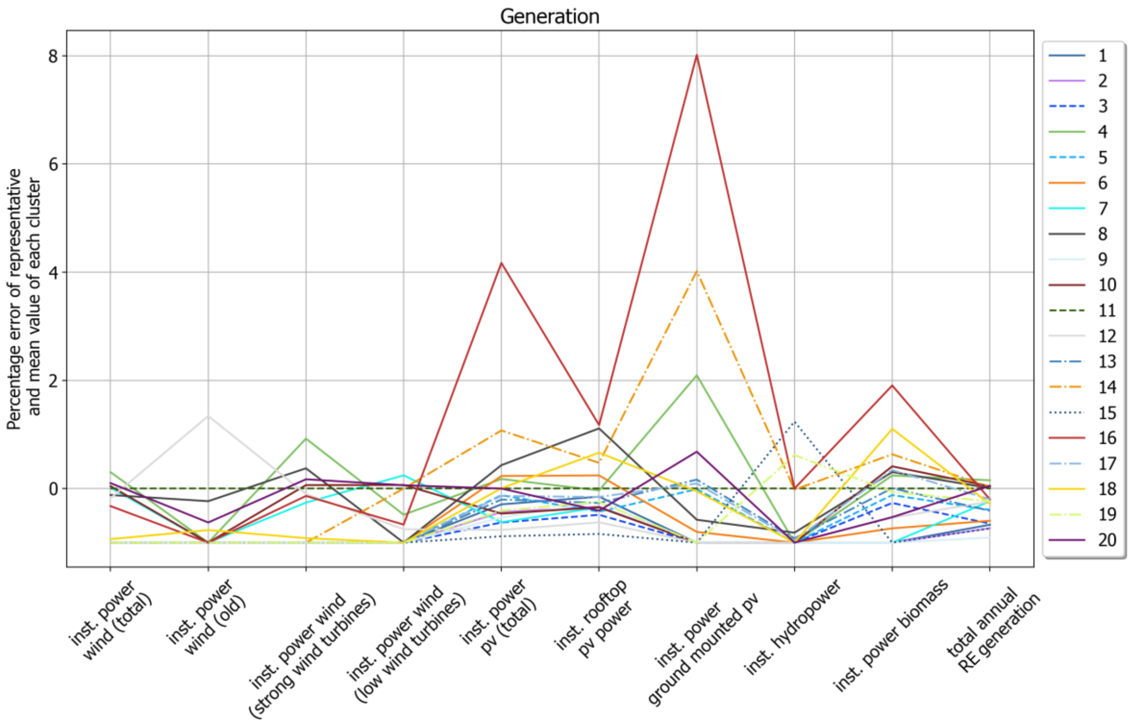



Figure 14-19: Percentage error of cluster mean and representative per feature and cluster in the category "generation".

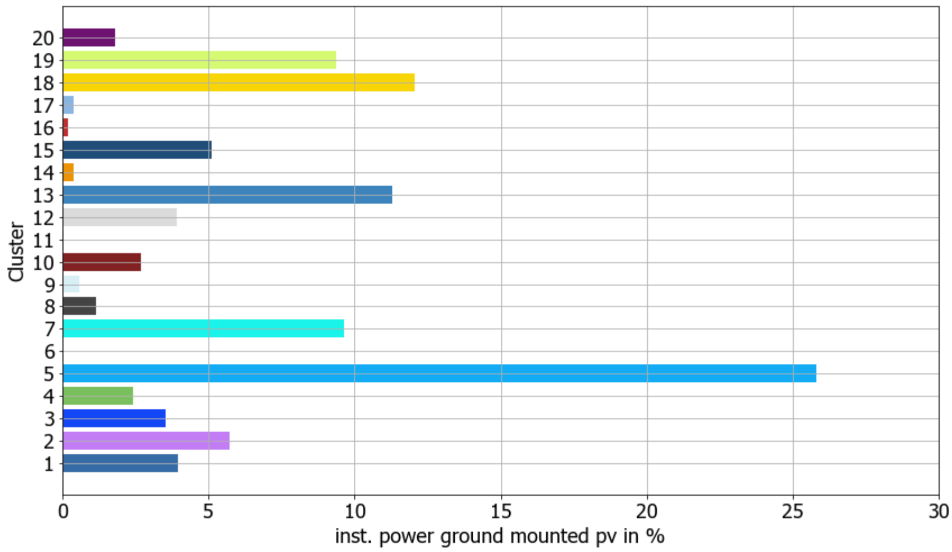



Figure 14-20: Distribution of German ground mounted PV in the resulting clusters (total).

