Aggregation of Distributed Energy Resources in Energy Communities: A Bottom-up Analysis

A thesis accepted by the faculty of Energy-, Process- and Bio-Engineering of the University of Stuttgart in partial fulfilment of the requirements for the degree of DOCTOR OF ENGINEERING SCIENCE (Dr.-Ing.)

by

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“Energy is the only universal currency: one of its many forms must be transformed to another in order for stars to shine, planets to rotate, plants to grow, and civilizations to evolve."

Vaclav Smil, Energy and Civilization: A History

“There are no separate systems. The world is a continuum. Where to draw a boundary around a system depends on the purpose of the discussion."

Donella H. Meadows, Thinking in Systems: A Primer

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Abstract

The European energy system is undergoing a transformation toward greater adoption of sustainable energy technologies. Concurrently, it witnesses a significant emergence of distributed energy resources (DERs), leading to decentralized generation, consumption, and storage of energy. A prominent example of this trend involves households engaging in self-consumption of electricity generated from rooftop photovoltaic systems, coupled with home storage systems. The expansion of smart grid infrastructure has opened up new possibilities for the decentralized organization of DERs in so-called energy communities (ECs), a concept endorsed by European policy frameworks such as the Clean Energy Package. However, from an overall system perspective, it remains unclear whether current market mechanisms and regulatory frameworks provide adequate incentives for the beneficial operation of decentralized energy systems (DESs), at the scale of a single household or an EC.

This dissertation undertakes a bottom-up assessment of DESs across various regulatory and market environments. Current literature reveals a significant gap: techno-economic analyses of DESs frequently neglect their systemic effects, and overall energy system studies inadequately model ECs. The overarching contribution of this dissertation lies in bridging these two domains. It provides a holistic systemic evaluation of DESs, simulating stakeholders' micro-economic behaviors within ECs, while simultaneously capturing emergent macro-level dynamics. The dissertation has methodological and substantive contributions on both community and overall system levels.

From a methodological standpoint, the thesis presents novel methods for modeling the aggregation of DERs in ECs. It frames the hierarchical decision-making interdependencies between an aggregator and its users as a Stackelberg energy trading game. This contribution is further expanded by formulating the resultant game as bilevel optimization problems. Additionally, the doctoral thesis proposes innovative techniques and algorithms to efficiently find the Stackelberg equilibrium and derive the optimal real-time pricing (ORTP) as an internal EC pricing mechanism.

This dissertation further introduces three methods to assess the systemic impacts of DESs. First, a market alignment indicator is presented, designed to measure the degree of congruence between DES operations and signals of scarcity or excess from

the wholesale market. Second, the agent-based electricity market model, AMIRIS, is enhanced to simulate a range of DES business models. Finally, a framework is proposed for automated bidirectional model-coupling between AMIRIS and the energy system optimization model, REMix. This coupling method serves to explore the economic granularity gap arising when households engage in self-consumption under various pricing and regulatory scenarios.

The methods developed in this dissertation are applied across various case studies, providing a thorough examination of two closely linked aspects of decentralized energy system business models in both current and future energy markets: (i) the operation of distributed energy resources – encompassing home and community energy storage systems as well as two crucial sector-coupling technologies, namely, heat pumps and electric vehicles, and (ii) pricing design – which includes static pricing, wholesale market-based real-time pricing, and community-tailored optimal real-time pricing. The research highlights the financial advantages of the operation of distributed energy resources for energy community stakeholders, especially in a future energy market with a high penetration of renewable energies. What sets these studies apart from existing research is their evaluation of the implications of optimal real-time pricing, illuminating the interconnected dynamics between community and wholesale markets.

The thesis findings reveal the inefficiency of time-invariant pricing designs from the perspectives of both EC actors and the overall system. One study shows that large-scale penetration of household self-consumption under current tariff structure significantly increases the required investment in generation and battery capacities. Real-time pricing schemes can effectively transmit system signals to DESs. This enhances not only the alignment between the operations of DER and the broader energy system, improving their cost-efficient integration, but also provides financial benefits to EC stakeholders. In this context, the proposed ORTP increases community welfare without notably distorting the wholesale market signals. Moreover, the thesis highlights the inefficiencies in Germany's current regulatory frameworks regarding the static volumetric regulatory charges imposed on consumer prices. These charges, among other factors, distort the market signals and thereby diminish the effectiveness of real-time pricing.

In summary, this dissertation introduces robust methodologies for modeling and analyzing the increasing complexity of energy markets, especially with the emergence of new small-scale actors. Additionally, its contributions provide valuable insights for policymakers in devising regulatory frameworks essential to address the emerging challenges of energy system decentralization.

Kurzfassung

Das europäische Energiesystem durchläuft gegenwärtig einen Wandel hin zu einer stärkeren Nutzung nachhaltiger Energietechnologien. Gleichzeitig ist ein deutliches Aufkommen dezentraler Energieressourcen zu beobachten, die zu einer dezentralen Erzeugung, einem dezentralen Verbrauch und einer dezentralen Speicherung von Energie führen. Ein Beispiel hierfür sind Haushalte, die den von Photovoltaikanlagen erzeugten Strom mit Heimspeichersystemen für den eigenen Verbrauch nutzen. Der Ausbau der Smart-Grid-Infrastruktur hat neue Möglichkeiten für die Organisation dezentraler Energieressourcen in so genannten Energiequartiere eröffnet, ein Konzept. Dies wird zudem durch politische Initiativen wie das „EU Clean Energy Package" unterstützt. Aus der Perspektive des Gesamtsystems bleibt allerdings unklar, ob die derzeitigen Marktmechanismen und regulatorischen Rahmenbedingungen geeignete Anreize für den vorteilhaften Betrieb dezentraler Energiesysteme im Maßstab eines einzelnen Haushalts oder eines Energiequartiers bieten.

In dieser Dissertation erfolgt eine Bottom-up-Bewertung dezentraler Energiesysteme unter verschiedenen Regulierungsszenarien und Marktbedingungen. Die derzeitige Literatur weist eine erhebliche Lücke auf: Technisch-ökonomische Analysen dezentraler Energiesysteme vernachlässigen häufig ihre systemischen Auswirkungen und Gesamtsystemstudien bilden Energiequartiere unzureichend ab. Der übergeordnete Beitrag dieser Dissertation liegt in der Verbindung dieser beiden Forschungsgebiete. Es wird eine ganzheitliche systemische Bewertung dezentraler Energiesysteme geliefert, indem das mikroökonomische Verhalten der Akteure innerhalb von Energiequartieren simuliert und gleichzeitig die entstehende Dynamik auf der Makroebene erfasst wird. Somit leistet die Dissertation methodische und inhaltliche Beiträge sowohl auf quartiers- als auch auf Gesamtsystemebene.

Aus methodologischer Sicht werden in der Dissertation neuartige Methoden zur Modellierung der Aggregation von dezentralen Energieressourcen in Energiequartiere präsentiert. Sie stellt die hierarchischen Entscheidungsinterdependenzen zwischen einem Aggregator und seinen Nutzern als ein Stackelberg-Energiehandelsspiel dar. Dieser Beitrag wird durch die Formulierung des resultierenden Spiels als zweistufiges Optimierungsproblem erweitert. Darüber hinaus werden in der Dissertation innovative

Techniken und Algorithmen entwickelt, um das Stackelberg-Gleichgewicht effizient zu finden und die optimalen Echtzeit-Preissetzungsmechanismen als internes Preissystem für das Energiequartier abzuleiten.

In dieser Dissertation werden außerdem drei Methoden zur Bewertung der systemischen Auswirkungen dezentraler Energiesysteme entwickelt. Erstens wird ein "Market Alignment Indicator" vorgeschlagen, der den Grad der Übereinstimmung zwischen dem Betrieb dezentraler Energiesysteme und den Knappheits- oder Überschusssignalen des Großhandelsmarktes messen soll. Zweitens wird das agentenbasierte Strommarktmodell AMIRIS erweitert, um verschiedene Geschäftsmodelle dezentraler Energiesysteme einzubeziehen. Schließlich wird ein Framework für die automatisierte bidirektionale Modellkopplung zwischen AMIRIS und dem Energiesystem-Optimierungsmodell REMix entwickelt. Diese Methode hilft bei der Untersuchung des "Economic Granularity Gap", der durch den Eigenverbrauch von Haushalten unter verschiedenen Preis- und Regulierungsszenarien entsteht.

Die in dieser Dissertation entwickelten Methoden werden in verschiedenen Fallstudien angewandt und bieten eine gründliche Untersuchung zweier eng miteinander verbundener Aspekte von Geschäftsmodellen für dezentrale Energiesysteme sowohl auf dem heutigen als auch auf dem zukünftigen Energiemarkt: (i) der Betrieb dezentraler Energieressourcen – dazu gehören Energiespeichersysteme für Haushalte und Quartiere sowie zwei wichtige Technologien zur Sektorkopplung, nämlich Wärmepumpen und Elektrofahrzeuge – und (ii) die Preisgestaltung - dazu gehören statische Preise, auf dem Großhandelsmarkt basierende Echtzeitpreise und auf die Quartier zugeschnittene optimale Echtzeitpreise. Die Analysen zeigen die finanziellen Vorteile des Betriebs dezentraler Energieressourcen für die Akteure des Energiequartiers auf, insbesondere in einem zukünftigen Energiemarkt mit einem hohen Anteil an erneuerbaren Energien. Was diese Studien von der bisherigen Forschung abhebt, ist ihre Bewertung der Auswirkungen von optimalen Echtzeitpreisen, die die miteinander verknüpfte Dynamik zwischen Quartiers- und Großhandelsmärkten beleuchtet.

Die Ergebnisse dieser Arbeit zeigen die Ineffizienz zeitinvarianter Preisgestaltungen sowohl aus der Sicht der Akteure des Energiequartiers als auch des Gesamtsystems auf. Echtzeit-Preisgestaltungen können effektiv Systemsignale an dezentrale Energiesysteme übermitteln. Dies verbessert nicht nur die Abstimmung zwischen dem Betrieb dezentraler Energieressourcen und dem Gesamtsystem und damit ihre kosteneffiziente Integration, sondern bietet auch finanzielle Vorteile für die Akteure des Energiequartiers. In diesem Zusammenhang erhöht die vorgeschlagene optimale Echtzeit-Preisgestaltung die Wohlfahrtsindikatoren des Quartiers, ohne die Signale des Großhandelsmarktes spürbar zu verzerren. Darüber hinaus zeigt die Arbeit die Ineffizienzen des derzeitigen deutschen Regulierungsrahmens hinsichtlich der statischen volumetrischen Gebühren auf, die den Verbraucherpreisen auferlegt werden. Diese verzerren unter anderem die Marktsignale und vermindern dadurch die Wirksamkeit der Echtzeitpreisbildung.

Zusammenfassend führt diese Dissertation robuste Methoden zur Modellierung und Analyse der zunehmenden Komplexität der Energiemärkte ein, insbesondere mit dem Auftreten neuer kleinskaliger Akteure. Darüber hinaus liefern die Beiträge wertvolle Erkenntnisse für politische Entscheidungsträger bei der Ausarbeitung von Regulierungsrahmen, die für die Bewältigung der sich abzeichnenden Herausforderungen der Dezentralisierung des Energiesystems unerlässlich sind.

Declaration of Authorship

I, Seyedfarzad Sarfarazi, hereby declare that this thesis, entitled “Aggregation of Distributed Energy Resources in Energy Communities: A Bottom-up Analysis", submitted for the degree of Doctor of Philosophy at University of Stuttgart, represents my original work and has not been submitted in whole or in part for any other degree or qualification at this or any other institution. All sources used in this thesis have been acknowledged and cited in accordance with the conventions of academic referencing. The work presented in this thesis is my own, except where otherwise stated. I further confirm that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project’s design and conception or in style, presentation, and linguistic expression is acknowledged.

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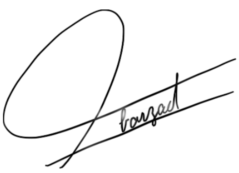
Signature: 

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3. S. Sarfarazi, S. Sasanpour, K.-K. Cao. 'Improving energy system design with optimization models by quantifying the economic granularity gap: The case of prosumer self-consumption in Germany'. In: *Energy Reports* 9 (2023), pp. 1859-1874, DOI: 10.1016/j.egyr.2022.12.145.
4. S. Sarfarazi, S. Sasanpour, V. Bertsch. 'Integration of energy communities in the electricity market: A hybrid agent-based modeling and bilevel optimization approach'. In: *Energy Reports* 12 (2024), pp. 1178-1196, DOI: 10.1016/j.egyr.2024.06.052.

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List of abbreviations

ABM	Agent-Based Model
BIOP	Bilevel Optimization Problem
BSS	Battery Storage System
CES	Community Energy Storage
DER	Distributed Energy Resource
DES	Decentralized Energy System
EC	Energy Community
ESOM	Energy System Optimization Model
EU	European Union
EV	Electric Vehicle
FiT	Feed-in Tariff
HES	Home Energy Storage
HP	Heat Pump
KKT	Karush-Kuhn-Tucker
LCOE	Levelized Cost of Electricity
MAI	Market Alignment Indicator
MILP	Mixed-Integer Linear Program
ORTP	Optimal Real-Time Pricing
PV	Photovoltaic
RES	Renewable Energy Sources
RTP	Real-Time Pricing
SP	Static Pricing
TS	Thermal Storage

Chapter 1

Introduction

1.1 Background and motivation

In the past decades, a large portion of the global energy consumption originated from fossil fuel resources [1]. An unsustainable energy provision, which depletes natural resources that are concentrated in limited regions of the world and greatly damages plants, animals and humans [2]. Emissions from the conversion of fossil fuels (largely made of CO_2) alter the radiation balance of the atmosphere, increasing the risk of climate change [3]. In recent years, the international community has become increasingly cohesive and has ratified agreements aimed at mitigating the underlying causes of this anthropogenic shift. One of the central pillars of this agreement is the commitment of the countries to transform their energy systems to a more sustainable one [4].

The transition to a sustainable energy system calls for a shift toward renewable energy sources (RES), such as solar and wind. The energy from RES is commonly generated in the form of electricity, which can be used to power a wide range of applications, including transportation, heating, industry, and households [5]. The electricity produced from RES stands out as significantly more environmentally friendly, with a notably smaller carbon footprint and other life-cycle assessment[1] indicators, such as eco-toxicity, that are at least as good as, if not better than, those associated with fossil fuels [7, 8].

One of the obstacles in the widespread adoption of RES technologies was their higher levelized cost of electricity (LCOE)[2] compared to conventional power generation, which posed a challenge to their cost-effectiveness. To confront this challenge, many

[1]Life-cycle assessment is a recognized method for quantifying the environmental impacts of products, processes, and services, facilitating standardized evaluations and the identification of significant ecological stress points. It comprehensively evaluates the entire environmental burdens and benefits associated with a product's life cycle, encompassing stages from raw material extraction to ultimate disposal [6].

[2]Defined as the average cost per unit of electricity generated over the lifetime of a power source.

countries across the globe introduced support schemes that mainly remunerated the electricity feed-in from RES. These subsidies were often justified by the lack of a level playing field in energy markets due to the externalities of conventional generation that were not sufficiently priced [9]. However, the rapid expansion of RES technologies has resulted in a significant reduction in their costs [10]. In particular, the cost of solar photovoltaic (PV) modules has decreased at a rate that exceeded the expectations of many energy scenarios [11]. The reduction in the LCOE of solar PV generation marked a significant milestone in 2012 in Germany, as small-scale PV power reached the so-called grid parity[1] [13]. Currently the cost of producing a megawatt hour from mature renewable technologies such as solar and onshore wind in many regions of the world is equal to, or less than, the cost of production from coal or natural gas [14].

The fluctuating nature of solar and wind energy, as two primary forms of RES, poses a significant challenge for their large-scale integration into the power grid. These short-term (daily, weekly) or long-term (seasonal) fluctuations test the system's efficiency and supply security from an energy planner's perspective. With variable renewable energies contributing more than 80% to the mix, even in an interconnected energy system, various types and sizes of storage systems become indispensable [15]. Traditional storage systems, such as pumped storage, stand alongside emerging power-to-gas technologies as attractive solutions for long-term storage during periods of low solar radiation and wind speed, scenarios referred to as dark doldrums (*Dunkelflaute* in German) [16]. Additionally, battery storage systems (BSSs)[2], with their rapid response times, high efficiency, low self-discharge, and scalable modular structure, are showing promise in mitigating the short-term intermittency of variable renewable energies [17]. Among various battery technologies, lithium-ion batteries have taken the lead as the most mature and widely used solution, owing to their high energy density and extended cycle life [18]. Alongside other RES technologies, the cost of lithium-ion BSSs has witnessed a precipitous decline in recent years, a trend projected to persist into the foreseeable future [19]. Figure 1.1 provides a glimpse into the scenarios and future projections of battery costs.

As the costs of RES generation and battery storage technologies decline, a growing number of residential and commercial electricity consumers are generating power on-site. While the decision to invest in self-consumption may be driven by consumer preferences [20], strong economic incentives also underlie this trend [21]. Specifically, the decision of consumers to become "prosumers" by investing in solar PV systems or

[1] Grid parity is achieved when the cost of generating electricity from RES is equal to or lower than the price of electricity from the grid [12].

[2] In this dissertation, the term BSS is used to refer to the battery system, encompassing all its applications. Specific terminology is employed when the context of the BSS application is central to the discussion: the term home energy storage (HES) is used to describe the behind-the-meter application of the BSS when combined with the PV system in a residential setting. Additionally, the term community energy storage (CES) is used to denote a grid-connected BSS that provides energy services to an energy community. When referring to the application of the battery system in a car, the term electric vehicle (EV) is employed.

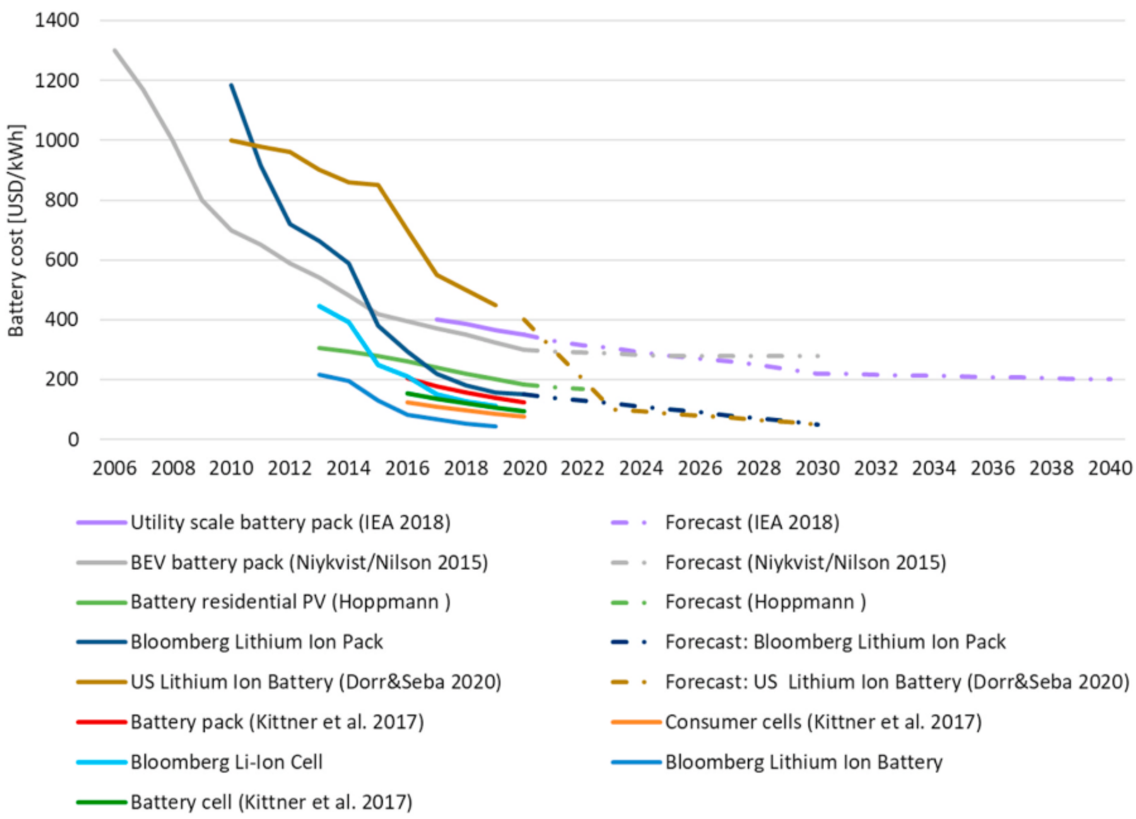

Figure 1.1: Scenarios and forecasts for the development of battery costs. Source: [14]

become "prosumagers[1]" by additionally installing home energy storage (HES) systems, depends largely on the costs of such investments as well as the retail and feed-in prices [23].

In Germany, the current regulatory framework for residential and commercial consumers and producers entails time-invariant volumetric retail prices and feed-in tariff (FiT) for grid consumption and feed-in. While behind-the-meter self-consumption of electricity is "free of charge", power consumers are obliged to bear the costs of procurement and sale, as well as grid fees and regulatory-induced charges when utilizing the grid electricity. Retail electricity prices for German consumers have witnessed a steady increase in recent years, climbing from 19.46 cents/kWh in 2006 to 38.57 cents/kWh in 2022 [24]. Until 2021, the escalation in consumer prices was primarily attributed to the growing RES levies (*EEG-Umlage* in German). However, since 2021, rising power procurement costs, largely influenced by increasing conventional fuel prices in European markets, have further intensified the already high prices [25]. Concurrently, the declining prices of PV systems have led to a reduction in FiT, decreasing from

[1] In this thesis, I adopt the naming convention suggested in [22] and refer to an electricity consumer with generation potential as a prosumer (producer and consumer). A prosumager additionally operates an energy storage system to increase self-consumption (producer, consumer and storage). I consistently use these two terms to distinguish between households with PV systems depending on the availability of BSS. However, there is one exception to this terminology. In the analyses presented in Paper 3, I use the term "prosumer" to refer to both groups of households.

an average annual value of 54 cents/kWh in 2006 to 6.7 cents/kWh in 2022 [26]. As depicted in Figure 1.2, alongside these price trends, investments in combined PV-storage systems have experienced a rapid surge.