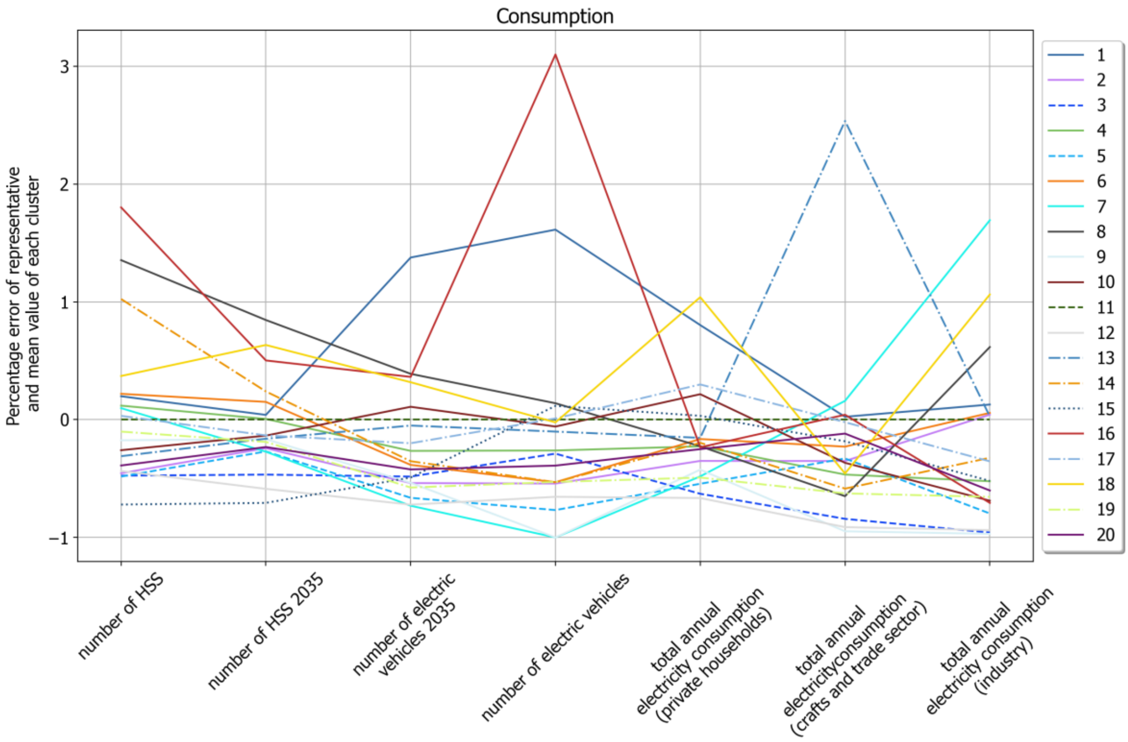



Figure 14-21: Percentage error of cluster mean and representative per feature and cluster in the category "consumption"