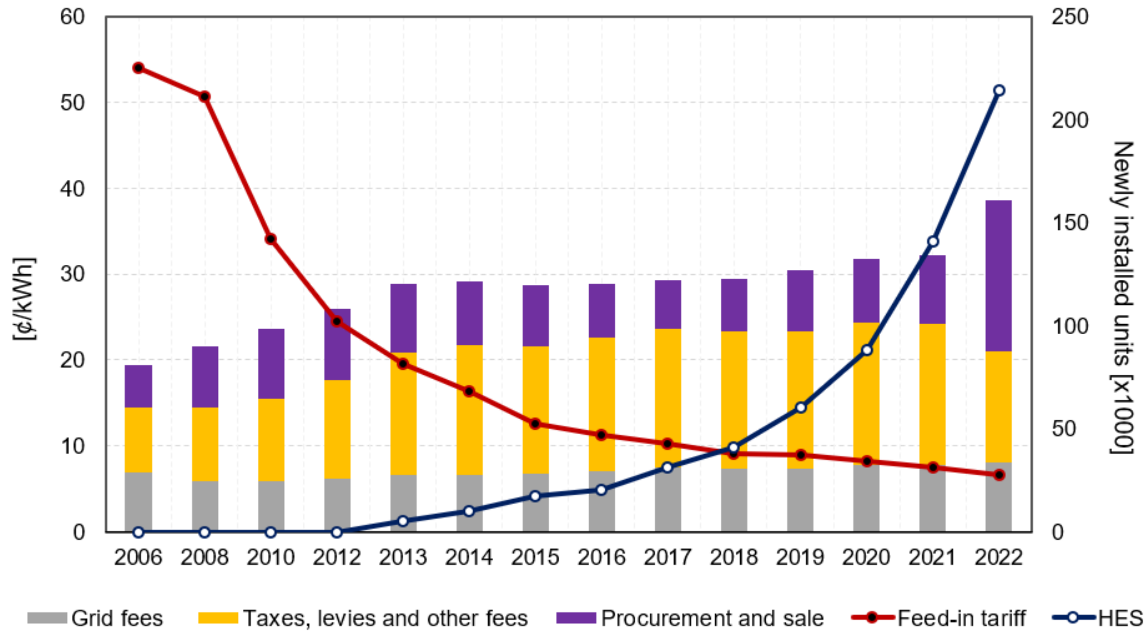

Figure 1.2: Development of different electricity retail price components [24], fixed FiT for small PV systems [26], and newly installed PV-storage systems in Germany [27].

The transition from an environment characterized by high FiT and low electricity tariffs to the reverse situation has diminished the incentive to sell PV electricity to the grid, leading to an increased emphasis on self-consumption of generated electricity. As the disparity between FiT and retail price continues to widen, coupled with the ongoing decline in BSS prices, the installation of behind-the-meter HES systems for higher level of self-consumption becomes increasingly economically attractive [28]. The interplay between these economic factors is illustrated in Figure 1.3. Further reductions in PV and HES costs will intensify the drivers for self-consumption. Energy scenarios, as presented in [29] and [30], anticipate that the total installed capacity of HES systems in Germany will exceed 50 GW by 2035.

While the immediate goal for prosumagers remains the self-consumption of solar electricity, the future of their interaction with the larger energy system is yet to be comprehensively defined. With the relentless advance of digitalization in the energy sector, the potential for the integration of prosumers and prosumagers into a wide array of market structures is rapidly expanding. These markets can range from peer-to-peer models with entirely decentralized architecture to more hierarchical prosumer-to-grid models [33].

Concurrently, the brisk advancement and adoption of sector-coupling technologies such as electric vehicles (EVs) and heat pumps (HPs), which hold potential for demand

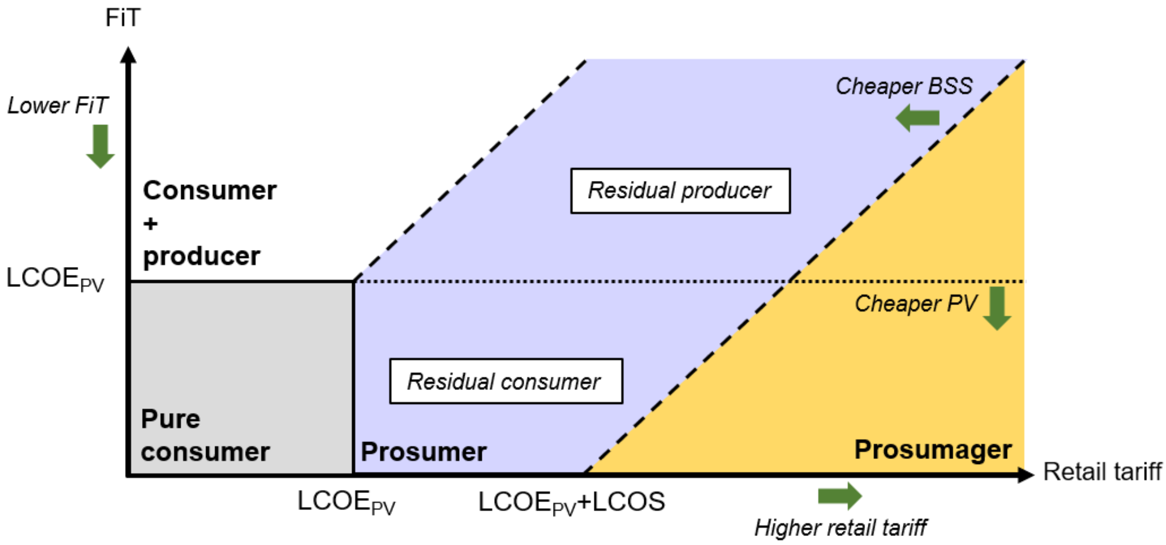

Figure 1.3: Illustration of incentives for investments in residential PV and battery systems as a function of FiT, electricity tariffs, and the LCOE and levelized cost of storage (LCOS). The green arrows show the observed trends in the past years. Source: own illustration based on references [31] and [32].

response [34], add another layer of possibilities for the decentralized organization of distributed energy resources (DERs)[1]. This, in turn, paves the way for the emergence of decentralized energy systems (DESs)[2] that surpass the scope of residential energy systems and extend to the scale of community energy systems. Within these community energy systems, the deployment of energy storage technology, often termed "community energy storage (CES)", provides an alternative to the conventional HES associated with the prosumager's self-consumption business model [35, 36]. Furthermore, community energy systems can act as a platform for the development and implementation of energy community (EC)[3] business models [41]. The growth and ac-

[1]The term DERs refers to a diverse range of decentralized power generation and storage technologies located in close proximity to the point of energy consumption.

[2]The term DES is widely used in literature to refer to an energy system that enables localized generation and storage of energy. In this thesis, I use this term as a general reference to both residential and community energy systems.

[3]The term "energy community" as it appears within this thesis necessitates further clarification due to its ambiguity and inconsistency across various academic discourses. The conception of "community" in community-based energy systems literature can often lack precision and uniformity [37]. For instance, some scholars interpret "community" in relation to social arrangements and governance mechanisms within energy systems (e.g., [38, 39]). Contrarily, in economics and engineering literature, there is a noticeable shift toward understanding the community as a geographical entity, a shift that emphasizes local economic objectives [40]. In alignment with the techno-economic focus of this thesis, I will adhere to this latter interpretation and will thus primarily consider the community as a defined location, sidestepping the social dynamics and institutional issues inherent in the broader definition. Consequently, when discussing the technological framework including the grid, generation, and storage technologies, I will employ the term "community energy system". Conversely, "energy community" will be used when focusing on business models and financial interests of a heterogeneous set of collective actors. This nuanced usage is intended to differentiate between the technical and economic aspects and is pertinent to the focus of this thesis, although it's acknowledged that usage may vary in other research domains.

ceptance of these models have been partially stimulated by political drivers, such as the European Union (EU) Clean Energy Package, which has been instrumental in fostering ECs through the promotion of community-based initiatives and the empowerment of energy citizens [42].

Distributed generation and consumption of electricity in regions of the world with inadequate grid infrastructure can indeed play a vital role in addressing energy poverty [43]. While this situation is not prevalent in the European energy system, increased local consumption of electricity in DESs can still have advantages, such as attracting private investments in clean technologies, reducing transmission and distribution losses, enhancing system resilience, and offering social benefits like fostering acceptance and raising awareness of the energy system transition [44]. Despite the benefits of DESs, their operation without proper coordination can pose challenges to the functionality of the broader energy system. One such challenge is the increased pressure on the distribution grid, which may necessitate extensive grid expansion [45]. The challenge is further intensified by sector coupling, especially with the increased penetration of EVs and HPs, which can result in a significant surge in power consumption within the distribution grid, potentially offsetting the benefits of energy-saving measures [46]. Additionally, a mismatch between the local self-consumption patterns and the availability of power generated from RES in the energy market can result in inefficient investments in power generation and storage technologies [47]. Addressing these challenges and exploring the prerequisites for a market-aligned operation of DESs is the central focus of this dissertation.

1.2 State of the art, literature gaps, and research questions

As the European energy system transitions towards sustainability, there is a simultaneous shift in its centralized paradigm, leading to the decentralization of electricity production and consumption. This transition is significantly influenced by the growing trend of self-consumption of solar PV power, among other factors. The decentralization of the power system brings about significant consequences and challenges. It necessitates substantial engineering, economic, and political efforts to efficiently integrate DERs into the existing power systems, mitigate the unintended negative impacts of energy system decentralization, and ensure the smooth operation of physical systems [48].

In recent years, there has been significant development and application of energy system models focused on the operation of DESs [49]. The scientific works related to this field can be broadly categorized into two groups. (i) Studies that primarily examine the techno-economic operation of DESs, with little or no consideration given to their impact on the wider energy system. (ii) Research that has a broader systemic scope but lacks an accurate modeling of the DESs. Recognizing the research gap between these two domains, this dissertation aims to explore the efficient integration of DESs into the broader energy system by addressing the granularity gap[1] between the aforementioned systemic scopes. The overarching objective of the thesis is to facilitate a more accurate systemic evaluation of DESs by modeling and simulating the micro-economic behaviors of stakeholders within ECs, while concurrently capturing the emergent macro-level system behavior using energy system models with broader scopes.

Adopting a bottom-up approach, the thesis establishes specific research questions and objectives at two system levels: the community energy system and the overall energy system. The overarching goal of this thesis is systematically approached by addressing two guiding questions, each further divided into a methodological and a substantive research question. In the remainder of this section, I will provide a literature review that is relevant to each guiding question. Additionally, I will introduce the research questions and outline their corresponding objectives.

Guiding question A. What operation strategies can intermediary entities employ to effectively organize DERs in ECs?

The first guiding question is motivated by the growing interest in ECs as a result of increasing penetration of DERs and the challenges of intermediary entities to organize these assets. The EC concepts involve coordination of end-users in community energy systems and emphasize self-consumption and energy sharing [51]. Various business models within the EC landscape are explored in the literature, each contributing differently to policy objectives, such as increasing renewable energy capacity, mobilizing private capital, and empowering consumers [52].

One facet of research focuses on the business model and regulatory framework design for ECs. The study in [53] presents 25 emerging options identified through a morphological analysis of 90 ECs. On a similar note, [41] systematically analyzes the value proposition offered by ECs, identifying eight community business model archetypes. The authors of [54] highlight the shift in European countries such as France, Germany, the Netherlands, and the United Kingdom toward more favorable regulatory frameworks for collective renewable energy prosumers.

Within this body of literature, a significant number of studies have proposed solutions that revolve around the fully decentralized organization of EC actors, through mechanisms like peer-to-peer energy trading. In this context, [55] provides an analysis of the global development of peer-to-peer energy trading, while [56] delves into consumer behavior within these communities. Addressing structural transitions, [57] examines the shift from hierarchical power systems to more decentralized models, highlighting the inherent challenges that need to be addressed to ensure the viability of peer-to-peer trading in today's energy market. In response to these challenges, innovative

[1] The granularity gap in energy system modeling refers to the deficiencies that arise when balancing the need for a comprehensive system's perspective with the level of detail or granularity that can be realistically achieved, due to computational and institutional limitations (e.g., data availability). This trade-off leads to simplifications in the model, introducing uncertainties and inaccuracies in representing the real-world system [50].

solutions have emerged. The authors in [58] use cooperative game theory and propose an algorithm for stable trading and addressing the challenge of unpredictability and intermittency of distributed generation. Moreover, the smart community management in [59] uses reinforcement learning to derive attractive real-time prices for the participants. Another example comes from [60], which proposes a co-simulation methodology for peer-to-peer trading and asserts its compatibility with existing grid operations.

On the other hand, a different segment of the literature emphasizes a more hierarchical structure for the EC [61]. Aggregators, defined as “market participants that combine multiple customer loads or generations for sale, purchase, or auction in any organized energy market”, recognized by the EU as pivotal players in the energy market, emerge as key entities in this context [62]. They can contribute to the EC in various ways, such as by managing local flexibility markets [63], and providing energy savings [64].

In this context, the study in [65] focuses on how an aggregator can effectively manage DERs under a real-time pricing (RTP) demand response program, thus maximizing profit despite uncertainties regarding RES generations and customers’ responsiveness. The research presented in [66] reveals how an aggregator can minimize net costs of participating in both day-ahead energy and secondary reserve markets by optimizing prosumagers’ flexibility. Using a two-stage stochastic optimization model, the study demonstrates the benefits of accounting for uncertainties in renewable generation, consumption, outdoor temperature, and house occupancy. Authors of [67] introduce a novel decentralized bilevel stochastic optimization approach. Here, the model considers multiple energy carriers and storage systems in multi-energy microgrids, enhancing network flexibility and potentially increasing total profit. The model in [68] sets up a real-time market platform for an aggregator and the contracted prosumers to increase the cost-efficiency of the wholesale market participation. The derived bilevel optimization problem (BIOP) seeks an optimal solution which is beneficial for both the aggregator and the prosumers.

Current literature on ECs provides substantial insights about their business models, regulatory conditions, and organizational structures. However, some significant research gaps persist. One is the insufficient development of methodologies for efficiently capturing the decision-making interdependencies among the EC stakeholders. For instance, the operation of energy storage systems by the aggregator as well as by users and the presence of sector-coupling technologies alongside prosumagers are not considered in the proposed models. This gap aligns with Research Question A.1, focusing on the modeling and optimization methods for representing the local aggregation of DERs in ECs. Another gap is the limited exploration of financial benefits for diverse ECs stakeholders, particularly within the context of the related regulatory frameworks in Germany. This gap corresponds to Research Question A.2, which seeks to explore the financial incentives for different actors to engage in EC business models. Addressing these research gaps could further the development of effective EC strategies and enhance understanding of the economics of ECs.

Research question A.1: *What modeling and optimization methods can be employed to represent the local aggregation of DERs in ECs?*

The concept of an EC encompasses a diverse array of business models, each characterized by distinct market structures, stakeholders, and technologies. In this thesis, the initial step is to establish a concept that can accommodate various EC use-cases. As the term "aggregation" in the research question – and also in the title of this dissertation – suggests, this thesis will primarily focus on ECs with a hierarchical structure.

To comprehend the microeconomic dynamics of such an EC, two fundamental steps are required. The first step involves the mathematical expression of the (primarily economic) objectives of the chosen EC stakeholders, along with the corresponding techno-economic constraints. This encapsulates the optimization problem formulation for various flexibility options[1]. The selected flexibility options are CES, HES, EVs, and HPs. Such formulation portrays the microeconomic behavior of the actors within a specific business model setting and a given regulatory framework. The second step involves using advanced mathematical techniques, including game theoretical methods, to capture the decision-making interdependencies that emerge due to the conflicting interests of stakeholders engaged in the EC energy trading scheme. Given the hierarchical structure of the EC, the focus is on the dependencies pertaining to the operational strategy of the aggregator, and the EC users.

Intuitively, trading prices serve as a critical link between the strategy of the aggregator and the behavior of the users. In the status-quo market, these prices are frequently set using predefined rules, such as Time-Of-Use or RTP schemes [70]. However, endogenous modeling of these prices, which in this thesis is referred to as "optimal real-time pricing (ORTP)", constitutes an important step toward understanding the EC economy. From the techno-economic perspective, such a mechanism allows for adaptable pricing, which is tailored to the dynamic community needs, resources, and preferences, each of which is subject to various uncertainties. Moreover, it creates incentives considering factors, such as cost of energy procurement, market conditions, grid constraints, and the value of energy services. From the system analytic perspective, endogenous modeling of the EC market provides a linkage between the operation of DESs and other segments of the energy system and allows for a holistic assessment of the future highly interconnected system.

Modeling of the EC's internal energy trading scheme results in complex BIOPs [71], which demand novel and sophisticated techniques for resolution. Development of efficient solving techniques holds significant importance, particularly when considering the comprehensive scope. This encompasses a temporal scope that extends beyond a single day and an economic scope that exceeds the boundaries of an EC. This research

[1]Flexibility options refer to technologies that enhance its ability to adjust and adapt its operation in response to anticipated or unanticipated changes in energy system behavior. These changes could include variations in network configuration, generation capacity, or load demand due to factors such as local climate conditions, user requirements, or network outages [69]. This term is mainly used in German research circles (*Flexibilitätsoptionen* in German).

question is therefore dedicated to developing novel methodologies to model and simulate the operation of the EC and providing effective algorithms to find the solution to the resulting energy trading problem. The developed methods and models deliver the necessary tools for investigating the subsequent research question.

Research question A.2: *What are the advantages of EC business models for the stakeholders involved?*

Having examined the methodological aspects of EC modeling, the focus of this research question shifts toward the techno-economic analysis of different business models[1]. While the related studies primarily emphasize the actor-specific financial benefits associated with these models, they also touch upon the potential technical benefits they can offer to the physical energy system.

To address this question, the first step involves defining specific EC use-cases[2], enabling model configuration and parameterization. This thesis concentrates on two crucial, interconnected aspects of EC business models [41] that have been prominently featured in scientific and political discussions. The first aspect concerns the distributed solar PV generation and the deployment of flexibility options as main energy resources within the community. The second aspect examines the pricing mechanism in the EC, along with its related cost and revenue streams.

Concerning the first aspect, the EC business models centrally feature the cost-minimizing prosumage operation, which combines the use of PV and HES systems, in addition to on-site direct power consumption by prosumers. Additionally, the practice of grid-connected electricity storage within the community energy system using CES is another key component. Incorporating CES operated by an aggregator provides further flexibility, aiming to propose two values to the EC: increasing community welfare and promoting self-sufficiency [72]. Moreover, the business models incorporate two pivotal sector-coupling technologies: the bidirectional charging of EV and the flexible operation of HP coupled with thermal storage (TS), aim to reduce user costs.

In terms of the second aspect, three pricing mechanisms are considered for the EC users. The ORTP scheme is proposed as the primary pricing mechanism in EC business models and is benchmarked against the status-quo static pricing (SP) design. Additionally, the RTP mechanism, which integrates time-variant wholesale market signals [73], is considered as an alternative pricing scheme. The internal pricing mechanisms, ORTP,

[1]Throughout this thesis, analysis of EC "business models" is considered as an overarching research objective in both guiding questions. It is important to mention that the analysis being undertaken diverges from a traditional comprehensive assessment of all business model components. Such a comprehensive analysis would involve evaluating their numerous building blocks, including but not limited to value propositions, customer segments, revenue streams, key activities, and resources. Given the complex and multifaceted nature of EC business models, and in alignment with the scope of the thesis (as outlined in Section 1.3), I define and analyze various representative EC "use-cases" or "scenarios" as proxies for evaluating the EC business models. Hence, a complete business model analysis extends beyond the confines of this study.

[2]The consistent usage of this term is lacking across all the papers included. In Papers 1 and 2, there is a discrepancy, with the term "scenario" and "case" being employed respectively to refer to the same concept.

offer two key value propositions: enhancing community welfare and providing grid relief.

The operation of DERs and pricing mechanisms are influenced by external regulatory factors. In particular, the regulatory frameworks pertaining to taxes, levies, and network charges imposed on power consumption from the public grid significantly contribute the success or failure of the real-world implementation of EC business models. Implications of these regulatory elements are observed not only in behind-the-meter self-consumption but also in the usage of grid-connected storage systems, such as CES. In recent years, the issue of double taxation on storage usage has been brought to the forefront of political debates [74]. Therefore, one remaining step to define the EC use-cases is specifying the regulations that affects the operation of DESs.

Upon defining the use-cases, the next objectives encompassed within this research question are the collection of data and the simulation of various case studies. The assessment of these simulation results provides the answers to this research question. In summary, this research question is devoted to exploring the potential techno-economic benefits of aggregating DERs within the EC under various settings. By pinpointing promising use-cases from the perspective of the EC stakeholders, I lay the foundation for probing the system integration of DESs in subsequent research questions.

Guiding question B. What are the broader energy system implications of emerging ECs?

The second guiding question of this thesis revolves around the influence of DESs operation on the broader energy system. While receiving increasing attention, the literature in this area is relatively new and less comprehensive compared to research dedicated to EC operation. However, various methodologies have been employed to examine the system-wide impacts of large-scale DES integration under different market and regulatory conditions. Among these methods, [47] introduces a market alignment indicator (MAI) to assess the potential systemic effects of prosumagers' self-consumption, without explicitly modeling the broader energy system. This indicator measures the ratio of the welfare generated by HES to that of an benchmark arbitrage battery.

Research that examines DES integration in a comprehensive systemic context predominantly employs energy system optimization models (ESOMs), investigating the optimal energy system operation and design, considering the self-optimizing function of DESs. These optimization models generally include cost-minimizing DES modules and a benevolent system planner. The presented studies in [75] and [48] examine the system contributions of HES in the case of France by 2030. The author of [75] identifies major systemic challenges in the seasonal backup power system related to variable PV integration and suggests a load management model based on the secondary use of HES to mitigate these impacts. In a similar study, the author of [48] asserts that solar PV self-consumption with HES reduces the systemic impacts of PV integration, such as daily balancing and annual back-up issues, compared to full PV grid injection.

Furthermore, [31] analyzes the investment decisions of prosumagers and the system effects of their operations on the German power sector in 2030, taking into account diverse pricing designs. Their research reveals that when higher fixed annual costs and lower volumetric costs for grid consumption are implemented, households contribute more toward non-energy power sector costs. The authors also propose that an hourly feed-in cap for households can alleviate distribution grid stress without necessarily causing detrimental effects on the prosumage model. Similarly, [76] studies the system compatibility of prosumagers' high self-consumption rate in an energy system with a significant share of RES. These studies indicate that entirely inflexible HES operation pursuing individual economic optimum could aggravate RES integration, and increase CO_2 emissions and system costs.

The presented studies in [77, 78] explore the influence of ECs on the European electricity and heating system through a stochastic programming model. Focusing on a Norwegian case study, [77] analyzes the cost-effectiveness of decarbonizing the energy system when the central power system is coordinated with the operation of building heating systems and electric vehicles' charging behavior. Their findings indicate that an efficient coordination can lead to a substantial decrease in average European electricity costs and a reduction in the expansion of the transmission grid. Applying the same model, [78] evaluates the impact of flexible ECs on the expansion of cross-border transmission capacity, and national generation and storage within the European electricity and heating system. While they emphasize the potential advantages of flexible ECs, they also highlight the conflict of interests between optimizing EC flexibility for local cost reduction versus broader European cost minimization. Therefore, the authors underscore the importance of appropriate local price signals and incentives that mirror the demand for flexibility at a European scale.

The application of agent-based models (ABMs) to simulate the bottom-up integration of DESs in the energy system while considering emerging market disequilibrium is relatively niche. The author of [79] explores the impacts of large-scale prosumage of electricity under varying energy system scenarios on the wholesale market in Germany by 2035. The study doesn't find a substantial shift in annual average prices, an outcome that is explained by the quasi-random correlation between HES operation and market prices, coupled with the relatively minor scale of the assumed HES capacity. The study in [80] integrates a prosumager investment model into an electricity market ABM to assess the long-term (2020-2050) impacts of HES diffusion on the German electricity market. The findings suggest that from a systemic perspective, the mode of operation of HES is more important than the amount of storage installed. These studies, aligned with the previously reviewed study in [31], suggest that regulatory adjustments, such as lowering the feed-in limit for residential PV, could incentivize a more system-friendly operation of HES.

The literature reviewed underscores the need for regulatory adjustments and suitable incentives for efficient DES and overall energy system coordination. However, there is still a noticeable gap in the research concerning the systemic impacts of ECs.

Methodologically, most studies model DES operation in an idealized energy system using ESOMs, thus failing to provide insights into their systemic effects in a more 'realistic' market environment. Furthermore, the complexity of EC business models is often overlooked. In particular, the role and interests of aggregators as a linking entity between households and the broader system are neglected. This gap informs Research Question B.1. Moreover, there is a lack of a comprehensive bottom-up analysis of system-friendly EC operation. Crucially, while relying on assumptions regarding incentive mechanisms for DES, none of the studies investigate the systemic implications of EC internal pricing, such as ORTP. In this context, the application of CES also remains largely unexplored. This literature gap aligns with Research Question B.2.

Research question B.1: *How can the potential system-wide impacts of large-scale integration of self-optimizing ECs be measured and quantified?*

The system-friendly operation of DES can be effectively categorized into two main areas of consideration. The first is grid-coordinated operation, which prioritizes the synchronization of DERs operations with the physical electricity network. This area encompasses mechanisms for frequency regulation, voltage control, and reactive power support, all of which contribute to maintaining grid stability and reliability. The second area is market-driven operation, which places an emphasis on aligning DERs operations with market signals. These signals can take various forms, including but not limited to, price fluctuations and the dynamics of supply and demand. This research question focuses on the latter category, with the aim of defining suitable indicators and robust methodologies to assess important systemic impacts.

Assuming an ideal, frictionless, and optimized power system, the extent to which the operation of ECs aligns with these market price patterns can be considered as a proxy to evaluate their system-friendly operation. The primary objective here is to extend the presented approach in [47] and define an indicator capable of measuring the degree of alignment between EC operation and market signals, along with developing a methodology to quantify this indicator. A key advantage of this approach lies in its independence from an overall energy system model for assessing systemic effects, thereby providing a tool to measure these effects without further modeling effort.

Other objectives of this research question revolve around assessing the overall system integration of ECs using two large-scale energy system models: an ABM and an ESOM. In recent years, ABMs have made significant inroads into the realm of energy system analysis. Although these models have diverse areas of focus, their most significant applications are arguably found in the modeling of energy markets [81]. AMIRIS is one such model, developed to analyze and evaluate the effects of energy policy instruments and their impacts on the actors within the simulation context [82, 83]. AMIRIS models the decision-making processes of typical actors in the electricity market, considering the influence of prevailing regulatory frameworks. It employs a merit-order model to simulate the market clearing process, which in turn allows for price derivation.

A defining characteristic of ABMs is their capacity to incorporate models within the model itself. This facilitates the linking and nesting of models, broadening the scope of simulation and analysis [79]. The second objective of this research question leverages this intrinsic feature of ABMs and involves the implementation of DES models, as developed in the context of Research Question A.1, within AMIRIS. Particularly, the integration of the bilevel optimization model in AMIRIS is an important step to enable a simultaneous analysis of the interconnected dynamics of EC and wholesale markets. This implementation process entails the creation of new agent types to represent EC stakeholders, including an aggregator, and the integration of optimization models into the AMIRIS infrastructure. Furthermore, it requires establishing an interface to couple the optimization models that cannot be directly translated into AMIRIS, thereby ensuring seamless integration and interaction between the different components of the model.

When employing AMIRIS for this thesis, the model had several limitations. Firstly, the model was nationally focused, which meant that cross-border electricity trade couldn't be endogenously calculated. Secondly, the model did not simulate the competition between market actors, particularly flexibility operators, making the simultaneous operation of multiple flexibility operators infeasible. Thirdly, the model did not take into account investment decisions, focusing only on deriving dispatch strategies.

Coupling an ABM with an ESOM was conducted by [84, 85] for determining the 'economic efficiency gap'. Such coupling has demonstrated that it enhances the capabilities of an ABM as well as transfers a more realistic system behavior to ESOM [50]. In the research presented in [86], authors use this approach by jointly applying the ABM PowerAce [87] and the optimal power flow optimization model ELMOD [88] to explore the long-term effects of market splitting in Germany. In this research, ELMOD provides the perspectives of the regulator and transmission grid operator, while PowerAce is used for market simulation and creating the companies' generation and storage expansion plan. A more pertinent case for this thesis is, however, the soft-linking between AMIRIS and the ESOM E2M2 [89, 90], as suggested in [84] and [85], which aims to determine the 'economic efficiency gap', i.e. the difference in system cost arising from non-ideal behavior of players in the market. Torralba-Díaz et al. [84] propose that a bidirectional coupling of ABM and ESOM represents a significant avenue for future research, allowing for an investigation of energy system design.

Against this background, the third objective of this research question is to build upon this approach by developing an automated bidirectional model-coupling framework that utilizes the ESOM REMix [91]. On the one hand, this approach offers a sound starting point for electricity market simulations, addressing the previously mentioned limitations of AMIRIS. On the other hand, it feeds the resulting DES dispatch from AMIRIS back into REMix to examine the influence of actor behavior on optimal system operation and design. This methodology permits the definition and quantification of the economic granularity gap arising in the context of self-optimizing DES.

The methodologies developed within the scope of this research question serve as the foundational framework for addressing the final question of this thesis.

Research question B.2 *Under what circumstances do ECs operate aligned with the needs of the broader energy system?*

In the final research question of this thesis, the focus is on studying the large-scale integration of DESs in the current and future energy systems with a significant share of power being generated from variable RES. To address this research question, the previously developed methods and models are employed to simulate the impact of different EC use-cases on energy system operation and design.

The primary objective of this thesis revolves around the definition of EC use-cases and collection of related data. Aligned with Research Question A.2, a key focus of these use-cases is on (i) two important applications of BSSs in the context of EC, namely, HES and CES as well as (ii) the introduced pricing designs SP, RTP, and ORTP. A similar objective is to compile relevant data to create future scenarios for the overall energy system, taking into consideration Germany's environmental targets for carbon emission reductions. These data-driven scenarios will be utilized to parameterize the employed energy system models, providing valuable insights into potential trajectories of the energy system.

The final objective in the context of this research question extends to conducting simulations of EC use-cases within the scope of current and future energy systems. An essential component of this objective is to perform sensitivity analyses, especially focusing on the impact of regulatory induced charges. This in-depth analysis aims to assess the effect of political instruments on the efficient system integration of ECs, allowing for an exploration of viable strategies toward sustainable energy solutions.

Figure 1.4 illustrates the main objectives associated with each research question and their bottom-up design, contributing to the pursuit of the research aim of the thesis.

In conclusion, the cornerstone contribution of this thesis resides in addressing a substantial gap observed in the existing research, pertaining to the holistic analysis of DESs. It pioneers a novel methodological approach, combining hybrid agent-based modeling approach with bilevel optimization, fundamentally bridging the described gap. This innovative methodology facilitates a comprehensive evaluation of the system integration of DESs, while accounting for complex market dynamics such as energy trading and price formation within ECs. The distinctive structural design of this modeling approach, as demonstrated in Figure 1.5, underscores the originality of this dissertation and represents a significant step in advancing the discourse on DES.

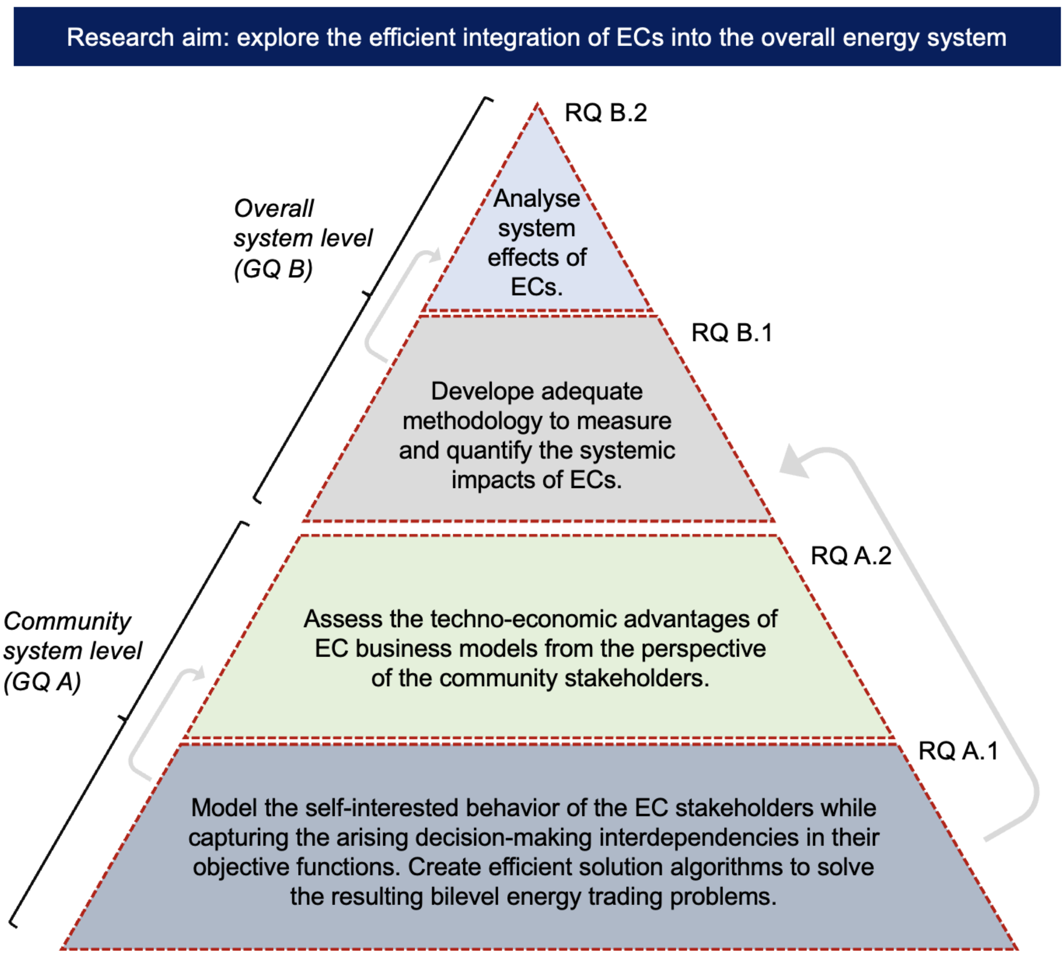

Figure 1.4: Schematic illustration of the bottom-up structure of the research questions and main objectives to achieve the research aim of this thesis.

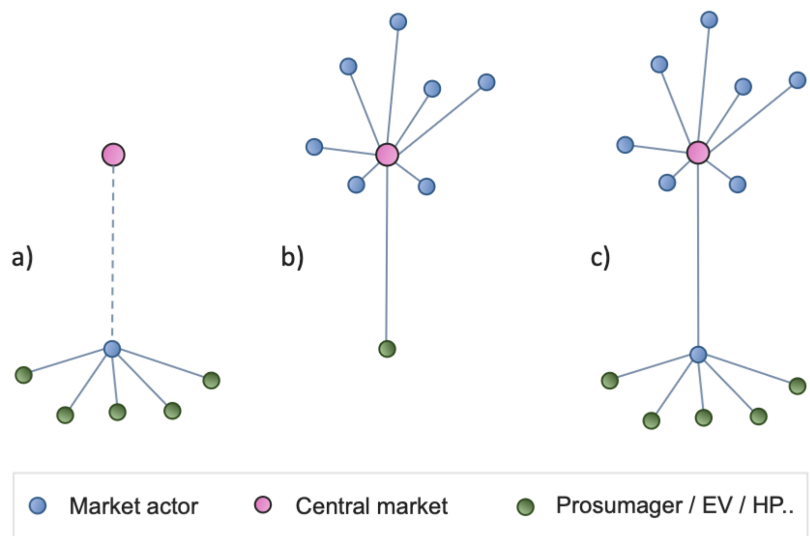

Figure 1.5: Model architectures used in the literature for: a) techno-economic evaluation of ECs; b) assessment of systemic effects of DESs; and c) the approach proposed in this dissertation.

1.3 Focus and scope

Established approaches for energy system analysis vary widely in their perspectives on spatial, temporal, technological, and economic dimensions [50]. The following section outlines the scope and focus of this thesis across these four dimensions. Each dimension encompasses certain intricacies that play an essential role in the bottom-up analysis of DERs operation within ECs. The aim by highlighting these aspects is to delineate the boundaries of the thesis, and present a clear structure, thus helping the reader gain a more accurate understanding of the methodology and the results. Note that a comprehensive presentation of the methods will follow in Chapter 2. Additionally, while I acknowledge some of the research's limitations here, I will extensively discuss them in more detail in Chapter 5.

Spatial dimension: The spatial scope of this thesis extends from the micro-level of individual households, broadening out to include the community or district level, and finally reaching a national scope. For the purposes of the study, with a "copper plate" assumption[1], communities can also be seen as virtually aggregated households. Moreover, Germany's energy system serves as the primary reference point for the broader energy system discussion. While the adopted model has an Europe and Maghreb scope in one of the included papers (Paper 3), a European-wide analysis is not extensively covered, due to the diverse national contexts, policies, regulations, and data accessibility challenges across countries.

Temporal dimension: Turning to the temporal dimension, an hourly resolution is employed for both simulations and optimization processes. This timescale is deemed effective for capturing important dynamics (including fluctuations in market prices as well as in power demand and supply) and balancing data availability with computational efficiency. The optimization horizon is set to a single day, leveraging the recurring daily energy patterns, prompt response capabilities, and operational efficiency potential. For scenarios where a one-day optimization is computationally impractical, a rolling horizon method is adopted to maintain an overall quasi-optimal outcome. Simulations run over a yearly timeframe, enabling the analyses to capture both short-term fluctuations and seasonal variations of RES.

Technological dimension: The technological scope of this thesis is primarily concentrated on the power sector. While acknowledging the crucial role of various sectors such as heat and mobility in a comprehensive energy system analysis, the focus here is explicitly on technologies and systems related to power generation and distribution. These include rooftop solar PVs systems, lithium-ion BSSs, and EVs, as well as HPs combined with TS systems. The overall energy system analyses within AMIRIS primarily includes conventional and renewable power plants. In these studies, the operation of sector-coupling technologies and other storage systems like pump storage are handled within REMix due to model constraints. Moreover, detailed modeling of

[1] In energy system modeling, the copper plate assumption neglects the constraints of grid infrastructure by assuming unrestricted power flow between generation and demand sites.

household appliances as well as distribution and transmission grids are beyond the scope of this study.

Economic dimension: The economic dimension of this research includes multiple layers, commencing with the micro-level economics of stakeholders within ECs and ultimately extending to the macro-level dynamics of the national energy market.

On the deepest layer, the thesis considers the end-consumers: While the models are adaptable to different power consumers, their principal application within this study pertains to residential end-users (i.e., individuals and households). When modeling the microeconomic decision-making of the end-users, many of their behavioral aspects, including lifestyle preferences, psychological factors, and social influences are generally neglected.

Next, in the economic dimension, companies are considered. Within the EC, a community-owned aggregator manages the power generation and consumption within the ECs and serves as an interconnection between EC and the wholesale market. Therefore, the scope of the thesis does not extend to community business models involving peer-to-peer trading or other decentralized local energy markets. In addition to the aggregator, large-scale market actors such as power plant operators are considered as market players. While cost optimization and maximizing financial gains remain primary objectives for these actors, the strategic bidding behavior of these large-scale operators is not a focal point of this thesis. All actors in AMIRIS operate under bounded rationality due to their limited foresight when predicting future prices, generation, and demands. However, the uncertainty of these factors is, except in Paper 3, neglected. Moreover, modeling the investment decisions of the actors, both within and outside of the EC, is beyond the focus of this research.

While shifting to the broader energy market, this thesis focuses on a single energy-only market. It also assumes that the current market design will remain in place until 2030. Lastly, all macroeconomic topics, such as the job market and energy security, are beyond the scope of this analysis. The spatial, temporal, technological, and economic scope covered in this dissertation is schematically illustrated in Figure 1.6.

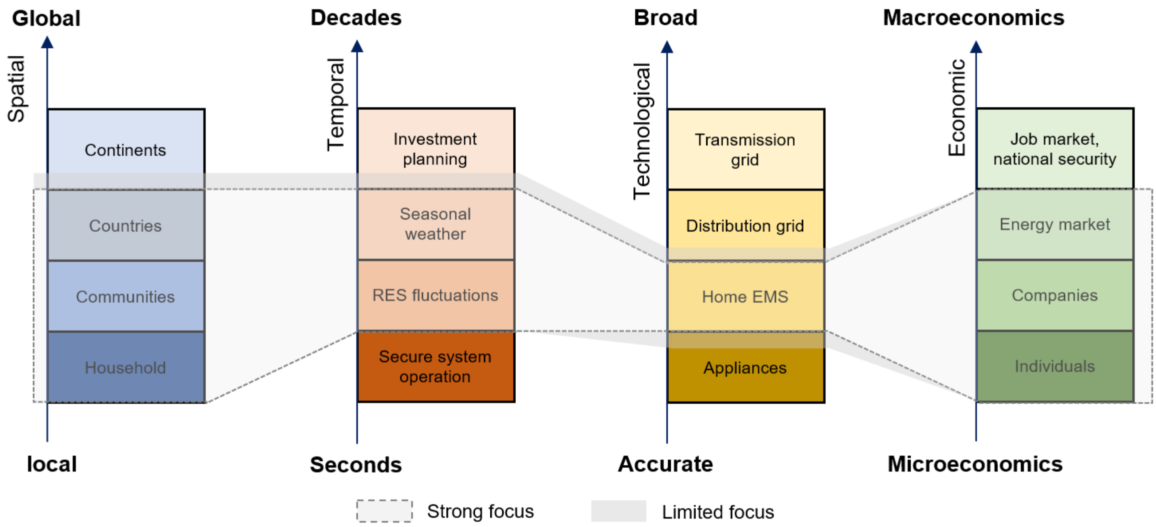

Figure 1.6: Schematic illustration of spatial, temporal, technological, and economic scopes of the energy system models applied in this thesis.

1.4 Approach and structure of this thesis

This thesis is structured around publications that have been either published in or submitted to peer-reviewed international journals. Each of these papers contains an extensive explanation and discussion of the methodologies developed and applied to address the corresponding research questions. Due to their diversity and intertwined nature, Chapter 2 explains the overarching methodological architecture of this thesis and provides a concise introduction of the methods used. Chapters 3 and 4 present four research articles that include a literature review, detailed methodological developments, and quantitative analysis pertaining to the research questions outlined in Section 1.2. Chapter 3 primarily focuses on addressing guiding question A, which concerns the operation of community energy systems and the “aggregation of distributed energy resources”. Despite the partial overlap, Chapter 4 primarily addresses guiding question B, which relates to the “system integration of decentralized energy systems”. Lastly, Chapter 5 summarizes the main findings and accomplishments of this thesis, discusses its limitations, and provides an outlook for future research. Figure 1.7 gives a schematic illustration of the thesis structure and the core elements of each chapter.

On aggregation of distributed generation and flexibility options (chapter 3): The initial two articles of this thesis primarily address the functioning of DES within the context of ECs. Although both Paper 1 and 2 employ a bottom-up approach to model a smart grid-connected EC, they differ in terms of community setup, modeled actors, and technologies. They are also distinguished by the mathematical problem formulation techniques and solution algorithms utilized to address the bidirectional energy trading problem between the aggregator and the EC users.