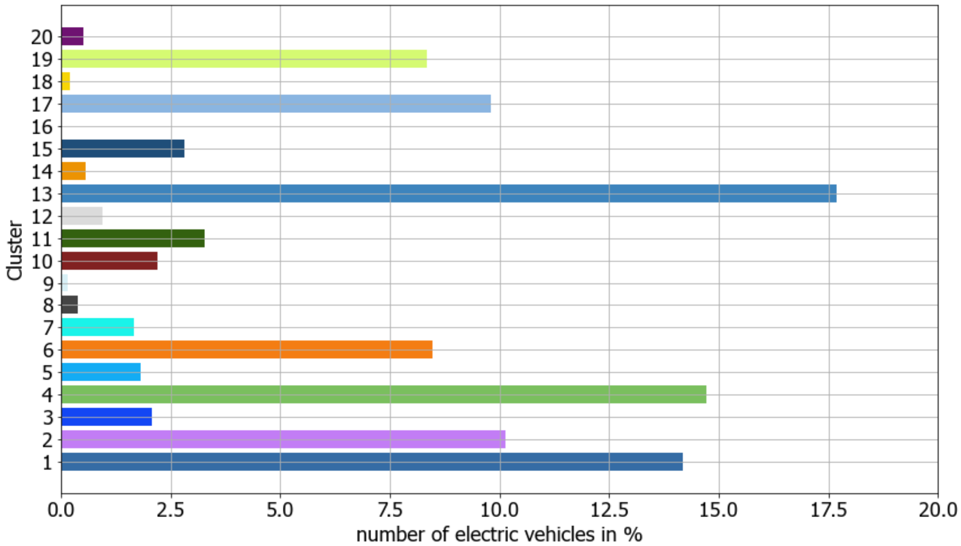



Figure 14-22: Distribution of German electric vehicles in the resulting clusters (total)

## 14.4 ESM Application

This section provides supplementary data, figures and explanations on the ESM application. This includes Error metrics.

### 14.4.1 ESM Errors

In this section, the prediction of all municipalities in the benchmark dataset are plotted against the ground truth for 2019 and 2035.

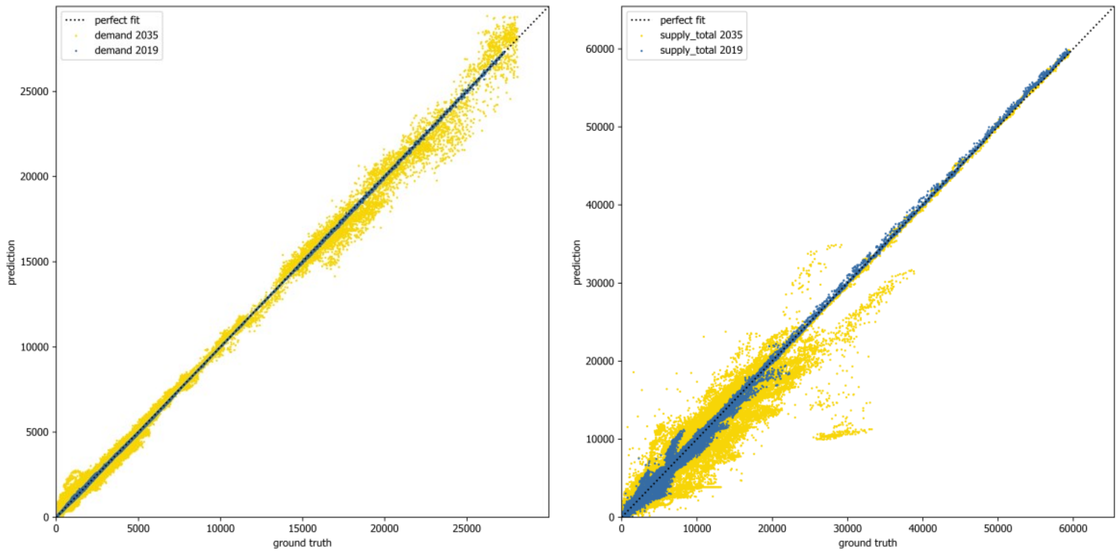



Figure 14-23: Plot of prediction vs ground truth in 123 benchmark municipalities for demand (left) and supply (right) for 2019 (blue) and 2035 (yellow)