Aggregation of households in community energy systems: An analysis from actors’

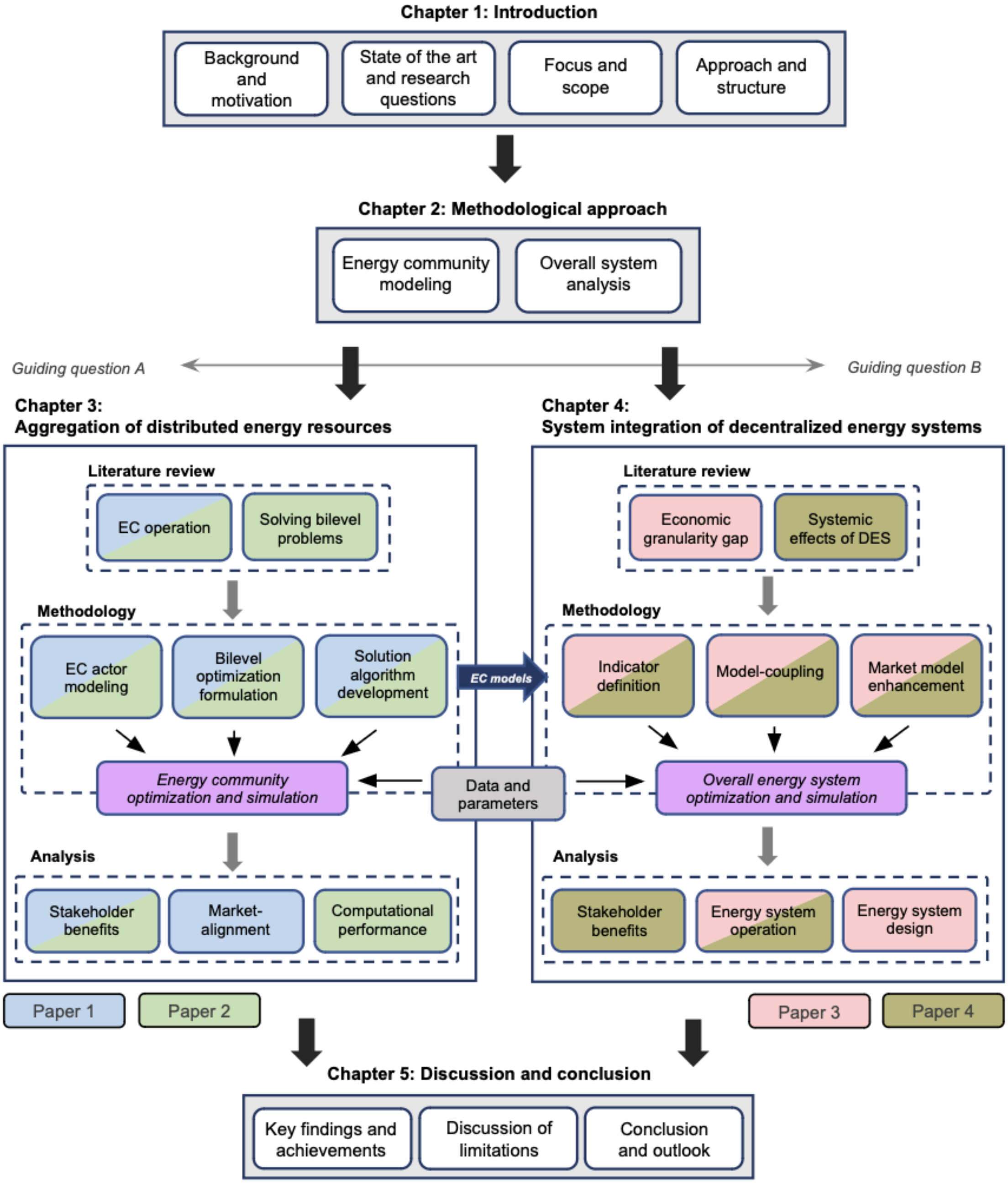

Figure 1.7: Overview of the structure of the thesis.

and market perspectives

by Seyedfarzad Sarfarazi, Marc Deissenroth, Valentin Bertsch
Published in October 2020 in Energies
Paper 1 corresponding to Section 3.1

Within the research presented in Paper 1, the study explores the novel strategies for an aggregator to effectively manage DERs within community energy systems. The analysis focuses on the aggregation of various household types, encompassing pure consumers, prosumers, prosumagers, and flexible consumers with HPs. The aggregator, operating a CES, employs price incentives and pursues either a cost or self-sufficiency optimization. The paper models the interplay between the aggregator and the heterogeneous households as a 1-leader, n-followers Stackelberg game and introduces an innovative approach to deal with the resulting energy trading game within the EC context. It employs genetic algorithms (GAs) to iteratively solve the optimization problems of both the aggregator and the participating households, facilitating the derivation of ORTP solution. Moreover, the proposed methodology introduces a MAI as a proxy for evaluating the system-friendly operation of the ECs. The study defines various use-cases and includes a thorough analysis of the EC business models from both actor and system perspectives. Consequently, this article makes noteworthy contributions toward addressing all research questions outlined in the previous section.

An optimal real-time pricing strategy for aggregating distributed generation and battery storage systems in energy communities: A stochastic bilevel optimization approach.

by Seyedfarzad Sarfarazi, Saeed Mohammadi, Dina Khastieva,
Mohammad Reza Hesamzadeh, Valentin Bertsch, Derek Bunn
Published in May 2023 in International Journal of Electrical Power & Energy Systems
Paper 2 corresponding to Section 3.2

Similar to the preceding article, Paper 2 presents a model of an EC managed by a community-owned aggregator. The model encompasses a generic user representation that can be parameterized to portray a consumer, a prosumer, a prosumager or an EV. The aggregator strategically formulates real-time prices to enable bilateral trade with the users within the EC, accounting for the uncertainties associated with user demand, generation, and market prices. The hierarchical trading problem in this paper is formulated as a stochastic BIOP. This paper employs a single-level reduction approach, involving Karush–Kuhn–Tucker (KKT) optimality condition and strong duality theorem, to transform the bilevel formulation to a single-level solvable problem. Furthermore, it introduces a novel modified branch and bound algorithm which applies a quasi-relaxation technique to efficiently deal with the non-linearity of the problem. To create the required scenarios for stochastic optimization, the paper proposes a cluster-based scenario generation algorithm. The analysis entails a comprehensive comparison of the outcomes derived from the developed real-time pricing and benchmark pricing designs, providing valuable insights into their performance. This paper contributes to answering research questions A.1 and A.2.

On system integration of distributed energy systems (chapter 4): Following the comprehensive exploration of EC operation in Chapter 3, Chapter 4 builds upon this foundation and shifts its focus toward investigating the implications of local electricity generation and consumption on the broader energy system (as per guiding question 2). This chapter features two publications, namely Papers 3 and 4. Both articles employ the electricity market model AMIRIS as their core analytical framework. However, they differ in terms of the specific DES settings considered and the overall system indicators examined within each study.

Improving energy system design with optimization models by quantifying the economic granularity gap: The case of prosumer self-consumption in Germany.

by Seyedfarzad Sarfarazi, Shima Sasanpour, Karl-Kiên Cao
Published in December 2023 in Energy Reports
Paper 3 corresponding to Section 4.1

Paper 3 focuses on quantifying the inefficiencies that arise due to self-consumption with PV-storage systems, introducing the economic granularity gap indicator as a means of measurement. To derive this indicator, this article proposes an automated workflow that combines the ESOM REMix with the AMIRIS. The methodology of the paper involves enhancing AMIRIS through the implementation of prosumager and aggregator agents. Focusing on the German power sector in 2030, the presented analysis examines the economic granularity gap resulting from a status-quo prosumage model, as well as the impact of dynamic tariffs on this gap. The study further explores the influence of residential self-consumption on both the operation and design of the overall energy system. This article contributes to the research questions B.1 and B.2.

Integration of energy communities in the electricity market: A hybrid agent-based modeling and bilevel optimization approach.

by Seyedfarzad Sarfarazi, Shima Sasanpour, Valentin Bertsch
To be published in December 2024 in Energy Reports
Paper 4 corresponding to Section 4.2

The model developments presented in Papers 2 and 3 serve as a robust foundation for analyzing the system integration of DERs within the electricity market. Paper 4 introduces a novel methodology that combines bilevel optimization and agent-based modeling, effectively integrating the EC model presented in Paper 2 with the AMIRIS developments proposed in Paper 3. This hybrid approach enables a comprehensive assessment of the systemic effects of distributed storage systems, specifically focusing on behind-the-meter HES and grid-connected CES. Moreover, the presented methodology improves the EC model by including regulatory induced charges on grid consumption, thereby facilitating a holistic evaluation of EC integration under various policy regimes. The study includes simulations in two energy system scenarios. The first scenario utilizes historic data to parameterize the model, representing the status quo energy system, while the second scenario represents the German energy system in the year 2030. This paper contributes to answering research questions A.2, B.1, and B.2.

Chapter 2

Methodological approach

This dissertation has employed a variety of methodologies to accomplish its research objectives. While these methods are extensively explained and discussed in the associated papers, given their diversity and complex interconnections, this chapter aims to provide a succinct overview. Figure 2.1 schematically illustrates the methodologies used in this thesis.

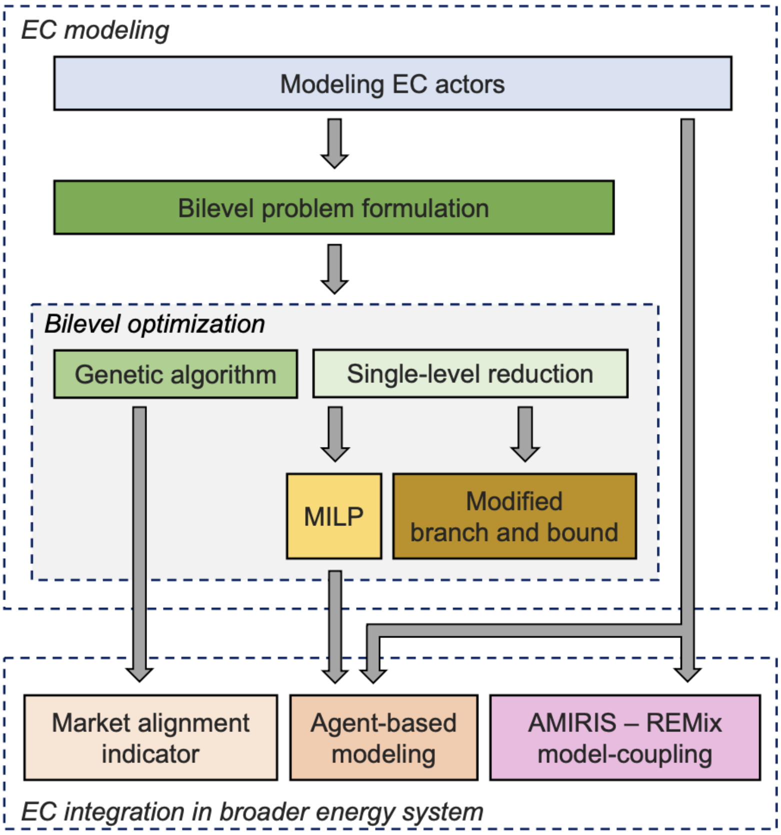

Figure 2.1: Overview of the methodologies in this thesis.

Following a bottom-up structure that mirrors the guiding research questions, this chapter is arranged as follows: Section 2.1 explains the methodologies applied at the EC level, which includes modeling the behavior of the EC actors and employing bilevel optimization. Subsequently, Section 2.2 elucidates the three approaches used to measure the systemic effects of DES integration into the broader energy system.

2.1 Energy community modeling

Developing models of the EC is a crucial step for accurately representing key emerging business models in this context. The focus of this modeling approach is on capturing the operational behavior of the actors within the EC. Initially, this behavior is captured for each stakeholder (as will be discussed in Section 2.1.1). Following this, the interdependencies between the decision-making of the aggregator and users are considered. This interaction is modeled as a bilevel problem, a concept that will be explored in detail in Section 2.1.2.

2.1.1 Modeling actors

In the previous section, key assumptions regarding the community energy system under investigation are described. The most important of these assumptions is the hierarchical structure of the actors, meaning that an aggregator acts as an intermediary entity between the users and the market. Figure 2.2 illustrates the structure, the modeled actors, and key information flows in the EC. In the following I will briefly introduce the rationale of each actor. A more comprehensive explanation including actor-specific mathematical formulations can be found in the publications included in this thesis. Note that some actors and modeling features explained here might be found in one paper, while others are implemented in all.

Assuming inelastic electricity demand, an EC consists of two types of inflexible actors. The first is a traditional power customer or "consumer", who does not own any DER and thus meets its electricity demand via the grid. The second is a "prosumer", conceptualized as a household that operates a PV system. It directly consumes the electricity generated, feeding residual generation back into the grid. During periods of no generation, their electricity demand is met from the grid.

All other EC users own and operate some form of energy storage to minimize their electricity costs, contingent on the EC sale and purchase prices. A "prosumager" is a household with a combined PV-HES system. Like prosumers, prosumagers directly consume the generated solar power and use the HES to optimize their interactions with the grid. A "flexible consumer" refers to a household that operates a combined HP-TS system[1]. An "EV owner" is an actor who uses an EV equipped with a lithium-ion

[1]It is assumed that TS serves as the only energy storage of the households. In more detailed modeling methodologies the thermal mass of buildings is considered an energy storage [92].

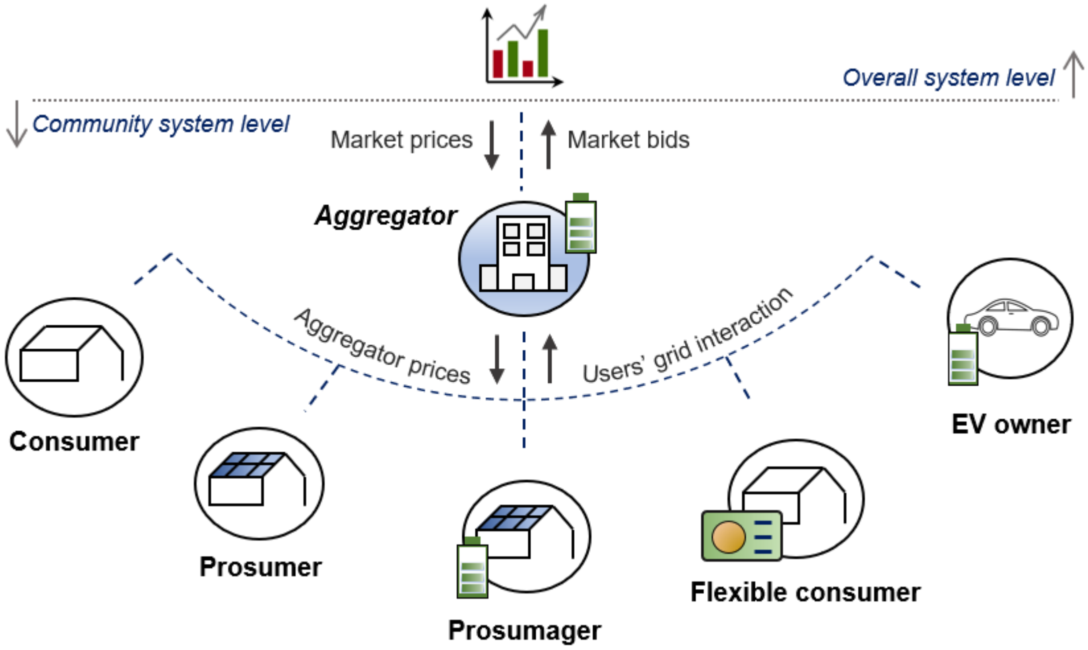

Figure 2.2: Structure, information flows, and actors in the considered EC business model.

BSS. The flexibility of an EV enables smart charging and discharging (vehicle-to-grid) according to the EC trading prices. A key feature of the EV model is that it considers the availability of the EV for trading, i.e., connection to the grid.

The "aggregator" is an intermediary entity between the users and the market and plays a central role in the EC model. The aggregator performs several tasks: it receives forecasts of upcoming market prices, creates sale and purchase prices for the users (which could be time-invariant – SP, mirror the pattern of market prices – RTP, or be tailored dynamic prices for the community – ORTP), may use CES to further optimize its strategy based on user responses, and trade in the wholesale market. The aggregator uses price incentives and CES as instruments to pursue two goals. The first is profit maximization. As mathematically shown in Paper 2, the welfare of the community (defined as the sum of all costs and revenues in the EC) obtained under this strategy is equivalent to a scenario where the aggregator's goal is to maximize community welfare. The second strategy involves self-sufficiency-driven operation, where the aggregator seeks to minimize exchange with the market as much as possible.

Table 2.1 provides a summary of the rationale behind the EC actors and specifies the respective papers where each actor is activated.

To capture the micro-economic behavior of EC actors, various optimization models have been developed, each with specific objectives as outlined in Table 2.1. These optimization models possess unique characteristics that correspond to the context of analysis and the specific actor under consideration. Nevertheless, in the following, I present a general formulation for both users and the aggregator, aiming to illustrate

Table 2.1: Summary of the EC actors' rationale

Actor	DER	Optimization goal	Strategy	Paper
Aggregator	CES	Profit Self-sufficiency	Storage optimization Create price incentives	1,2,3,4
Prosumager	PV HES	Cost reduction	PV direct consumption Self-consumption with HES	1,2,3,4
EV owner	EV	Cost reduction	Smart charging vehicle to grid	2
Flexible consumer	HP TS	Cost reduction	Load shifting with TS	1
Prosumer	PV	-	PV direct consumption	1,2,3,4
Consumer	-	-	-	1,2

the interdependencies of decision-making within the EC.

Assuming a prosumager – aggregator interaction shown in 2.3, the objective function of the cost-driven optimization of user i can be described with (2.1).

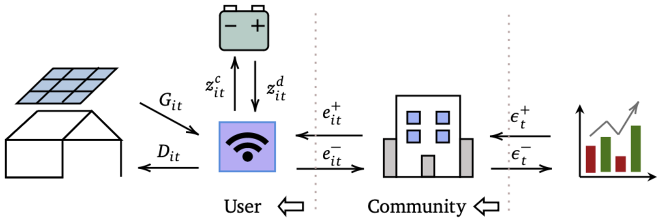

Figure 2.3: Virtual power flows in a simplified EC model.

$$\text{Minimize } c_i = \sum_t (e^+_{it} \cdot p^s_t - e^-_{it} \cdot p^p_t). \tag{2.1}$$

c in (2.1) is the cost of prosumager i during the optimization period. e^+_{it} and e^-_{it} are the used and fed-in electricity to the grid by the user at time step t. p^s_{it} and p^p_{it} are aggregators sale and purchase prices at this time step. The key constraints to this optimization problem are:

$$a_{it} = (1-\delta_i) \cdot a_{i(t-1)} + \eta^c_i \cdot z^c_{it} - \frac{z^d_{it}}{\eta^d_i}, \tag{2.2}$$

$$z^c_{it} = e^+_{it} + G_{it} - D_{it} - e^-_{it} + z^d_{it}, \tag{2.3}$$

$$\underline{A}_i \leq a_{it} \leq \theta_i, \tag{2.4}$$

$$a_{i0} = A_{i0}, \tag{2.5}$$

$$0 \leq z^c_{it} \leq \overline{Z}^c_i, \tag{2.6}$$

$$0 \leq z^d_{it} \leq \overline{Z}^d_i. \tag{2.7}$$

In Equation (2.2), the state of charge (a_i) of the BSS at time step t is expressed considering the battery self-discharge rate δ_i, charge and discharge efficiencies (η_i^c and η_i^d), as well as the charged and discharged power (z_{it}^c and z_{it}^d). Equation (2.3) presents the power balance for the user-side energy system, where G_{it} and D_{it} are the power generation and demands in time step t, respectively. In Paper 2, G_{it} and D_{it} are considered to be subject to uncertainties. Constraint (2.4) ensures that the state of charge of the BSS remains above a minimal acceptable value ($\underline{A}$) and does not exceed the battery capacity (θ_i). Equation (2.5) sets the initial state of charge to A_{i0}. Lastly, Equations (2.6) and (2.7) limit the amount of charging and discharging power in each time step, depending on the performance of the battery ($\overline{Z}_i^c$ and $\overline{Z}_i^d$).

The problem formulated above is a linear optimization problem[1]. This can be solved using various commercial solvers. Nonetheless, this thesis also develops and utilizes a dynamic programming model for storage optimization as explained in Paper 1. Dynamic programming offers several advantages compared to commercial solvers. These advantages include its ability to handle complex constraints effectively and to reduce computational effort through efficient memory usage [95].

The aggregator's profit maximization objective function can be formulated in a simplified form as shown in Equation (2.8),

$$\text{Maximize } r = \sum_t \left(P_t^m \cdot (\epsilon_t^- - \epsilon_t^+) + \sum_i (e_{it}^+ \cdot p_t^s - e_{it}^- \cdot p_t^p) \right), \tag{2.8}$$

where r represents the profit of the aggregator, P^m is the forecasted market price, and ϵ_t^- and ϵ_t^+ represent the traded power in the wholesale market. Depending on the specific case, the aggregator can operate CES (as discussed in Papers 1 and 4), consider the restrictions of the distributed grid (Paper 2), and take into account uncertainties regarding the market prices (Paper 2). Nonetheless, in a simplified scenario, the optimization is subject to the constraints outlined in Equations (2.9) and (2.10).

$$\underline{P_t^s} \le p_t^s \le \overline{P_t^s}, \tag{2.9}$$

$$\underline{P_t^p} \le p_t^p \le \overline{P_t^p}. \tag{2.10}$$

In the absence of competition among multiple aggregators, Equations (2.9) and (2.10) ensure that the internal EC prices remain within an acceptable range. Here, $\underline{P_t^s}$ and

[1]Depending on the setup, the problem formulation for HES can become complex and non-linear [93]. For instance, it may require the introduction of binary variables to define the status of controllable uninterruptible appliances [94]. However, in the context of standard prosumager optimization, some literature, such as [47], uses a binary variable to prevent simultaneous charging and discharging of the battery. In Paper 2, it is mathematically shown that under certain conditions, relaxing the binary variable doesn't impact the results.

$\underline{P_t^p}$ represent the lower limits and $\overline{P_t^s}$ and $\overline{P_t^p}$ denote the upper limits for the sale and purchase prices respectively. These limits are determined based on the market price range during the optimization period.

Examining the objective functions of the users in Equation (2.1) and the aggregator in Equation (2.8), the interdependencies of their strategies become evident. The users' strategy depends on the trading prices, and the aggregator's pricing strategy hinges on the power usage and grid feed-in of the users. This intertwined relationship precludes the possibility of solving the problem independently. In the following section, the concept of bilevel optimization is introduced, illustrating the general approaches employed in this thesis to address the demonstrated hierarchical problem that arises in EC modeling.

2.1.2 Bilevel optimization

BIOPs, characterized by the interaction between two decision-making entities – a leader and a follower – find special significance in economics and energy system modeling. In these models, the leader, or the upper-level decision maker, optimizes an objective function subjected to certain constraints, while anticipating the responses of the follower, who optimizes his/her own objective function based on the decisions imposed by the leader. This strategic interaction can be modeled as a form of Stackelberg game, thus making game theory one of the principal applications of bilevel optimization. However, even when all functions involved are linear, these problems pose significant computational challenges due to their inherent characteristics, such as nonconvexity, nondifferentiability, and potential for nonunique optimal solutions for the follower's problem, proving them to be NP-hard[1] [96].

To navigate these challenges, a wide range of methodologies have been developed and applied [97]. To address these challenges, this thesis adopts two methodologies: GAs from the category of intelligent heuristic methods (in Paper 1), and a classical method known as the single-level reduction approach (in Papers 2 and 4).

2.1.2.1 Genetic algorithm

Inspired by natural selection, GAs are search-based optimization methods that employ operations such as mutation, crossover, and selection to evolve a population of potential solutions toward an optimal or near-optimal solution. The use of GAs to solve BIOPs involves encoding the decision variables of both the leader and the follower into a chromosome representation, and defining a fitness function that quantifies the quality of a solution.

[1] In computer science, a problem is considered NP-hard when it is as hard as the most difficult problems in a class of problems known as NP. This means there's no known efficient way to find an exact solution, and verifying a given solution can also be quite difficult.