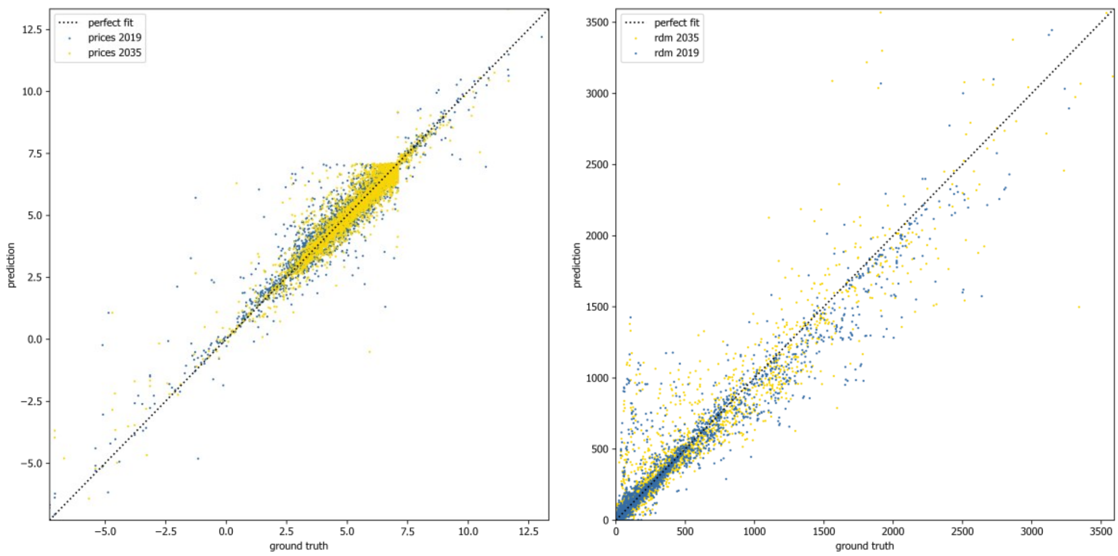



Figure 14-24: Plot of prediction vs ground truth in 123 benchmark municipalities for LEM prices (left) and RDM (right) for 2019 (blue) and 2035 (yellow)

### 14.4.2 ESM Validation

An advantage of ESM over "black-box" ML models is the possibility to validate or correct any ESM result by re-simulating it. This means that if a regression result which was generated by the ESM is needed for deeper or detailed research, which requires high model accuracy, it can be re-simulated, and the results validated and (if necessary) corrected.

The predictive uncertainty (epistemic and aleatoric uncertainty) of an ML-based regression model can be quantified using different methods (e.g., Bayesian techniques, heterogeneous or deep ensembles) [256]. As done in [A3], ensemble methods (e.g., decision trees) can be used as a means of sampling additional training data or to identify results with high uncertainty. In the case of this work, every regression result could be assigned with an uncertainty estimation. If necessary, a threshold can be determined to identify those municipalities or time steps that should be simulated instead of predicted, since the ESM is not confident in its prediction.

This approach improves the overall accuracy while increasing computational costs. It can be used to identify those predictions with high uncertainty, to either generate additional samples and improve the ESM (method see [A3]) or to substitute uncertain ESM results with simulated ones. The latter is viable when only a few results have high uncertainty and the focus is not on improving the ESM but on high quality results.

## 14.5 Energy-Economic Results

In this section, the results of the grid search and model training are depicted.

### 14.5.1 Use Case: Regional Direct Marketing

Figure 14-25 depicts the distribution of the RDM potential, normalized on demand and supply for all clusters in 2019. A price close to 2.05 ct/kWh implies that almost all demand within the municipality can be supplied by renewables ≤ 2 MW within 4.5 km. This is considered a municipality with a high RDM potential. Conversely, this means that in municipalities with permanently high potential, much supply cannot be marketed locally. From the point of view of the suppliers, this is inefficient and disadvantageous since only a fraction of their supply gains additional revenues. In contrast, in communities with low prices (close to 0 ct/kWh), there is very little supply compared to demand (low SDR). Consumers hardly benefit from the RDM. However, this is good for the few suppliers, as all electricity can be marketed locally.

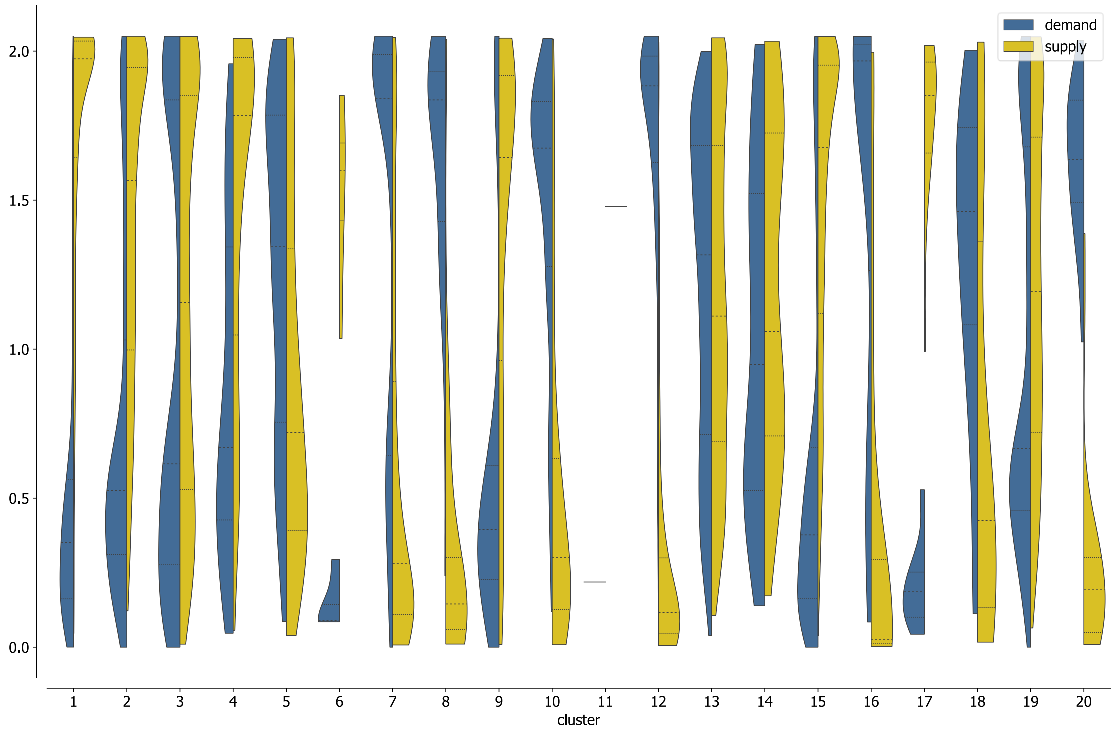



Figure 14-25: Violin plot for RDM in ct/kWh per demand in each cluster for 2019 and 2035