Paper 1 models the hierarchical aggregator-household interaction as a 1-leader, n-followers Stackelberg game and employ GA to solve the resulting bilevel problem. This game (γ) can be formally defined by its strategic form as:

$$\gamma = \{(H \cup R), \{E_h\}_{h \in H}, \mathcal{Q}, \{u_h\}_{h \in H}, Z\} \tag{2.11}$$

In equation (2.11), $(H \cup R)$ is the set of actors, where the households in H act as followers in response to the prices set by the aggregator R as the game leader. $\{E_h\}_{h \in H}$ is the set of strategies of households, at time t. This strategy represents the grid usage and feed-in of households in each time step. $\mathcal{Q}$ is the strategy set of the aggregator, which consists of energy trading prices. $\{u_h\}_{h \in H}$ corresponds to the set of utilities for each household h at time t and represents the benefits or rewards obtained by households from their chosen strategies. Z represents a measure of performance or outcome in the game. It could be the net income of the aggregator or another relevant metric that characterizes the success of the game, such as the level of EC self-sufficiency.

One suitable solution for the proposed Stackelberg game γ is the Stackelberg equilibrium, in which the leader obtains its optimal prices given the followers' best responses. At this equilibrium, neither the leader nor any follower can benefit, in terms of net income (or level of self-sufficiency), by unilaterally changing their strategy [98]. A set of strategies $(E_h^*, q^*(t))$ constitutes an Stackelberg equilibrium of this game if and only if it satisfies the following set of inequalities:

$$\begin{aligned} & u_h(E_h^*, q^*(t)) \geq u_h(e_h(t), E_{-h}^*, q^*(t)), \quad \forall h \in H, \quad \forall e_h(t) \in E_h, \\ & Z(E_h^*, q^*(t)) \geq Z(E_h^*, q(t)), \quad \forall q(t) \in \mathcal{Q}, \end{aligned} \tag{2.12}$$

where $E_{-h}^* = [e_1^*(t), e_2^*(t), .., e_{h-1}^*(t), e_{h+1}^*(t), .., e_H^*(t)]$ and $E_h^* = [e_h^*(t), e_{-h}^*(t)]$. Therefore, when all players in $(H \cup R)$ are at equilibrium, the aggregator cannot improve its position by changing its prices from the equilibrium prices $q^*(t)$. Similarly, no household can reduce its costs by choosing a different grid interaction $e_h^*(t)$.

The GA algorithm involves an aggregator-side and user-side optimization, as schematically shown in Figure 2.4. On the aggregator's side, the algorithm begins with population initialization, generating a population of chromosomes that represent power trading price sets. Each chromosome corresponds to a specific optimization period. The aggregator decodes the chromosomes to determine the electricity tariff elements, such as procurement costs, grid charges, and other regulated components. These prices are then announced to the households.

On the households' side, the households receive the electricity prices from the aggregator and calculate their own strategies, specifically the grid interactions, based on the prices. Each household solves the follower's problem using to minimize the costs. The households then send back the predicted grid interactions to the aggregator.

The aggregator receives the optimal strategies of the households, including the pre-

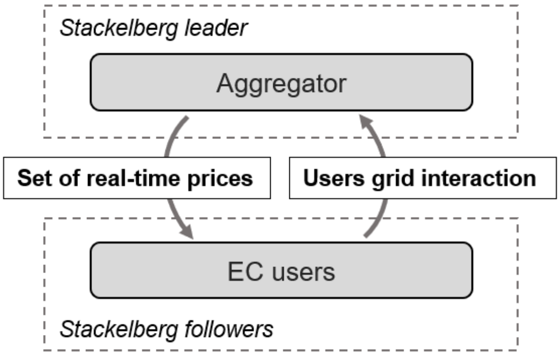

Figure 2.4: Schematic illustration of the aggregator–user interaction in one iteration.

dicted grid interactions. The aggregator optimizes its own strategy by considering constraints and evaluating its profit or the self-sufficiency level of the EC, depending on the use-case. From this evaluation, the fitness value for each chromosome can be derived. After each iteration, new generations of chromosomes are created through crossover and mutation operations. The process continues until the convergence condition is met, i.e., when the difference between the average fitness and the best fitness of the current population is below a specified threshold.

2.1.2.2 Single-level reduction

The GA approach allows for the exploration of the solution space and the convergence to a near-optimal solutions for complex bilevel problems. However, it does have several limitations: Due to their stochastic nature, they do not guarantee finding the global optimal solution and their performance heavily depends on parameter tuning and problem-specific design. In addition, they may require a significant number of fitness function evaluations, which can be computationally expensive for complex problems [99]. To overcome these limitations, a popular approach involves transforming the bilevel problem into a standard single-level optimization problem. A common strategy for this transformation involves the KKT conditions, which provide necessary and sufficient conditions to represent the followers' problem.

In the context of an energy trading game within an EC, the aggregator's and users' problems (expressed in (2.8) and (2.1)) are respectively the upper- and lower-level problems. The BIOP in this energy trading problem can be formulated in its general form as follows:

$$\begin{aligned} \min_{x \in X, y \in Y} \quad & f(x, y) \\ \text{subject to} \quad & g(x, y) \leq 0, \\ & h(x, y) = 0, \\ & y \in \arg\min_{y' \in Y} \{F(x, y') : G(x, y') \leq 0, H(x, y') = 0\}, \end{aligned} \tag{2.13}$$

where $f(x, y)$ is the objective function of the aggregator, $g(x, y)$ and $h(x, y)$ represent the constraints of the aggregator, and $F(x, y)$ is the objective function of the users. Here, x could represent the decisions made by the aggregator (e.g., the amount of energy traded in the market and the price sets for the users), and y could represent the decisions made by the users (the traded power with the aggregator). X and Y are the feasible regions for the aggregator's and the users' decisions, respectively.

The single-level reduction approach, applied in Paper 2, to transform the bilevel problem into a single optimization problem involves the following steps:

- Formulate the KKT conditions, including primal and dual feasibility as well as stationary and complementary slackness conditions [100], for the users' problem, treating the prices set by the aggregator as given parameters:

$$
\begin{aligned}
G(x, y) &\leq 0, && \text{(Primal Feasibility)} \\
H(x, y) &= 0, && \text{(Primal Feasibility)} \\
\mu &\geq 0, && \text{(Dual Feasibility)} \\
\nabla_y L(x, y, \mu, \lambda) &= 0, && \text{(Stationary)} \\
\mu^T G(x, y) &= 0. && \text{(Complementary Slackness)}
\end{aligned}
\tag{2.14}
$$

  Here, μ and λ are the Lagrange multipliers associated with the inequality constraints and equality constraints of the users' problem, respectively, and $L(x, y, \mu, \lambda)$ is the Lagrangian of the users' problem.

- Replace the users' problem in the original bilevel formulation with its KKT conditions, expressed in equation 2.14.

- Replace the complementary slackness conditions with strong duality conditions. If the users' problem is a linear program the strong duality theorem holds and the optimal value of the lower-level problem is equal to the optimal value of its dual problem (equation (2.15)), thus eliminating the need for explicit complementary slackness conditions [101].

$$F(x, y) = D(\mu, \lambda). \tag{2.15}$$

  This replacement brings multiple advantages. Most importantly, it reduces the number of constraints in the problem, which can make the problem easier to solve. Moreover, it can eliminate some binary variables that may have been introduced to model due to the complementary slackness condition, reducing the size and complexity of the resulting mixed-integer problem.

- The bilevel problem is now transformed into a single-level optimization problem, which includes both the aggregator's and the users' decisions:

$$\begin{aligned}
\min_{x\in X, y\in Y, \mu\geq 0, \lambda} \quad & f(x,y) \\
\text{subject to} \quad & g(x,y) \leq 0, \\
& h(x,y) = 0, \\
& \nabla_y L(x,y,\mu,\lambda) = 0, \\
& G(x,y) \leq 0, \\
& H(x,y) = 0, \\
& F(x,y) = D(\mu,\lambda).
\end{aligned} \tag{2.16}$$

- The single-level problem (equation 2.16) of the energy trading game has non-linearities due to the multiplication of two variables (e^*_{it} and p^*_t). To eliminate the emerged non-linear terms, it can be assumed that one these variables take discrete values. In the proposed methodology, the internal EC trading prices (p^*_t) are discretized and the Big-M method [102] is applied to force the variable to adopt discrete values.

  After this step, the bilevel problem has been successfully transformed into a problem. This transformation allows the application of commercial solvers to find the optimal solution. In this thesis, the mixed-integer linear program (MILP) problem is solved using CPLEX, which employs a branch-and-bound algorithm, on the GAMS platform.

The utilization of the Big-M method introduces additional binary variables into the MILP model, leading to increased computational complexity. Another limitation of Big-M is that the effectiveness of the solver relies on choosing an appropriate value for the parameter M. In order to address these drawbacks, an alternative approach is employed in Paper 2 to deal with the bilinear terms, i.e., (e^*_{it} and p^*_t). This technique involves a linear quasi-relaxation approach, which is based on the method introduced in [103] and further generalized in [104]. As comprehensively described in Paper 2, this methodology transforms the problem into a linear programming problem and effectively deals with the disjunctive nature of the discretized variables through a modified branch and bound algorithm.

One drawback of discretization in optimization is that it can lead to a loss of precision and potentially overlook fine-grained features of the problem's continuous landscape. To enhance result precision and approach the global optimum of the original bilevel problem, the proposed modified branch and bound algorithm is equipped with a "dynamic partitioning" feature. With this feature, the algorithm doesn't halt upon discovering an optimal solution to the discretized problem. Instead, it dynamically selects a finer solution region around the previous solution and further refines its discretization. This approach enables a more efficient exploration of the solution space, allowing for improved proximity to the global optimum without substantially increasing the granularity of the entire continuous space. As a result, the computational efficiency is significantly enhanced.

2.2 Overall system analysis

In this section, I elucidate the developed and applied methodologies to investigate the potential systemic impacts of ECs on the broader energy system. Section 2.2.1 explains the first approach, which involves defining and quantifying the MAI, as proposed in Paper 1. The subsequent analyses regarding the system integration of ECs, as presented in Papers 3 and 4, use agent-based modeling. Details about ABM AMIRIS and model improvements incorporated in this thesis are covered in Section 2.2.2. Finally, Section 2.2.3 provides an in-depth explanation of the model-coupling methodology. This approach is designed to evaluate the economic granularity gap that emerges in case of local self-consumption within the EC.

2.2.1 Market alignment indicator

The idea behind this methodology is that in a perfect power system characterized by minimal friction and optimal efficiency, wholesale market prices serve as reliable indicators of energy availability or excess within the system. Therefore, assessing the degree to which the operation of EC aligns with these market price patterns can provide valuable insights into their compatibility with the overall system operation. To achieve this, a MAI is being developed, which aims to estimate the level of agreement between EC operation and market signals without the need for simulating energy markets.

The concept of the MAI is first introduced in [47] and has proven to be an effective tool for assessing how well the operation of PV-storage systems aligns with market dynamics. In this context, MAI compares the performance of a HES system, denoted as the achieved welfare W_{HES}, with a benchmark system of the same physical characteristics. This ratio is described in Equation (2.17). The benchmark case in this study is defined as an arbitrage BSS[1], which perfectly follows market signals without interruption.

$$\begin{aligned} MAI &= \frac{W_{HES}}{W_{benchmark}}, \\ W_{HES} &= W_{PV+HES} - W_{PV}. \end{aligned} \tag{2.17}$$

[1]The traditional concept of arbitrage typically involves buying in one market and selling in another to exploit price differentials. However, in the context of energy markets, the term “energy arbitrage” is often, for example in [105] and [106], used in a broader sense to include strategies that take advantage of price differences within a single market.

The obtained welfare of the systems (W_x) is generally described as:

$$W_x = \sum_t P_t^m \cdot (e_t^- - e_t^+) \tag{2.18}$$

In the realm of evaluating the system integration of prosumagers, the given methodology shown to be significantly beneficial. Nevertheless, its constraints surfaced while engaging with more complex systems that encompass numerous stakeholders and a variety of technologies. In particular, the issue of selecting an appropriate benchmark EC arises in this context. For instance, can the operation of sector-coupling technologies, such as HP, be equated with arbitrage BSS? In intricate use-cases wherein the stakeholders exhibit a diverse array of "flexibilities", a rudimentary comparison to an arbitrage BSS appears to fall short. This raises the need for a more robust comparison framework within the energy economics landscape.

To address this gap, this thesis enhances the original strategy and proposes a novel methodology that quantifies the market alignment of heterogeneous ECs. In alignment with its predecessor, the new methodology also contrasts the performance of an EC in a specific use-case with a benchmark use-case. However, the benchmark in the revised methodology diverges from the original conception. The reference point for the operation of the EC is redefined as a use-case in which an aggregator holds control over all flexibility options within the community. Consequently, it is equipped with the capacity to trade effectively within the market. This use-case mirrors the operational conditions of an arbitrage BSS operator, where the aggregator optimally aligns with market signals, bounded only by the technical constraints of the EC. The proposed definition of MAI is formulated as follows:

$$\begin{aligned} MAI &= \frac{W_{EC} - W_{ref}}{W_{benchmark} - W_{ref}}, \\ W_x &= \sum_t P_t^m \cdot (\epsilon_t^- - \epsilon_t^+). \end{aligned} \tag{2.19}$$

In equation (2.19), W_{ref} denotes the welfare in a reference use-case that utilizes a status quo pricing structure, devoid of any incentives for flexibility. The benchmark use-case is constructed using the same game-theoretic model discussed previously. In this use-case, the objective function of the aggregator simplifies to

$$\text{Maximize } W_{benchmark}, \tag{2.20}$$

while the price limitations encapsulated in equations (2.9) and (2.10) are effectively relaxed[1]. Therefore, the aggregator's prices p_t^s and p_t^p operate as control signals that the aggregator employs to optimize its market trading profit.

[1]That is, an expansive range is selected.

2.2.2 Agent-based modeling

The introduced MAI can be utilized as a proxy to evaluate the system-friendly operation of various ECs. A significant drawback of this approach, however, is that it fails to account for the impact of ECs on market prices. This limitation is particularly pronounced when the community expands considerably, or when a multitude of small communities with analogous operational behaviors emerge. Addressing this constraint, alongside an in-depth analysis of the market integration of DER, particularly in future markets, necessitates a direct linkage to an energy market model. For this purpose, this thesis uses the agent-based modeling approach.

Agent-based modeling is a computational methodology that enables the exploration and understanding of complex systems composed of interacting, autonomous entities known as "agents" [107]. By modeling agents individually, ABM permits the examination of simple rules and behaviors, which can range from simple logic to complex learning algorithms, that can result in complex patterns on the aggregate level. This unique perspective allows ABM to bridge micro-level interactions to macro-level outcomes, thereby offering valuable insights into the emergence of system-wide phenomena [108]. Importantly, ABMs enables the representation of systems in disequilibrium, acknowledging the often unbalanced, transitioning reality of markets, a feature that conventional equilibrium models do not typically accommodate [79].

Applying ABM to energy system modeling presents promising opportunities to investigate the impacts of individual decisions on overall energy system dynamics. AMIRIS, developed at the German Aerospace Center (DLR), is one application of ABMs[1] in energy system modeling that captures the decisions of different actors, such as RES plant operators and traders. By employing a bottom-up modeling approach, AMIRIS can effectively illustrate the complexities and intricacies of energy systems, offering valuable insights into the factors that shape the market and the outcomes of policy decisions [82]. This holistic approach makes AMIRIS an essential tool for exploring the future of energy systems.

AMIRIS[2] enables an endogenous simulation of an Energy-Only-Market with an hourly resolution. Bids are submitted by market participants, after which the energy exchange ranks them according to the merit order principle. Every hour, the market reaches a clearing point where the wholesale market price is identified at the juncture of the supply and demand curves.

Within AMIRIS, power plants bid their electricity output based on their own marginal costs. These costs are evaluated by taking into account specific plant parameters like

[1]Besides AMIRIS, EMLab Generation [108] developed at Delft University of Technology and PowerACE [87] developed at Karlsruhe Institute of Technology (KIT) are examples of well-established energy market ABMs.

[2]AMIRIS is developed in Java using the FAME-core framework [109]. While a significant portion of AMIRIS is open-source [110], the developments in this thesis are not publicly available at the time of publishing.

efficiency and variable costs, in addition to fuel and CO_2 prices. Furthermore, certain policy regimes may provide renewable energy plants with a market premium can influence the bidding strategy of the RES power plants. AMIRIS is equipped with an integral forecasting agent, capable of providing predictions regarding upcoming market dynamics to other agents. These forecasts can be flawless or carry a certain degree of error. The predicted prices are particularly vital for actors possessing some sort of flexibility, such as operators of storage systems. The reader can refer to [79] for a more detailed explanation of AMIRIS model mechanics as well as model input/output.

A notable characteristic of ABMs is their ability to encompass "models within models", enabling a thorough, multi-layered view of systems. For instance, AMIRIS includes a merit order bidding model used to simulate the market clearing process and compute wholesale electricity prices. This thesis capitalizes on this feature and integrates the developed EC models into AMIRIS. This integration process entails the implementation of new agents, the adaptation of existing infrastructure to accommodate linear optimization models, and the creation of the necessary model interface to carry out the developed bilevel optimization.

Agents: Two new actors are incorporated into AMIRIS. The *aggregator* serves as the intermediary entity between the market and the *end-users*. End-user represents an abstract agent which, depending on the parameterization, can denote a pure consumer, a prosumer, a prosumager, or an EC. The information flow among these AMIRIS agents closely mirrors that of the introduced EC models: The aggregator receives a forecast of upcoming market events, and subsequently formulates and communicates a set of purchase and sale prices to the contracted end-users. If they are flexible, the end-users optimize their strategy and communicate their power consumption or grid feed-in to the aggregator. Based on the information from the end-users, the aggregator formulates demand or supply bids for the market. If the aggregator operates a CES, the bidding strategy is further refined before submission. Figure 2.5 illustrates the information exchange and virtual power flows between the newly implemented agents and the rest of AMIRIS.

Optimization models: Altogether, three models are implemented to guide the EC agents in their operational decision-making. Two of these models are linear optimization models associated with HES and CES dispatch. For efficient model development, both models are re-implemented using the built-in dynamic programming module AMIRIS. While the implemented models are similar to those of EC models, one new feature is added to the CES optimization model: using a methodology developed in [111], the storage operators in AMIRIS can account for their market power, when optimizing their strategy. In this case, the operator is possesses comprehensive information about the merit-order curve[1] and can therefore take into account its influence on the prices. This feature is also integrated in the CES optimization model.

[1]Delivering the upcoming orderbook to an agent is part of the perfect foresight assumption. This approach is of course not applicable in the reality. However, this method can mitigate the model artifact that results from the perfect foresight of a large storage entity.

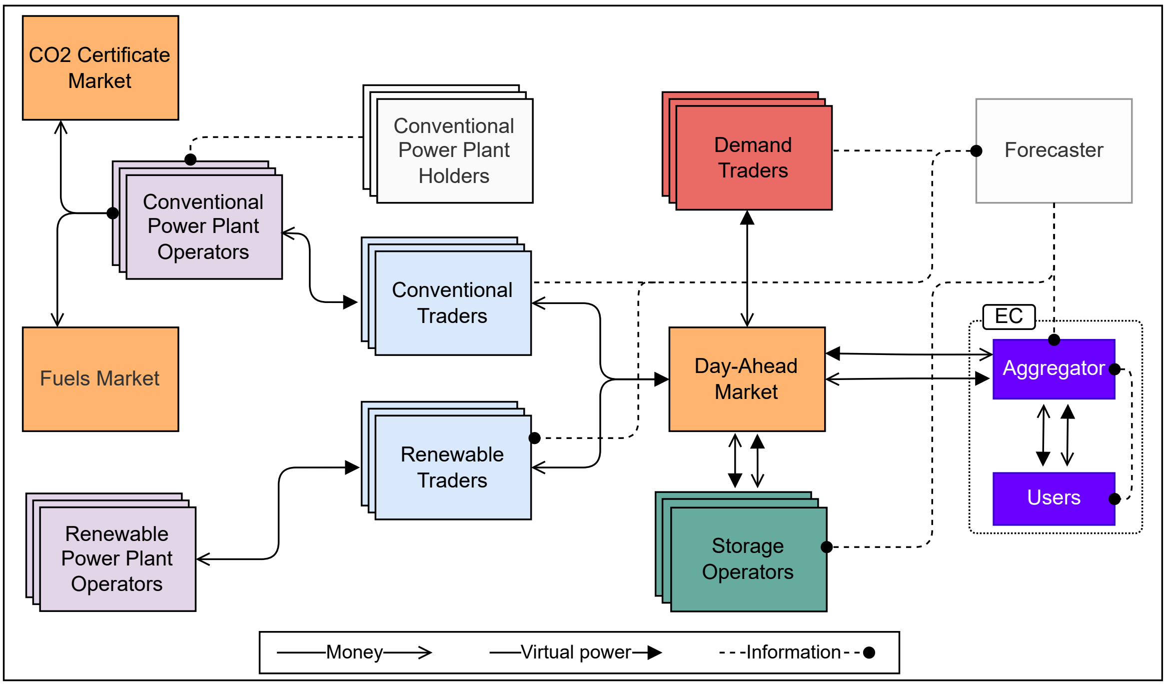

Figure 2.5: Schematic representation of the agents in AMIRIS.

The third model pertains to the EC energy trading BIOP. As explained, this thesis proposes two approaches to model and solve this problem. The first approach has a distributed structure and employs a GA to iterate between two problem levels to find the optimal solution. The second approach merges the two levels into a single, solvable problem. While the distributed algorithm used in the first approach aligns more with the logic and structure of the ABM (e.g., each agent solving its own problem), iterations between agents to find the equilibrium is not compatible with the AMIRIS infrastructure. Therefore, the second BIOP model is implemented in AMIRIS.

In this scenario, the BIOP model must be incorporated in either the aggregator, or the end-user agent. The proposed approach chooses the latter and delineates the two functionalities of the aggregator in the model. Although the aggregator agent continues to be responsible for market trading activities, it forwards the market price forecast to the end-user, and the energy trading game is solved within the internal optimization of this agent[1]. The implementation of this approach is explained in more detail in Paper 4.

The use of the AMIRIS model presents several noteworthy limitations, as will be discussed in Chapter 5. Acknowledgment of these limitations is pivotal to comprehending one necessity for a model-coupling approach, which I explicate in the subsequent section.

One prominent drawback of AMIRIS is its constrained national perspective, which

[1]On a technical note, since the bilevel optimization utilizes a MILP solver that isn't available in the JAVA language, an API [112] is employed to facilitate communication between the GAMS model and AMIRIS.

lacks the feature of market coupling. Consequently, the model cannot endogenously calculate cross-border trades, such as power imports and exports with neighboring countries. Furthermore, AMIRIS's operation of flexibility operators is dependent on forecasts provided by a singular forecaster agent. This approach enables the optimization of only one actor in a feasible manner. The simultaneous responses of multiple large-scale storage systems to identical price predictions could potentially induce model artifacts, known as 'avalanche effects' [113]. Lastly, AMIRIS falls short in its inability to model investment decisions made by market actors in various technologies. As a result, AMIRIS can merely simulate the operation of an existing energy system, not the transformative processes that lead to its evolution.