### 14.5.2 Use Case: Pricing in Local Energy Markets

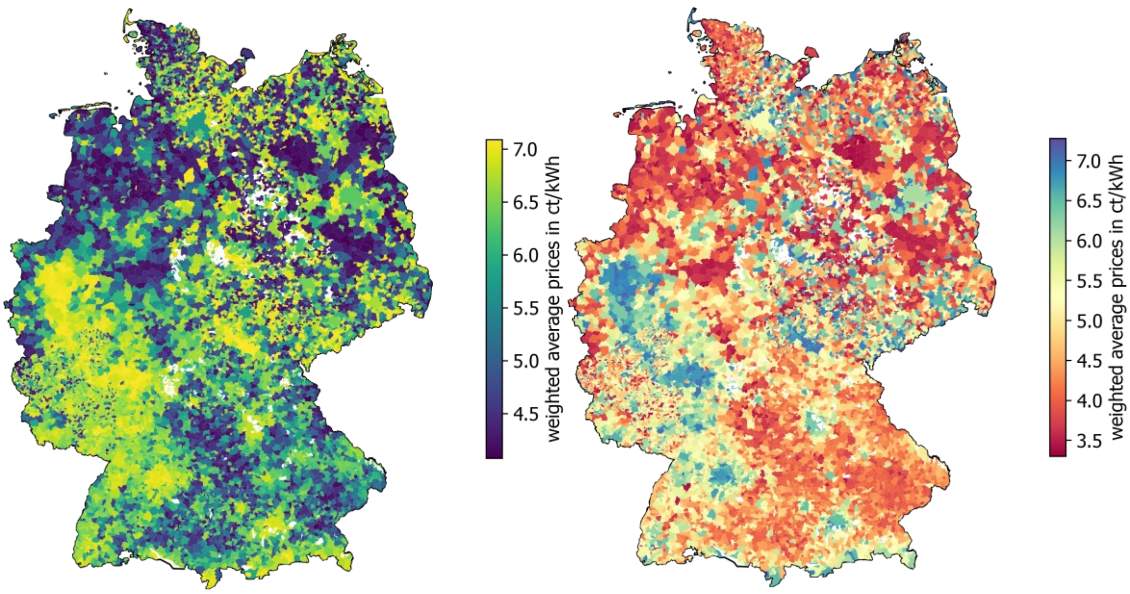



Figure 14-26: Weighted LEM prices by demand (left) and supply (right) in 2019

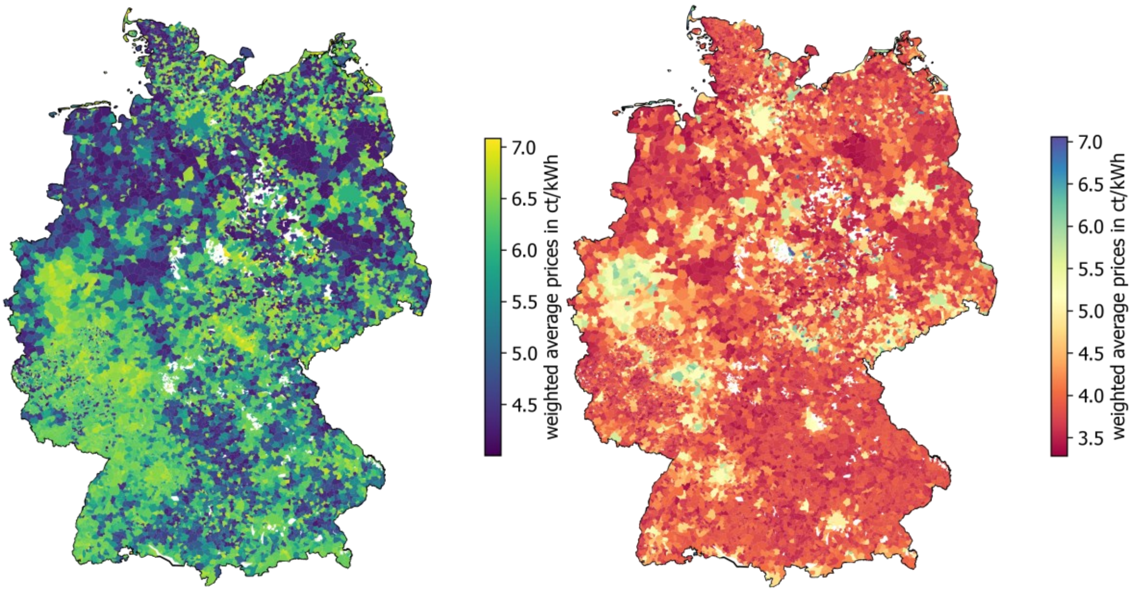



Figure 14-27: Weighted LEM prices by demand (left) and supply (right) in 2035

### 14.5.3 Comparison and Synergies of Use Cases

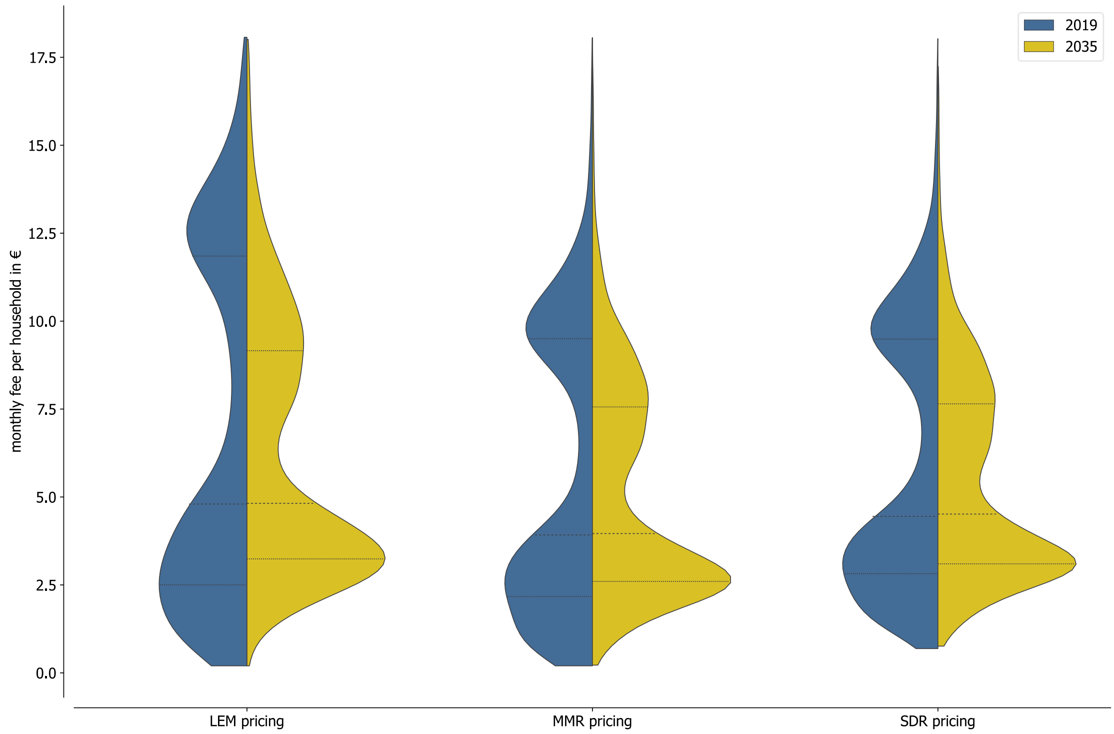



Figure 14-28: Violin plot monthly fee per household in €

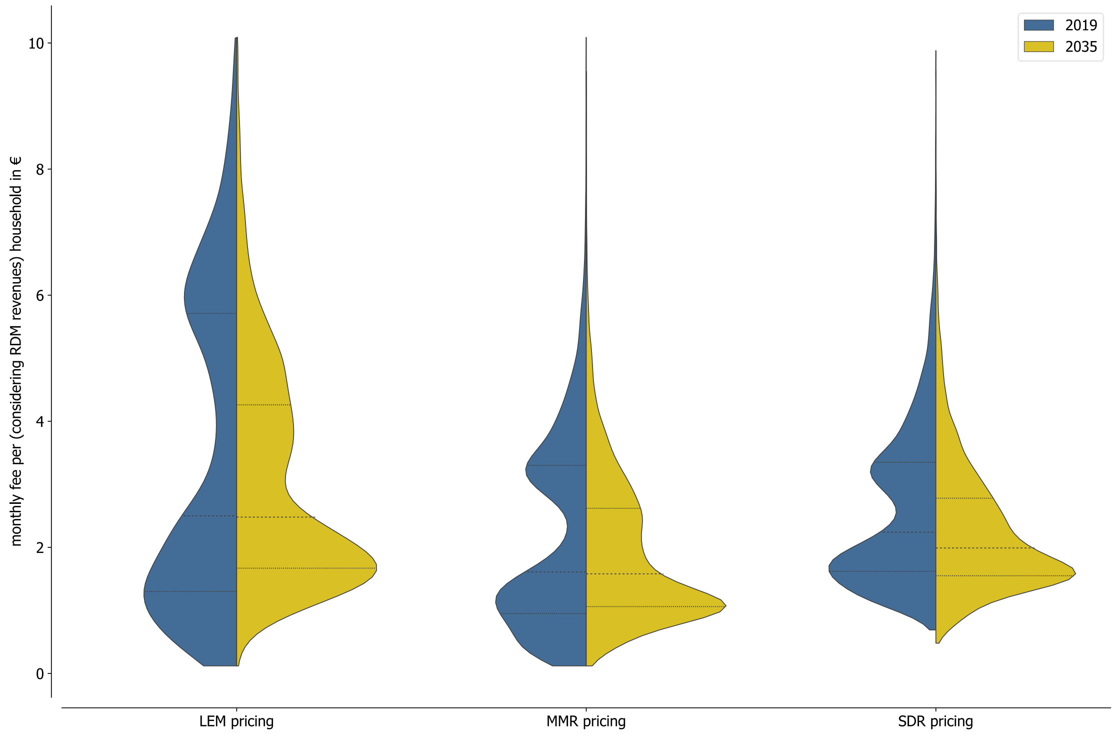



Figure 14-29: Violin plot monthly fee per household in €, considering RDM revenues to cover ESP losses