2.2.3 Model-coupling

This section details the applied model-coupling methodology used to examine the implications of ECs in the future energy system. This methodology entails the integration of an ABM with an ESOM. The model-coupling method developed in this dissertation is based on earlier works by Torralba-Díaz et al. in [84] and [85].

Linking the two large-scale energy system models, as presented in Paper 4, is employed to launch the ABM simulations (*initialization*), addressing the previously noted limitations. The model-coupling demonstrated in Paper 3 is bidirectional (*Bidirectional feed-back*); the resulting actor behavior from ABM is looped back to ESOM for subsequent analysis.

Initialization: Unlike ABMs, ESOMs have a long-established trajectory of development and application. They are often used to investigate the uptake of RES power generation and the deregulation of power markets from a macro perspective [114]. ESOMs deliver a comprehensive and aggregated insight into the system's optimal operation and investment across diverse energy generation and storage technologies, taking into account transmission networks and overarching policy constraints. Thus, ESOMs are frequently employed in designing future energy systems in line with significant policy targets, such as goals for greenhouse gas mitigation.

REMix, an ESOM designed for the planning of large-scale energy systems that span multiple countries, is one such model [91]. Its geographic scope encompasses Europe and Maghreb, and it operates on a temporal scale of one year with an hourly resolution. The REMix model includes a spectrum of power plant technologies, energy storage facilities, and power transmission capacities. It also considers electricity demand from conventional consumers, heat pumps, heat boilers, and electric vehicles.

In Paper 4, REMix establishes the initial conditions for the AMIRIS simulations set in the year 2030. Given the constraints related to future carbon and fuel prices and the phasing out of nuclear energy and carbon [29], REMix provides the necessary parameters concerning generation and storage capacity expansions. Additionally, it supplies time-series data on net national demand and the dispatch of storage systems.

This data is foundational in configuring AMIRIS to simulate the detailed behavior and dynamics of EC within the prescribed system context.

Bidirectional feed-back: While ESOMs provide a basis for designing idealized system scenarios, discrepancies inevitably arise when comparing these scenarios to the real world. These discrepancies reveal granularity gaps across several dimensions of the model, encompassing temporal, spatial, technological scales, and an additional consideration of the economic scale [50]. Among these dimensions, the economic granularity gap holds particular significance for this thesis.

Economic granularity gap signifies the discrepancies between the idealized economic behaviors and decision-making processes assumed in the model and the realities of the actual economic landscape. This gap arises due to factors such as imperfect market information, decision-making under uncertainty, and regulatory framework conditions that may not be accurately captured in the model. Bridging the economic granularity gap is crucial for ESOMs to achieve a more realistic representation of the energy system and to formulate effective policy measures.

Considering the strengths of ABMs in modeling microeconomic actor behaviors in energy markets, model-coupling appears to be a promising solution for addressing the economic granularity gap [50].Integrating different economic scopes of an ABM and an ESOM by model-coupling helps address the gap between the idealized model assumptions and the complex decision-making processes and market dynamics of the real world. In Paper 3, this approach is deployed to identify the economic granularity gap for the case of electricity prosumage and assessing various instruments to bridge this gap, i.e., to make the behavior of prosumagers closer to that of an idealized system. As will be discussed in Section (5.2), the author considers the model-coupling approach to be more advantageous than altering the scopes, such as attempting to model actor behavior in an ESOM or determining optimal system operation and design using an ABM.

The overall approach for the proposed model-coupling consists of three major phases: 1) Model harmonization 2) Identifying the modeling delta 3) Deriving the economic granularity gap.

1. *Model harmonization:* The proposed workflow is initiated by harmonizing both models. In this phase, the models are configured with an identical set of values for parameters and time-series to ensures that the results generated by both models are identical. Specifically, if AMIRIS is configured with a macroeconomic ideal energy system expansion and system-cost minimizing storage dispatch derived from REMix, the power system operation of both models becomes congruent, with no deviation.

2. *Modeling delta:* In contrast to the harmonization phase, where REMix determines the operation of all storage technologies, this phase focuses on optimizing the dispatch of a selected storage technology in both models. While both models aim to minimize

system costs through storage optimization[1], the resulting deviation is attributed to distinct implementations of storage operation in REMix and AMIRIS. This deviation is referred to as the modeling delta. If the modeling delta is sufficiently small, one can infer that the observed deviation in the subsequent application of the model-coupling setup primarily represents the economic granularity gap rather than variations resulting from different real-world abstractions of energy storage.

3. *Economic granularity gap:* In this phase, AMIRIS incorporates stakeholder behavior, specifically focusing on the use-case of prosumager self-consumption. Instead of minimizing total system costs, storage units within AMIRIS emulate the behavior prosumagers within the current market and regulatory conditions in Germany. Subsequently, REMix is executed for a second time, with the dispatch of the PV-storage system constrained based on the prosumager behavior modeled by AMIRIS. This enables the assessment of the impact of prosumagers' self-consumption patterns on the optimal system design, including system expansion, thereby capturing the economic granularity gap. Finally, by subjecting prosumagers to different implementations of dynamic pricing, options to bridge the existing gap between the optimal and actual operations are explored. The initial two phases, namely model harmonization and modeling delta, mirror the suggested preparatory procedures outlined in [84]. However, the third phase extends beyond the unidirectional coupling of the two models seen in prior studies. Instead, it integrates the behavioral outcomes of actors back into the ESOM, enabling exploration of deviations in optimal energy system design attributable to prosumager behavior.

Figure 2.6 delineates the four-step process to derive the economic granularity gap. This process includes an initial optimization by REMix, translation of REMix results through the iog2x tool[2], subsequent simulation by AMIRIS, and a final round of REMix optimization, which is adjusted based on AMIRIS results. The integration of necessary data processing into a streamlined, executable workflow is achieved using the Remote Component Environment (RCE) software [116].

[1] In AMIRIS, the optimization for minimizing system costs in storage also relies on perfect forecasts of market dynamics. Consequently, unlike REMix, the concurrent operation of system-cost minimizing flexibility options is not achievable within the current framework of AMIRIS.

[2] iog2x, a Python-based software tool that employs the open-source workflow manager ioproc[115]

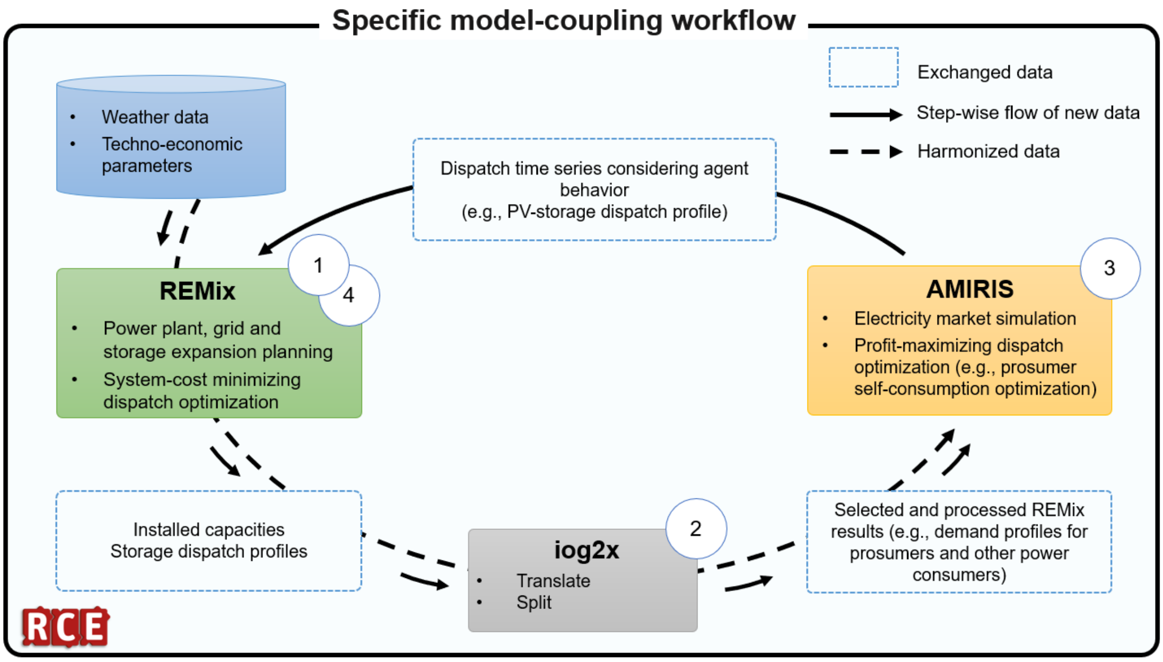

Figure 2.6: Model-coupling workflow for bidirectional coupling of AMIRIS and REMix. Source: Paper 3.

Chapter 3

Aggregation of distributed energy resources

3.1 Paper 1: Aggregation of households in community energy systems: An analysis from actors' and market perspectives

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Aggregation of Households in Community Energy Systems: An Analysis from Actors' and Market Perspectives

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Abstract: In decentralized energy systems, electricity generated and flexibility offered by households can be organized in the form of community energy systems. Business models, which enable this aggregation at the community level, will impact on the involved actors and the electricity market. For the case of Germany, in this paper different aggregation scenarios are analyzed from the perspective of actors and the market. The main components in these scenarios are the Community Energy Storage (CES) technology, the electricity tariff structure, and the aggregation goal. For this evaluation, a bottom-up community energy system model is presented, in which the households and retailer are the key actors. In our model, we distinguish between the households with inflexible electricity load and the flexible households that own a heat pump or Photovoltaic (PV) storage systems. By using a game-theoretic approach and modeling the interaction between the retailer and households as a Stackelberg game, a community real-time pricing structure is derived. To find the solution of the modeled Stackelberg game, a genetic algorithm is implemented. To analyze the impact of the aggregation scenarios on the electricity market, a "Market Alignment Indicator" is proposed. The results show that under the considered regulatory framework, the deployment of a CES can increase the retailer's operational profits while improving the alignment of the community energy system with the signals from the electricity market. Depending on the aggregation goal of the retailer, the implementation of community real-time pricing could lead to a similar impact. Moreover, such a tariff structure can lead to financial benefits for flexible households.

Keywords: decentralized energy system; energy community; community energy storage; community energy system; game-theory; Stackelberg

1. Introduction

The levelized cost of electricity from Photovoltaic (PV) systems has fallen below the electricity retail price in many countries worldwide, a development that has incentivized the investment in PV systems for many households [1,2]. Similar to PV systems, battery storage has experienced a significant reduction in system prices. Several studies indicate that this trend will continue in the next few years [3,4]. As a result, PV storage systems began to become economically viable for households under certain support schemes and generation potentials [5,6]. Next to PV-storage systems, heat pumps are expected to play an important role in the future energy system. In Germany, for example, about 40 to 85% of the heat demand of buildings could be generated by electric heat pumps by 2050 [7]. Such a high penetration implies a large demand response potential in residential energy systems.

From a market perspective, current regulatory regimes and business models are unable to incentivize the prosumers and consumers to adapt their interaction with the electricity grid to market signals of scarcity or excess (expressed by the wholesale prices for electricity, assuming a frictionless, optimized power market). Therefore, the electricity feed-in by PV and battery storage systems, as well as the residential electricity consumption, do not necessarily correspond to the share of renewable energies in the market at a particular point in time [8,9].

For better integration of the distributed generation and a more efficient deployment of the flexibility potentials at the residential level, several solutions are presented in the literature and in political debates. For instance, [10] suggests that regulatory interventions, such as variable feed-in tariffs, can contribute to a better adaptation of prosumers to wholesale market signals. Pudjianto, Ramsay and Strbac [11] consider virtual power plants as a way to aggregate the distributed generation. Energy communities constitute another option that is promoted and supported in several energy and climate policies, e.g., in the European union clean energy package [12]. According to this document a citizen energy community is a legal entity with the primary purpose of providing environmental, economic, or social benefits for shareholders or members of the community or for the local areas in which it operates [13]. Beyond technical and economic benefits, this cooperation can deliver positive social impacts such as building consumer engagement and increasing the acceptance of energy transition [14]. These promising benefits have led to an increasing number of established local energy communities in Europe. A prominent example in this regard is the growth in the number of local energy cooperatives in Germany, where 869 cooperatives with 183,000 private members have been founded since the year 2006 [15].

Among the core elements of the energy community business models are Community Energy Storage Systems (CES). According to [16] CES is a subgroup of electricity storage systems that "provides services based on balancing strategies for an association of prosumers, renewable energy producers and loads that are connected to the same distribution grid" and "at least one of the following operation strategies has to be implemented: maximizing self-consumption for all participants, increasing shareholder's profits in electricity markets, or optimizing community welfare." Additionally, CES may offer several applications for managing power demand and generation supply [17]. In Germany, the investment in CES is currently hampered due to high investment costs and imposed taxes and levies on storage operations by current regulatory frameworks [17–20]. Despite these investment uncertainties, studies have analyzed various aspects of CES business models. By conceptualizing CES as a complex socio-technical system, Koirala et al. describe CES systems with a three-layer structure consisting of the physical system, the actor-network, and the external environment (Figure 1) [17]. In [21], Parra et al. review the perspectives of end-users, utilities, and policymakers in CES business models. According to Arghandeh et al., deployment of CES could improve the reliability of the power system operation by offering peak shaving and auxiliary grid services [22]. Lombardi and Schwabe [23] suggests that a sharing economy-based business model may increase the profitability of operating battery storage systems compared to the case of a single user.

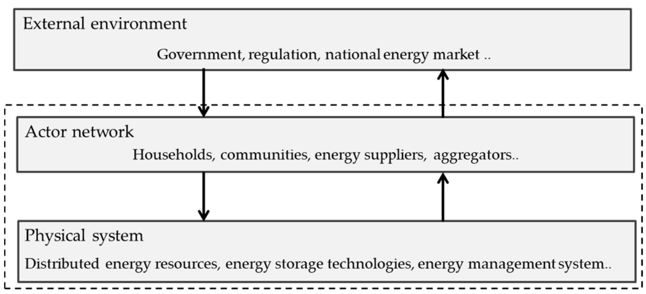

Figure 1. Community Energy Storage (CES) business models as a complex socio-technical system (own presentation based on [12]).

Next to CES, energy management systems that allow the aggregation of flexibility options via control or price signals are an important measure in community energy systems. Several studies have analyzed the implementation of such measures using CES. For example, using cooperative game theory, authors in [24] analyze the possibility of cooperative investment and operation of CES by consumers. Mediwaththe et al. propose a competitive energy trading framework, in which the CES operator sets real-time electricity prices for prosumers in a competitive manner to maximize its profit [25]. By comparing the results with a benevolent strategy, the authors show that a competitive CES model gives the best trade-off operating environment. The energy management system in [26] consists of prosumers and an energy storage system. The authors in [26] implement a stochastic programming approach for day-ahead planning of electricity trade under uncertainty. The authors then use a Stackelberg game approach to obtain real-time purchase and sales prices for the prosumers that lead to an optimized intraday electricity trade for the energy storage operator.

One limitation of game-theoretic approaches in modeling the community energy systems is the necessary simplification to find the solution of the resulting problem analytically. Examples of these simplifying assumptions are:

- Neglecting the plurality of actors in the community, i.e., considering a single household type, for example, prosumers.
- Simplified modeling of electricity market prices or energy demand. For example, [25] assumes that the unit electricity price of the grid has a variable component, which is proportional to the total grid load.
- Considering the electricity production costs as the only component of the electricity tariff and modeling the electricity tariffs modeled without considering the influence of the regulatory frameworks.

Another limitation of these studies is their mere focus on modeling of the energy management systems. While they investigate the merits of energy management systems for the actors of a community energy system (e.g., prosumers or the CES operator), the consequences of the increased local consumption of electricity for the larger energy system are not studied extensively.

To overcome these shortcomings, this article investigates the research question: "how does aggregation of the households in a community energy system under different system configurations impact the actors and the alignment of the community energy system with the signals from the electricity market?" Our contribution connects two interrelated bodies of literature. On the one hand, it is embedded in the broader literature on smart grid solutions and CES business models. On the other hand, it is part of a more specific debate on the merits of decentralized generation and consumption and the system-level implications of its increasing diffusion. Our main contributions are:

- We propose a bottom-up model to investigate the aggregation of households in a community energy system. To model the interactions between the actors of the community energy system, we employ a Stackelberg game approach. Stackelberg games are widely used to model hierarchical competitions in the energy system such as the one between a retailer and households [25–28]. By integrating a Stackelberg game structure in our model, we implement a real-time pricing tariff for the community. In contrast to the existing literature, we focus on the heterogeneity of actors in the community energy system and distinguish between households with an inflexible load and those with flexibility options, i.e., battery storage and heat pumps. Moreover, we avoid modeling of electricity market prices. Instead, we use real wholesale market prices and, by taking the regulatory influences into account, model the end-user prices endogenously.
- We introduce an indicator to evaluate the market alignment of community energy systems. This indicator can assess the behavior of communities with decentralized generation potential with respect to the electricity wholesale market. We then use this indicator to evaluate the relative economic efficiency of an energy community compared to an idealized benchmark case that is completely aligned with wholesale market price signals.

The remainder of this paper proceeds as follows. In Section 2, we elaborate on the contributions mentioned before and explain our analysis procedure. Section 3 describes the input data and the actors' rationale in the community energy system model. In Section 4, we present the model results. Section 5 concludes and gives a discussion on the implications and limitations of our analysis.

2. Analysis Procedure

In this section, we introduce the general model assumptions, build the aggregation scenarios, and describe the analysis indicators for the evaluation of the developed scenarios. The definitions of notations in the subsequent sections are given in Appendix A.

2.1. Community Energy System Structure

We define a community energy system as a part of a local low-voltage distribution grid. Figure 2 gives an overview of the system's structure. In Section 2.1.1, the actors in the community energy system and the technologies each actor owns are described. The external environment impacting the community energy system, i.e., the electricity market and the regulatory framework, is explained in Section 2.1.2.

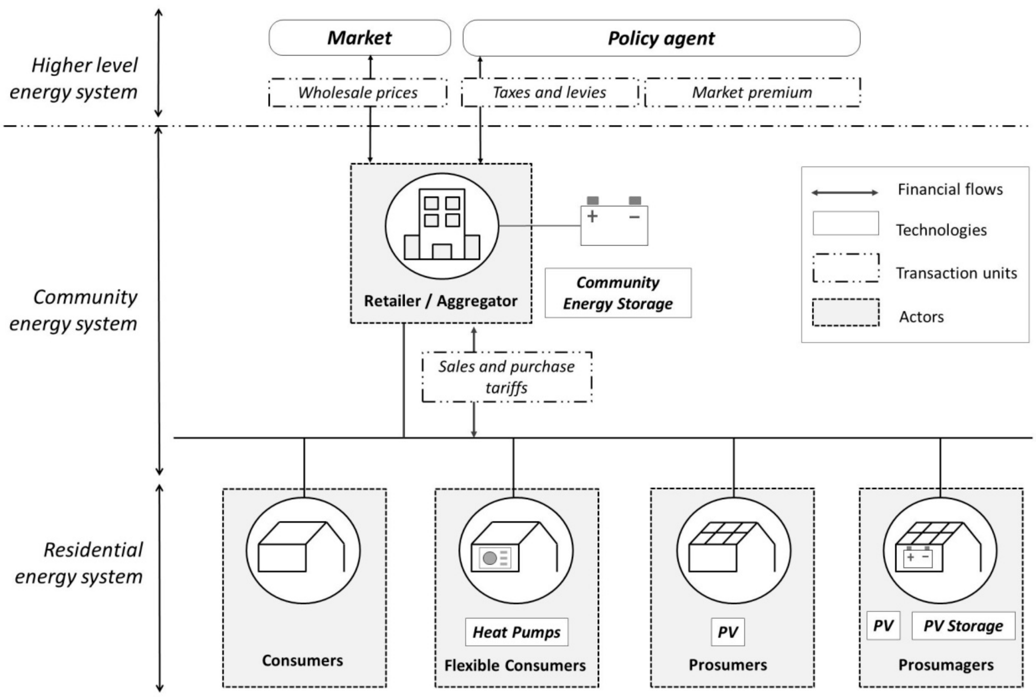

Figure 2. Schematic overview of the community energy system model.

2.1.1. Actors and Physical System

Households in a local distribution grid and consequently in a community energy system, own a variety of different technologies that offer flexibility and generation potential. In this analysis, depending on the technologies that households own and use, four types of households are modeled. These household types can be embedded in broader categories of inflexible and flexible households:

- Inflexible households are households that do not operate any storage system and are, therefore unable to shift their electricity load or feed-in at any time of the day. In this category, we distinguish between the consumers and prosumers. Consumers are actors, who own neither a PV system nor a flexibility option. Similar to the consumers, prosumers do not have a flexibility option but they operate a PV system. Prosumers may generate electricity and cover part of their electricity demand themselves.

- Flexible households are actors with load and feed-in shifting potential. These actors are assumed to be equipped with smart meters, which enable them to receive price signals and manage their load and feed-in accordingly. We divide these actors into flexible consumers and prosumagers. Prosumagers are households, who are not only equipped with PV rooftop systems but also own battery storage systems. Prosumagers can use their battery capacity to shift both their grid electricity usage and grid feed-in. Flexible consumers are households that own heat pumps and thermal storage systems, which give them the potential to shift a part of their electricity load.

We assume that households do not seek a behavioral change to shift their energy demand manually. Therefore, the flexibility in our work implies a flexible interaction with the grid due to the availability of battery or thermal storage systems. Moreover, we assume that the households are able and willing to share a forecast of their grid interactions over the next day with the retailer.

The electricity load and feed-in of the local grid is managed by one local retailer. In this regard, we assume that households are unable to switch to another retailer. Two-way communication infrastructure in the community allows the retailer to send the hourly price signals to the households and receive their grid interaction forecasts on an hourly basis. Based on these forecasts, the retailer decides on the hourly amount of electricity it trades in the wholesale market. The retailer can also be equipped with a CES. In this case, the CES gives the retailer prominent flexibility for trading with the households and the wholesale market.

2.1.2. External Environment: Market and Regulations

The retailer in a community energy system could potentially participate in several markets such as day-ahead, intraday, and reserve markets. In this model, the retailer is only able to trade in the day-ahead spot market. It is also assumed that the retailer has perfect foresight of the electricity market prices one day in advance. The used wholesale prices are an exogenous input for the model (see Section 3.1). Throughout this paper, we refer to the electricity spot market simply as the market.

Induced costs and incentives due to the regulatory framework have a substantial impact on the profitability of the decentralized business models for the involved actors. As a case study, we look at Germany and model the regulatory impact on several financial transactions. The policy agent keeps track of the induced incentives and payments due to the regulation. An overview of the electricity and financial flows in the community energy system model is given in Figure 3.

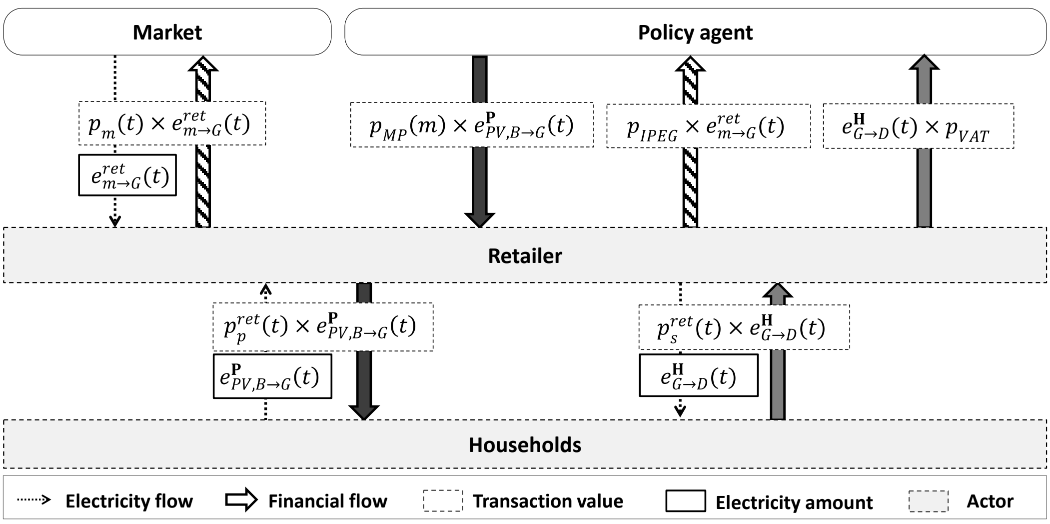

Figure 3. Overview of the regulatory induced financial flows in the model. Arrows with similar patterns or color show related financial flows.

In Germany, taxes, levies, and grid charges make up around 75% of the household electricity price [29]. Throughout this paper, we refer to these charges as Induced Price Elements by the Government (IPEG). The consumed electricity by households is always subject to the value-added tax, which is collected by the retailer and passed completely to the policy agent. The retailer is charged by a variety of IPEG such as electricity tax (According to German regulations two types of taxes are imposed on the electricity consumption: electricity tax (Stromsteuer or Ökosteuer) and value added tax (Umsatzsteuer or Mehrwertsteuer).), levies, and grid charges when purchasing electricity from the market (Equation (1)). In contrast, the electricity sale in the market is exempted from IPEG. The modeled community energy system is located in a retailer-owned private grid. Based on this assumption, the IPEG on the electricity flows inside the community grid are neglected. Consequently, charging and discharging the CES is exempted from the regulatory induced costs. Regarding the self-consumption of generated electricity by prosumers and prosumagers, we assume a complete relief from charges induced by IPEG or value-added tax.

$$p_{IPEG} = p_{levies} + p_{tax} + p_{GC} \tag{1}$$

One component of the IPEG is the EEG levy, which aims to support the expansion of electricity generation from renewable sources. Based on the Renewable Energy Act (Erneuerbare Energie Gesetz, EEG), the collected EEG levies are distributed among the renewable power plant owners, for example as a market premium on the per-unit grid electricity feed-in [30]. In the case of PV systems, the electricity grid feed-in should be put on the market by a so-called direct marketer [30]. The sold electricity by the direct marketer can be entitled to EEG remunerations under certain conditions (depending on the size and the technology of the installed plant as well as the commissioning date of the plant). The energy storage technologies that are used for an intermediary storage of renewable energies are entitled to receive the EEG privileges [31]. In such cases, this remuneration would be allocated in the form of a market premium [31]. The value of the market premium is calculated as the difference between the feed-in tariff and the PV market values (calculated for each technology and can be defined as the average value of the overall sold generation in Germany in each month [32]) [33]:

$$p_{MP}(m) = FiT - mv_{PV}(m) \tag{2}$$

where $p_{MP}(m)$ and $mv_{PV}(m)$ are the monthly market premium and PV market values and FiT is the feed-in tariff respectively. In the model, the retailer undertakes the role of the direct marketer and receives the market premium from the policy agent (according to EEG, the feed-in tariff is paid by transmission grid operator. In this work, we assume that the policy agent undertakes this role.)

2.2. Aggregation Scenarios

The usage of storage technologies by the actors of the community energy system allows a temporal shift of the households' aggregated electricity production and usage. The retailer, for example, can use the CES to store the purchased electricity (from the households or the market) for a later trade. Together with the households' storage capabilities, the CES increases the overall available energy storage capacity of the community energy system and with it, its flexibility.

The components of community energy system business models that are considered to have a major impact on the interaction between households, CES, and the market, are (i) the electricity tariff structure and (ii) the retailer's aggregation goal. In the following, these components and the considered variations are explained.

(i) Electricity tariff: The electricity tariffs offered by the retailer to the households can influence the way the already existing storage systems operate. The financial incentives the electricity tariffs provide could motivate the households to adapt their usage of energy storage systems accordingly. The electricity tariff (p_s^{ret}), which households have to pay for electricity consumption, depends on the following three building blocks (these building blocks of the electricity tariffs are model assumptions for an exemplary private grid. We therefore, do not consider other taxes and levies that are imposed to the electricity tariff according to the regulations in Germany):

(1) Electricity procurement charges, which denote the retailer's average per unit cost of buying electricity on the market. These charges are part of the retailer's business model.
(2) Community grid charges (p_{CGC}) as a fixed per-unit component of the electricity tariffs that cover the costs due to investment and maintenance of the community grid. We assume that these charges are also part of the business model (in the reality, the grid charges in Germany are a regulated part of the electricity tariff).
(3) Value-added tax (p_{VAT}) that is collected by the retailer and passed on to the policy agent (see also Figure 3). p_{VAT} is a regulated component of the electricity tariff and, in contrast to the other building blocks, it is not part of the business model.

To investigate the effect of different electricity tariffs on the actors' net income, we construct three electricity tariffs. The tariffs differ from each other with respect to the electricity procurement charges the retailer has to pay at the market. The community grid charges and value-added tax remain untouched. These tariffs are (see also Table 1):

- Static Pricing (*SP*): The *SP* tariff structure follows the status quo pricing logic in Germany. Charges regarding the procurement of the electricity are based on the mean cost of acquiring electricity from the market, which we assume to be the annual average value of the market prices (p_M^{ave}). Therefore, this tariff contains no hourly varying component and the electricity prices for the customers are constant at any time of the day.
- Market Real-Time Pricing (*M-RTP*): In this tariff, an hourly forecast of the market prices (p_M) of the following day is used as a per-unit charge of acquiring electricity. The electricity prices in this tariff contain a real-time price component, which represents the market price signals.
- Community Real-Time Pricing (*C-RTP*): This tariff consists of optimized real-time procurement charges ($p_{proc,s}$), determined by the retailer. The values of these elements may be influenced not only by hourly market prices, but also by the level of local electricity generation and demand in each hour. These charges may fluctuate between p_{proc}^{min} and p_{proc}^{max} and adopt values higher or lower than market prices in each hour. The calculation of variable procurement elements in this tariff is discussed in Section 3.3.

Table 1. Overview of constructed tariff structures.

Tariff	$p_s^{ret}(t)$	Real-Time Component
SP	$p_{CGC} + p_{VAT} + p_M^{ave}$	None
M-RTP	$p_{CGC} + p_{VAT} + p_M(t)$	$p_m(t)$, exogenous model input
C-RTP	$p_{CGC} + p_{VAT} + p_{proc,s}(t)$	$p_{proc,s}(t)$, derived endogenously (See Section 3.3)

To purchase the electricity generated by PV systems, the retailer also offers purchase prices to households. Purchase prices, as opposed to the electricity tariffs, include the price building block (1) but do not include the community grid charges and the value-added tax, i.e., block (2) and (3). We assume that the purchase prices are built analogous to the electricity procurement charges of the corresponding electricity tariff. Therefore, the electricity purchase prices are the average market prices (p_M^{ave}) and hourly forecast of the market prices (p_M) in cases of *SP* and *M-RTP* tariffs. If the *C-RTP* tariff is chosen, the purchase prices are the retailer's optimized hourly real-time prices ($p_{proc,s}$).

(ii) Retailer's Aggregation Goal: Community energy systems can be set up to serve different purposes [17]. We distinguish between a goal of maximum profit for the retailer and one that seeks the maximum self-sufficiency of the community, i.e., the traded amount of electricity with the market should be minimized. The retailer's aggregation goal influences the optimization of the CES as well as the real-time component in the *C-RTP* tariff.

Table 2 shows the discussed tariffs, aggregation goals, and the corresponding scenario names. The Business As Usual (BAU) scenario represents a reference case for a status quo community, in which no CES is used and in which the households are not exposed to any real-time hourly prices. Apart from this scenario, we investigate four different community energy system scenarios, in which the retailer operates a CES.

Table 2. Scenarios.

Scenario	Tariff	Aggregation Goal
Business As Usual (BAU)—no storage	*SP*	None
Static tariff	*SP*	Maximum profit
Market signal	*M-RTP*	Maximum profit
Community competition	*C-RTP*	Maximum profit
Self-sufficiency	*C-RTP*	Maximum self-sufficiency

The analysis of these scenarios allows an understanding of the effect of using a CES on the economic figures of households and retailer. A comparison among the Static tariff, Market signal, and community competition scenarios gives a clear picture of the role of tariff structures in the net income of households and retailers (see also Section 2.3). By comparing community competition and self-sufficiency scenarios, the effect of the aggregation goal on the overall electricity trade of the community with market or community welfare can be observed, among others. Section 2.3 discusses the used indicators to evaluate and compare the different scenarios.

2.3. Evaluation Indicators

To answer our research questions, we require indicators that capture the impact of the aggregation scenarios on actors and the higher-level energy system. In this section, these evaluation indicators in two categories of actors' and system perspective are presented. For a better demonstration of the effects of interest, these indicators are defined in a relative form.

2.3.1. Actor's Perspective

When analyzing the scenarios from the actor's perspective, we evaluate the net income of each actor type, explained in Section 2.1.1. The net income of actor $i \in \mathbf{I}$ (u_x^i) in each hour and for the simulation period (U_x^i) is calculated by Equations (3) and (4) respectively:

$$u_x^i(t) = r_x^i(t) - c_x^i(t) \tag{3}$$

$$U_x^i = \sum_{t=1}^{T_{sim}} u_x^i(t) \tag{4}$$

where $r_x^i(t)$ and $c_x^i(t)$ represent revenue and cost of actor i in scenario x at time t. Note that the net income for consumers and flexible consumers with no source of revenue adopt negative values. In Section 3, the actors' specific revenue and cost functions will be described. The net income of actor $i \in \mathbf{I}$ in scenario x relative to the BAU scenario for the simulation period is as:

$$U_x^{i,\,rel} = \frac{U_x^i - U_{BAU}^i}{U_{BAU}^i} \times 100 \tag{5}$$

Besides the net income of each actor, we investigate the community welfare, defined as the cumulative net income by all actors in the community energy system. The community welfare for scenario x (W_x^{Com}) can be described as:

$$W_x^{Com} = \sum_{i \in \mathbf{I}} U_x^i \tag{6}$$

where U_x^i is the net income of each actor $i \in \mathbf{I}$, calculated from Equation (4). The relative community welfare is then calculated as follows:

$$W_x^{Com,\, rel} = \frac{W_x^{Com} - W_{BAU}^{Com}}{W_{BAU}^{Com}} \times 100 \tag{7}$$

2.3.2. System Perspective

Studying the welfare of the community actors due to CES usage and different tariffs is important to evaluate the economic feasibility of such energy systems. Additionally, a community energy system interacts with the higher-level energy system via the retailer and by trading with the market. As mentioned above, this interaction strongly depends on the retailer's aggregation goal. A self-sufficiency aggregation goal minimizes the trade with the market, a maximum profit goal might enhance the trading activities. In order to value the interaction with the market and thus with the higher-level system, a Market Alignment Indicator *(MAI)* is defined. This indicator is based on market prices, as prices are a good signal for the evaluation of the excess or scarcity of electricity in the energy system (assuming a frictionless power system and neglecting the grid congestions). Purchasing electricity from the market at low prices and selling it at higher prices is then in alignment with the market.

We adopt the definition of the *MAI* from Klein et al. [10], who defines the *MAI* as the ratio of the welfare of operation of PV storage systems over the welfare of a benchmark system with the same size. In the benchmark system, the battery storage is operated for arbitrage trading (this battery would follow the market signals without distortion, i.e., store electricity by buying electricity at comparatively low market price and discharge by selling electricity at high prices [10]), as such a battery would serve the market perfectly (neglecting grid constraints). Following this definition, the *MAI* for the energy communities is described as the contribution of scenario x to the welfare of the retailer (W_x^{ret}):

$$MAI_x = \frac{W_x^{ret}}{W_{Benchmark}^{ret}} \tag{8}$$

The retailer's welfare in scenario x is obtained by calculating the difference of the electricity sold by the retailer on the market ($e_{G \to M}^{ret}$) and the electricity bought from the market ($e_{M \to G}^{ret}$), multiplied by the market price in each hour (Equation (9)). Note that in contrast to U_x^{ret}, the cost and revenue streams in the calculation of W_x^{ret} are reduced to the electricity trade in the market.

$$W_x^{ret} = \sum_{t=1}^{T_{sim}} \left(e_{G \to M}^{ret}(t) - e_{M \to G}^{ret}(t) \right) \times p_M(t) \tag{9}$$

The benchmark scenario is considered to be the case in which the retailer has full control over not only CES but also other available flexibilities in the community (i.e., PV storage and heat pumps). The aggregated flexibility potential of the households together with the CES can then be used to trade in the electricity market. Assuming a frictionless power system and neglecting any grid constraints, this is the most aligned behavior of the community energy system with the larger energy system. The retailer's welfare in the benchmark scenario ($W_{Benchmark}^{ret}$) is then calculated from Equation (9). We described the methodology behind such a benchmark scenario later in Section 3.2.3.

In Equation (10), the value of *MAI* relative to the *BAU* scenario is calculated. A *MAI* equal to +1 describes a scenario that demonstrates alignment with the market signals as good as the benchmark scenario, while a *MAI* value equal to 0 describes a performance as good as the BAU scenario. As there is no limit to the inefficiency of dispatch from the market perspective, negative values can also occur, but we did not encounter them in the scenarios under investigation in this analysis.

$$MAI_x^{rel} = \frac{W_x^{ret} - W_{BAU}^{ret}}{W_{Benchmark}^{ret} - W_{BAU}^{ret}} \tag{10}$$

3. Community Energy System Model

By embedding the described actors, technologies, markets, and regulations in a community energy system model, the evaluation indicators will be investigated. In this section, first, the used data for the model parameterization are explained. Subsequently, the actors' rationale, i.e., actor-specific cost and revenue functions as well as the optimization problems regarding the scheduling of different storage technologies, will be described. These optimization problems are formulated in this section and are explained in further detail in Appendix B. To solve the optimization problems, a dynamic programming model, which allows a fast computation in comparison to analytical optimization tools, is used [34]. The implementation of this method is demonstrated in Appendix C. At the end of this section, the interaction between the retailer and households will be formulated as a Stackelberg game, and an algorithm to find the Stackelberg equilibrium will be presented.

3.1. Data and Model Parameterization

To demonstrate the effects of interest, a consistent set of time series, comprising PV feed-in, market prices, and PV market values, of the year 2018 in Germany is used. To calculate the actual electricity production by PV systems, the share of generated electricity per each kWh installed PV capacity in the year 2018 in Germany (data is taken from [35]) is scaled up using the peak power and the performance ratio of the PV systems (See Appendix D). The data source also includes the day-ahead spot market prices. In Figure A3, the day-ahead spot market prices together with the monthly market values of PV, which are from [36], is presented. For the calculation of market premium, we adopt the value of *FiT* for the PV rooftop systems with the peak power lower than 10 kWp that are commissioned in the year 2017 [37].

For the household electricity demand profile, in this work, the data from [38] is used. The dataset contains high-resolution measured load profiles of 74 different households. By aggregating these profiles, a single demand profile with an hourly resolution is generated. Due to smoothing effects, this aggregation yields roughly the shape of the standard load profile [38]. We use this profile as the demand profile of an average household and assume that all households in the community have the same electricity demand profile (a standard load profile can be accepted as a good approximation of cumulated load profiles even for 100 households [39]). This profile does not consider the additional electricity demand caused by electric heating, i.e., by heat pumps. The households' heat demand profile in the flexible consumers model is from [40,41]. Descriptive statistics of the demand profiles are provided in Table 3.

Table 3. Descriptive statistics of the households' demand time series.

Input Parameter	Unit	Resolution	Mean	Min	Max	Total
Electricity demand (l_{BD}^{h})	kWh	Hour	0.53	0.19	1.33	4685
Heat demand (l_{HD}^{h})	kWh	Hour	2.28	0.12	7.17	19,996

The scale of the community could be as big as a few residential blocks to a large district and it could contain both residential and industrial units. Moreover, the scale of electricity generation in the community could vary depending on the number of prosumers and prosumagers.

In this paper, an illustrative community energy system that consists of 40 residential units is investigated. The community consists of an equal number of actors from each category introduced in Section 2.1.1: 10 consumers, 10 flexible consumers, 10 prosumers, and 10 prosumagers. The sizing of the different available technologies in the community energy system depends on numerous economic and non-economic variables. For example, PV-storage sizing can be over-scaled to increase the degree of self-sufficiency [42]. We therefore do not consider optimal investment planning within the analysis in this paper. Instead, the sizing for CES, PV modules, PV storage, heat pump, and thermal storage is set heuristically. The optimization and simulation periods are set to 24 h and one year respectively. The assumed values for the model parameterization are given in Table 4.

Table 4. Model parameters.

Parameter	Unit	Value	Source
FiT	cent/kWh	12.3	German Solar Association [37]
p_{levies}	cent/kWh	7.68	BDEW [29]
p_{GC}	cent/kWh	7.3	BDEW [29]
p_{taxes}	cent/kWh	3.71	BDEW [29]
p_{CGC}	cent/kWh	18	Model assumption
VAT	%	19	Förster et al. [43]
S_{PV}^{max}	kW	6	Model assumption
PR_{PV}	%	84	Khalid et al. [44]
K_{B}^{psg}	kWh	6	Model assumption
S_{HP}^{max}	kW	8	Model assumption
cop_{HP}	-	3	Forsén et al. [45]
K_{TS}^{fcs}	kWh	14	Model assumption
K_{CES}^{ret}	kWh	100	Thorman et al. [46]
η_d	%	95	Klein et al. [10]
η_c	%	95	Klein et al. [10]
$E2P$	-	1	Thorman et al. [46]
$C_{CES}^{O\&M}$	%	1	Klein et al. [10]
r_{dis}	%	4	Model assumption
L_{CES}	years	20	Model assumption
I_{CES}^{0}	€/kWh	510 and 250	Schick et al. [47]
T_{opt}	hours	24	Model assumption
T_{sim}	hours	8760	Model assumption

3.2. Actors' Rationale

The households in each household category are assumed to be similar. An aggregated model for each household category represents the cumulative behavior of the respective category. For the aggregated models of households, the time series for energy consumption and electricity generation as well as technology sizes are scaled up linearly, see also Appendix D. In the remainder of this paper, the model descriptions and results for households refer to these aggregated models.

In the rest of this section, the actor's rationale and actor-specific cost and revenue functions are explained in more detail.

3.2.1. Inflexible Households

Consumers and prosumers are actors without a load shifting potential. The electricity load of these households is reduced to their home appliances. The cost function of consumers can be described by the cost of electricity consumption (c_x^{cs}):

$$c_x^{cs}(t) = l_{BD}^{cs}(t) \cdot p_s^{ret}(t) \tag{11}$$

where $l_{BD}^{cs}(t)$ and $p_s^{ret}(t)$ refer to the electricity load of the consumers and retailer's electricity tariff at time t, respectively. Owning a PV system with the specifications mentioned in Table 4, the prosumers' electricity demand is partly covered by self-generated electricity. The interaction of prosumers with the electricity grid can be formulated as:

$$s^{ps}(t) = l_{BD}^{ps}(t) - g_{PV}^{ps}(t) \tag{12}$$

where $s^{ps}(t)$ is the residual load of the prosumers at time t. An electricity generation higher than the electricity demand in each hour (negative residual load) indicates PV electricity feed-in ($e_{PV\to G}^{ps}(t)$). The electricity feed-in by prosumers will be remunerated with $p_p^{ret}(t)$. In case the electricity generation cannot cover the demand fully, the residual load will be supplied from the grid ($e_{G\to D}^{ps}(t)$). Note that the self-consumption of electricity by prosumers is free of charge (see also Section 2.1.2) and therefore is not considered as a part of the cost function. In summary:

$$s^{ps}(t) = \begin{cases} e_{G\to D}^{ps}(t) & s^{ps}(t) \geq 0 \\ e_{PV\to G}^{ps}(t) & s^{ps}(t) < 0 \end{cases} \tag{13}$$

$$r_x^{ps}(t) = e_{PV\to G}^{ps}(t) \cdot p_p^{ret}(t) \tag{14}$$

$$c_x^{ps}(t) = e_{G\to D}^{ps}(t) \cdot p_s^{ret}(t) \tag{15}$$

3.2.2. Flexible Households

Unlike inflexible households, energy storages and smart meters enable flexible consumers and prosumagers to optimize the grid interactions in response to the electricity price signals. The energy storage system for flexible consumers is the thermal storage of the heat pump systems. To reduce their electricity bill, the thermal storage can be deployed to shift the heat pump electricity usage ($e_{G\to HP}^{fcs}$) according to the retailer's price signals. As can be seen in Figure 4, the total electricity consumption of flexible consumers ($e_{G\to D}^{fcs}$) is the sum of the heat pump grid usage ($e_{G\to HP}^{fcs}$) and the electricity consumption by other appliances as the inflexible part of the electricity demand (l_{BD}^{fcs}). The mathematical modeling of the flexible consumers is given in Appendix B.1.

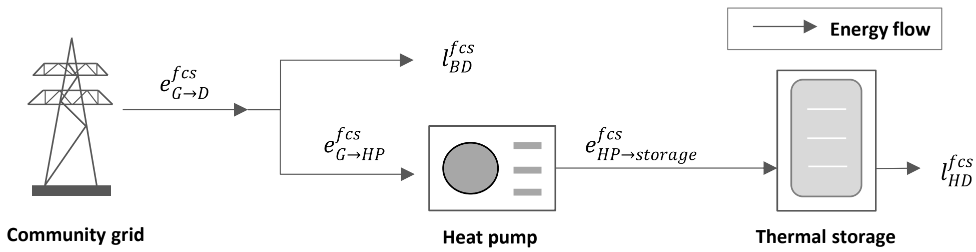

Figure 4. Energy flows in the flexible consumers' model.