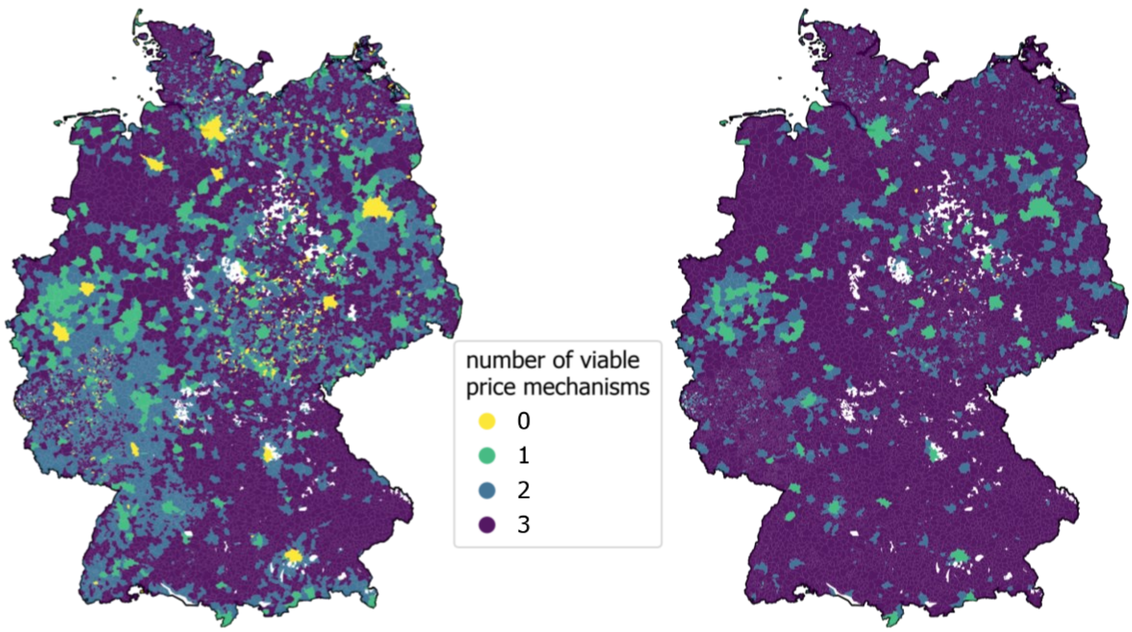



Figure 14-30: Number of viable price mechanisms (for all stakeholders), after consideration of a monthly fee, paid by consumers to cover the losses of the ESP (considering RDM potentials) in 2019 (left) and 2035 (right)

Table 14-7: Summary of the Model Results

| Category | MMR pricing | | LEM | | SDR pricing | | Static Retail Price (Status Quo Consumer) | Wholesale Price (Status Quo RE) |
|---|---|---|---|---|---|---|---|---|
| | 2019 | 2035 | 2019 | 2035 | 2019 | 2035 | | |
| **Average weighted price for demand in ct/kWh** | 6.35 | 6.30 | 5.95 | 5.76 | 5.59 | 5.47 | 7.09 | 4.10 |
| **Average weighted price for RE supply in ct/kWh** | 6.30 | 4.04 | 5.01 | 4.03 | 4.10 | 3.63 | 7.09 | 3.50* |
| **Average cost reduction of consumers in %** | 10.38 | 11.19 | 16.03 | 18.75 | 21.18 | 22.85 | 0 | 42.17 |
| **Average revenue increases of RE in %** | 30.78 | 14.53 | 41.15 | 14.37 | 15.36 | 3.030 | 103.57 | 0 |
| **Average losses of revenue of the ESP in %** | 49.10 | 54.27 | 62.83 | 68.23 | 53.16 | 57.63 | 0 | 0 |
| **Average losses of revenue of the ESP in % with RDM revenues** | 18.91 | 20.16 | 32.6 | 34.13 | 22.97 | 23.52 | 0 | 0 |
| **Price spreads and flexibility incentives** | low | | medium | | high | | - | very high |
| **reflection of local demand & supply** | medium | | high | | very high | | - | - |
| **Long-term price stability** | - | | - | | - | | yes | - |
| **risk of market manipulation** | - | | yes | | - | | - | - |