The electricity cost for flexible consumers is then:

$$c_x^{fcs}(t) = e_{G\to D}^{fcs}(t) \cdot p_s^{ret}(t) \tag{16}$$

Based on Equation (16), flexible consumers optimize their heat pump dispatch ($e_{G\to HP}^{fcs}$) to maximize their net income:

$$\max \sum_{t=t_{initial}}^{t_{initial}+T_{opt}} u_x^{fcs} \tag{17}$$

Figure 5 shows the schematic sketch of the prosumagers' model. The generated electricity, in this case, is directly used to cover the electricity demand. The residual generation in each hour can be stored in the battery ($e_{PV\to B}^{psg}$) or be sold to the retailer ($e_{PV\to G}^{psg}$). In case the electricity demand exceeds the generated amount in each hour, the residual load is covered from the grid ($e^{psg}_{G\rightarrow D}$) or the stored electricity in the battery ($e^{psg}_{B\rightarrow D}$). The battery system may also be charged from the grid ($e^{psg}_{G\rightarrow B}$) or sell the stored electricity back to the grid ($e^{psg}_{B\rightarrow G}$). In Appendix B.2, the mathematical model of prosumagers is explained in more detail. The self-consumption of electricity from PV and the battery is considered to be free of charges, since it does not involve the community grid. Therefore, the cost and revenue functions of the prosumagers are reduced to the interactions with the grid:

$$c^{psg}_x(t) = \left(e^{psg}_{G\rightarrow D}(t) + e^{psg}_{G\rightarrow B}(t)\right)\cdot p^{ret}_s(t) \tag{18}$$

$$r^{psg}_x(t) = \left(e^{psg}_{PV\rightarrow G}(t) + e^{psg}_{B\rightarrow G}(t)\right)\cdot p^{ret}_p(t) \tag{19}$$

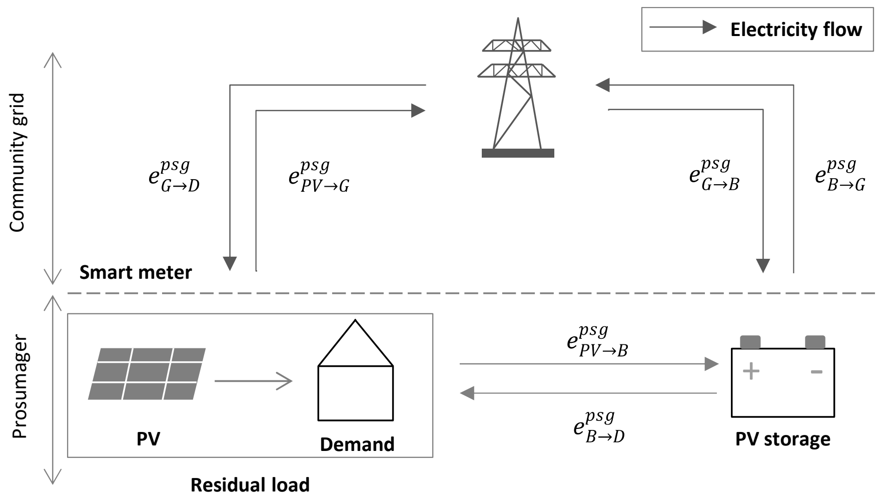

Figure 5. Schematic sketch of the prosumagers' model.

Similar to flexible consumers, the prosumagers minimize their costs by optimizing the usage of the PV storage system:

$$\max \sum_{t=t_{initial}}^{t_{initial}+T^{opt}} u^{psg}_x \tag{20}$$

3.2.3. Retailer

Besides using a CES, the retailer can adopt different tariff structures and aggregation goals (see also Table 2). The cost and revenue streams of the retailer depend on its market activities, its trade with households, as well as charges and rewards due to the regulation. An overview of the retailer's cost and revenue streams is already given in Figure 3. The retailer trades the electricity deficit or surplus in the community in the market and pays the incurred taxes and levies (p_{IPEG}) to the policy agent. Moreover, the paid VAT as part of the electricity tariff is passed completely to the policy agent. Furthermore, the retailer is rewarded with the market premium for marketing the fed-in electricity by households into the community grid. Based on these streams, the cost and revenue function of the retailer can be summarized as:

$$c^{ret}_x(t) = e^{ret}_{M\rightarrow G}(t)\cdot(p_M(t) + p_{IPEG}) + e^{\mathbf{P}}_{PV,B\rightarrow G}(t)\cdot p^{ret}_p(t) + e^{\mathbf{H}}_{G\rightarrow D}(t)\cdot p_{VAT}(t) \tag{21}$$

$$r^{ret}_x(t) = e^{ret}_{G\rightarrow M}(t)\cdot p_M(t) \ + e^{\mathbf{H}}_{G\rightarrow D}(t)\cdot p^{ret}_s(t) \ + e^{\mathbf{P}}_{PV,B\rightarrow G}(t)\cdot p_{MP}(m) \tag{22}$$

where $e^{\mathbf{H}}_{G\to D}(t)$, $e^{\mathbf{P}}_{PV,B\to G}(t)$, refer to the total consumed and fed-in electricity by households at time t, are calculated by Equations (23) and (24). Moreover, the $p_{VAT}(t)$ in Equation (21) is the collected value-added tax per kWh sold electricity to households at time t:

$$e^{\mathbf{H}}_{G\to D}(t) = \sum_{h\in\mathbf{H}} e^{h}_{G\to D}(t) \tag{23}$$

$$e^{\mathbf{P}}_{PV,B\to G}(t) = e^{psg}_{B\to G}(t) + \sum_{p\in\mathbf{P}} e^{p}_{PV\to G}(t) \tag{24}$$

$$p_{VAT}(t) = p^{ret}_{s}(t).\Big(\frac{VAT}{1+VAT}\Big) \tag{25}$$

Note that the p^{ret}_{s} in Equation (22) also contains a component to cover the community grid costs (p_{CGC}). For simplification, we assume that the community grid infrastructure is already available and that the incurred costs do not depend on the grid usage. Therefore, the community grid expenses are not included in the retailer's cost function.

The profit-maximizing retailer in the *BAU*, Static tariff, Market signal, and Community competition scenarios aims to maximize its net income:

$$\max \sum_{t=t_{initial}}^{t_{initial}+T_{opt}} u^{ret}_{x} \tag{26}$$

In contrast, the retailer in the self-sufficiency scenario optimizes its flexibility options so that the interaction with the higher-level energy system, namely the market, is minimized. The retailer's goal in this scenario is formulated as:

$$a(t) = e^{ret}_{M\to G}(t) + e^{ret}_{G\to M}(t) \tag{27}$$

$$\min \sum_{t=t_{initial}}^{t_{initial}+T_{opt}} a(t) \tag{28}$$

The households in the community are unable to use the service of other retailers. To avoid an unattractive outcome for the households in the *C-RTP* tariff, we add a constraint to this optimization:

$$\begin{cases} u^{h}_{No\ storage} \leq u^{h}_{Community\ competition} \\ u^{h}_{No\ storage} \leq u^{h}_{Self-sufficiency} \end{cases} \tag{29}$$

The constraints in Equation (29) prevent the retailer from offering prices that reduce the net income of households below the corresponding value in the BAU scenario.

As explained in Section 2.3.2, we define the *MAI* indicator as the retailer's welfare with respect to a benchmark scenario. In this scenario, the retailer controls the flexibility options inside the community and therefore its cost and revenue streams are reduced to its expenses and incomes from the market activities:

$$c^{ret}_{Benchmark}(t) = e^{ret}_{M\to G}(t).p_{M}(t) \tag{30}$$

$$r^{ret}_{Benchmark}(t) = e^{ret}_{G\to M}(t).p_{M}(t) \tag{31}$$

The retailer maximizes its net income (expressed by Equation (26)) and determines the hourly traded electricity in the market ($e^{ret}_{M\to G}(t)$ and $e^{ret}_{G\to M}(t)$). Using these values, the retailer's welfare in the benchmark scenario ($W^{ret}_{Benchmark}$) and subsequently the *MAI* can be calculated.

3.3. Endogenous Calculation of the Real-Time Pricing Components in the C-RTP Tariff

The retailer in the community energy system acts first to set the electricity prices (electricity tariff and purchase prices) and then the households adjust their individual grid interactions based on these prices. The characteristics of Stackelberg games are suitable to model such sequential events. Therefore, we model the hierarchical interplay between the retailer and the households as a one-leader and multi-follower Stackelberg game with the structure presented in Figure 6. By solving the resulted bi-level problem, the real-time pricing components in the *C-RTP* tariff can be derived endogenously.

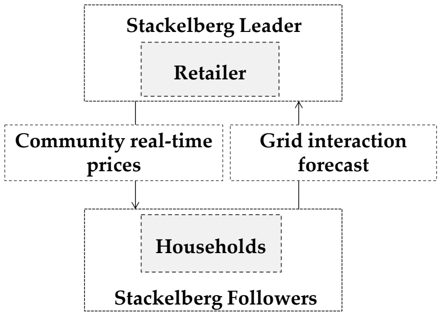

Figure 6. Two-level Stackelberg game structure in the *C-RTP* tariff.

Acting as Stackelberg leader on the upper decision level and anticipating the lower-level reactions by receiving their grid interaction forecast, the retailer modifies the real-time prices to reach its aggregation goal, namely profit or self-sufficiency maximization. The households then follow the leader's actions to maximize their net income by rescheduling their flexibility. Inflexible households, which cannot shift their load and feed-in, do not directly take part in the game. In the rest of this section, the modeling of the Stackelberg game and the algorithm to find the Stackelberg equilibrium will be presented.

3.3.1. Formulation of the Non-Cooperative Stackelberg Game

We develop a Stackelberg game-theoretic framework to model the *C-RTP* tariff and analyze the hierarchical retailer–household electricity trading interactions. This game is formally defined by its strategic form as:

$$\gamma = \left\{ (\mathbf{H} \cup \mathbf{R}),\ \left\{ \mathbf{E}^h \right\}_{h\in\mathbf{H}},\ \{Q\}, \left\{ u^h(t) \right\}_{h\in\mathbf{H}}, Z \right\} \tag{32}$$

This formulation consists of the following elements:

a. $(\mathbf{H} \cup \mathbf{R})$ is the set of actors, where the households in the set $\mathbf{H}$ act as followers in response to the prices set by the retailer $(\mathbf{R})$ as the game leader.
b. $\left\{ \mathbf{E}^h \right\}_{h\in\mathbf{H}}$ is the set of strategies of households, at time t, from which they select their strategy. This strategy represents the grid interaction of households in each time step.
c. Q is the strategy set of the retailer at time t, which consists of electricity tariffs and purchase prices.
d. $\left\{ u^h(t) \right\}_{h\in\mathbf{H}}$ is the set of households' utilities at time t as presented.
e. Z in the community competition scenario is the net income of the retailer for trading with users and the market at time t, $u^{ret}_{Community\ competition}(t)$, calculated from cost and revenue functions described in Equations (21) and (22). Z in the self-sufficiency scenario represents the electricity exchange with the market at time t, $a(t)$, calculated from Equation (27).

One suitable solution for the proposed game is the Stackelberg Equilibrium (SE), in which the leader obtains its optimal prices given the followers' best responses. At this equilibrium, neither the leader nor any follower can benefit, in terms of net income (or the amount of market exchange in the self-sufficiency scenario), by unilaterally changing their strategy.

Definition 1. *In the Stackelberg game γ, a set of strategies ($\mathbf{E}_*^{\mathrm{h}}$, $q_*(t)$) constitutes an SE of this game if and only if it satisfies the following set of inequalities*:

$$u^h\Big(\mathbf{E}_*^h,\ q_*(t)\Big) \geq\ u^h\Big(\ e^h(t), \mathbf{E}_*^{-h},\ q_*(t)\Big),\ \forall h \in \mathbf{H},\ \forall e^h(t) \in \mathbf{E}^h,\ \forall t \in [1, T_{sim}] \tag{33}$$

$$Z\Big(\mathbf{E}_*^h,\ q_*(t)\Big) \geq\ Z\Big(\mathbf{E}_*^h,\ q(t)\Big),\ \ \forall q(t) \in \boldsymbol{Q} \tag{34}$$

where $\mathbf{E}_*^{-\mathrm{h}} = \Big[e_*^1(t), e_*^2(t), .., \ e_*^{h-1}(t),\ e_*^{h+1}(t),\ .., e_*^{\mathbf{H}}(t)\Big]$*and* $\mathbf{E}_*^{\mathrm{h}} = \Big[\ e_*^h(t), e_*^{-h}(t)\Big]$.

Therefore, when all players in $(\mathbf{H} \cup \mathbf{R})$ *are at SE, the retailer cannot reduce its costs by changing its prices from the SE price $q_*(t)$. Similarly, no household can improve its net income by choosing a different grid interaction to $e_*^h(t)$.*

3.3.2. Solving the Stackelberg Game

The introduced Stackelberg game model consists of two-stage, sequential decision-making problems. The common solution concept for such a problem is the sub-game perfect equilibrium. This equilibrium can be determined using the general method of backward induction. According to backward induction, we first start from the followers and analyze the households' strategies to maximize their utilities, given the retailer's strategy. Moving backwards, in the next step, we investigate the retailer's *C-RTP* tariff based on the households' expected grid interactions. To derive the optimal Stackelberg strategies for this game, an analytical solution both for the followers' and the leaders' problems must exist. However, the followers' problem, which is a sum of separable sub-problems, as well as the retailer's problem are non-differentiable. In [48], Meng and Zeng suggest a Genetic Algorithm (GA) for finding the Stackelberg equilibrium in such a real-time pricing game between retailer and customers. Similarly, we adopt a GA to solve the retailer's profit maximization and self-sufficiency maximization problems in the *C-RTP* tariff. GAs are good tools for bi-level optimization problems, although the convergence to the global optimal solution cannot be proved [49].

The GA-based decision-making algorithms for retailers' and households' sides are shown in Algorithms 1 and 2:

Algorithm 1 retailer's side GA based real-time pricing algorithm

1: Population initialization, i.e., generating a population of L chromosomes randomly; each chromosome denotes an electricity acquiring price set for the optimization period.
2: **for** $l = 1$ **to** L **do**
3: The retailer decodes the l^{th} chromosome (representing the $p_{proc,s}$ and $p_{proc,p}$) and by adding the other electricity tariff building blocks, i.e., p_{CGC} and p_{VAT}, calculates its strategy $\boldsymbol{Q}$ (p_s^{ret} and p_b^{ret}) for the T_{opt}. The prices are then announced to the households.
4: The retailer receives the optimal strategies of the households including the grid interaction forecasts for the optimization period: $\left\{e_*^h(t)\right\}$.
5: Considering the constraints in Equation (29), at this stage the retailer optimizes the CES using the dynamic programming model and then, depending on the aggregation goal, evaluates its net-income ($u_{Community\ competition}^{ret}$) or the amount of traded electricity(a) for the optimization period (T_{opt}) as the fitness value of its strategy based on the chromosome l.
6: **end for**
7: A new generation of chromosomes is created by using the crossover and mutation operations of the GA.
8: Steps 2–7 are repeated until the convergence condition is reached.
9: The retailer announces the finalized prices to the households at the beginning of the scheduling horizon.

Algorithm 2 Households' side grid interaction optimization

1: Households receive electricity prices from the retailer.
2: Each household calculates its strategy, i.e., the grid interactions in response to prices, by solving the followers' problem using the dynamic programming model.
3: Households send back the predicted grid interactions during the optimization period to the retailer.

The algorithms are performed for each optimization period (T_{opt}). The algorithm on the retailer's side uses the Jenetics java library to generate and evaluate the fitness of the chromosomes [50]. The generated chromosomes in step 3 of Algorithm 1 represent the real-time variable procurement element ($p_{proc,s}$ and $p_{proc,p}$) in the *C-RTP* tariff (as described in Section 2.2). Here, the solution space is limited to the range [3, 6] cents per kWh. In the benchmark case, this range is expanded to [−100, 100] cents per kWh to ensure that the retailer achieves full control over the flexibility options. Moreover, in step 3, the other electricity tariff elements, i.e., community grid charges and value-added tax, are used to calculate the electricity prices (p_s^{ret} and p_b^{ret}) as the retailer's strategy. After retrieving the response of the households to these prices, the retailer evaluates the fitness of its strategy (step 5). To generate a new set of electricity prices, in step 7, the existing chromosomes are altered using the crossover operation, i.e., the new solutions are produced by combining the chromosome with higher fitness values (parent chromosomes). In this step, we also use the mutation, to ensure that the entire search space is explored and the convergence to a local optimum is prevented [50]. The convergence condition in step 8 is satisfied when the difference between the average fitness and the best fitness of the current population is less than 0.01%. When this criterion is satisfied, the most profitable prices for the retailer in the community competition scenario, or the lowest market trade in the self-sufficiency scenario, for the optimization period are found. Correspondingly, on the follower side, the grid interaction that maximizes the net income of households is obtained. The process is continued for the following optimization periods until the end of the simulation (T_{sim}) is reached. Further details on the used parameters in the genetic algorithm are given in Table 5.

Table 5. GA parameters; the detailed description of the parameters can be found in [50].

Parameter	Value
Population size	60
Offspring fraction	0.2
Mutation	0.6
Single point crossover	1
Population convergence threshold	0.01%

4. Results

In this section, after a short presentation of the electricity prices in different tariffs, the impact of aggregation scenarios from the actors' perspective is analyzed. Subsequently, the impact of each scenario on the higher-level energy system using the developed market alignment indicator is evaluated. The results presented in this section will be discussed later in Section 5.

The simulation of the electricity tariffs, as described in Section 2.2, for the simulation period of one year leads to electricity tariffs with the statistical characteristics shown in Table 6. As can be seen, the mean values of the electricity tariffs over the entire year vary only marginally. The market signal scenario shows the highest standard deviation, which results from the presence of very high and very low prices. It can also be seen that both *C-RTP* tariffs show a similar price range, limited by the searching space limitations of the genetic algorithm. The duration curves of the electricity tariffs for the simulation period are shown in Figure 7. A comparison of these prices for one optimization period (24 h) as well as the seasonal statistics of the electricity tariffs are presented in Appendix E.

Table 6. Scenario-specific statistic values of electricity tariffs.

Scenario	Tariff	Mean Value [cents]	Standard Deviation [-]	Price Range [1] [cents]
BAU/Static tariff	*SP*	26.76	0	[26.76, 26.76]
Market signal	*M-RTP*	26.76	2.09	[14.40, 36.68]
Community competition	*C-RTP*	26.83	0.96	[24.99, 28.56]
Self-sufficiency	*C-RTP*	26.58	1.01	[24.99, 28.56]

[1] The price range shows the minimum and maximum values of the electricity tariffs during the simulation time.

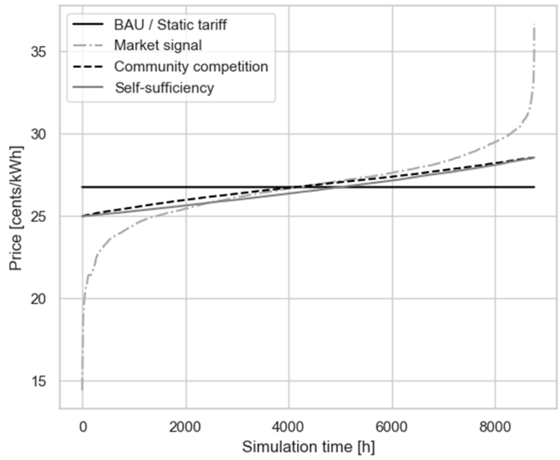

Figure 7. The duration curve of electricity tariffs in different scenarios.

4.1. Actor's Perspective

In Figure 8, the actors' net income relative to the BAU scenario, calculated from Equation (5), is shown. The driver of changes in the households' net income is the electricity tariff. The results show that in all scenarios under investigation the flexible households (flexible consumers and prosumagers) profit more from real-time pricing tariffs in comparison to inflexible households. This stems from the possibility of the flexible households to coordinate their grid usage and feed-in schedule with the real-time price signals (examples of such behavior for flexible consumers and prosumagers are demonstrated in Appendices F.1 and F.2). The inflexible households with no load shifting potential, on the other hand, are unable to take advantage of electricity price fluctuations. This translates to lower net income for inflexible households. For this reason, the consumers and prosumers in the market signal scenario are worse off than in the BAU scenario. The community competition and self-sufficiency scenarios show improvement for all households. This result, especially for the inflexible households in the community competition scenario, is driven by the predefined constraints in the *C-RTP* tariff, i.e., rejecting the prices that reduce the net income of households below the BAU scenario, see also Equation (29). Due to lower electricity prices, the most financially feasible scenario from the households' perspective is the self-sufficiency scenario (see also Table 6).

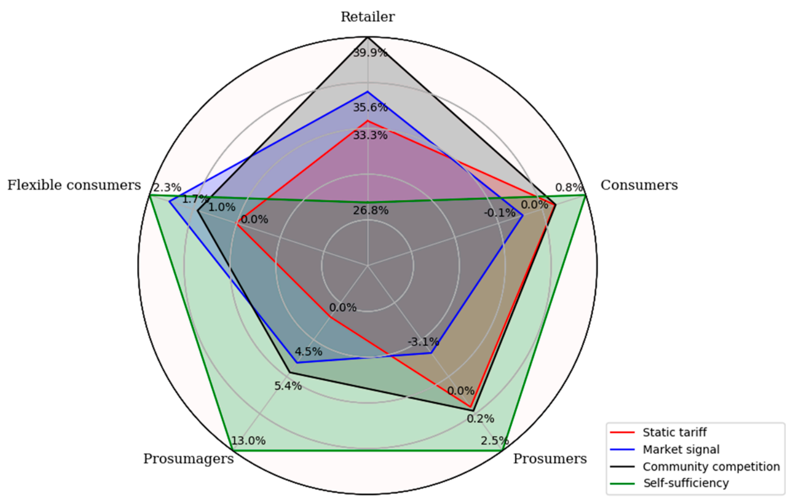

Figure 8. Actor's utilities relative to BAU scenario. A positive value indicates an increase in the net income, negative values represent a decrease in net income.

Deployment of CES in the static tariff scenario increases the net income of the retailer significantly (33.3%) in comparison to the BAU scenario. Among the scenario with CES, the self-sufficiency and the community competition scenarios demonstrate the least and most feasible performance from the retailer's perspective respectively. Looking at the retailer's cost and revenue, presented in Figure 9, reveals the following:

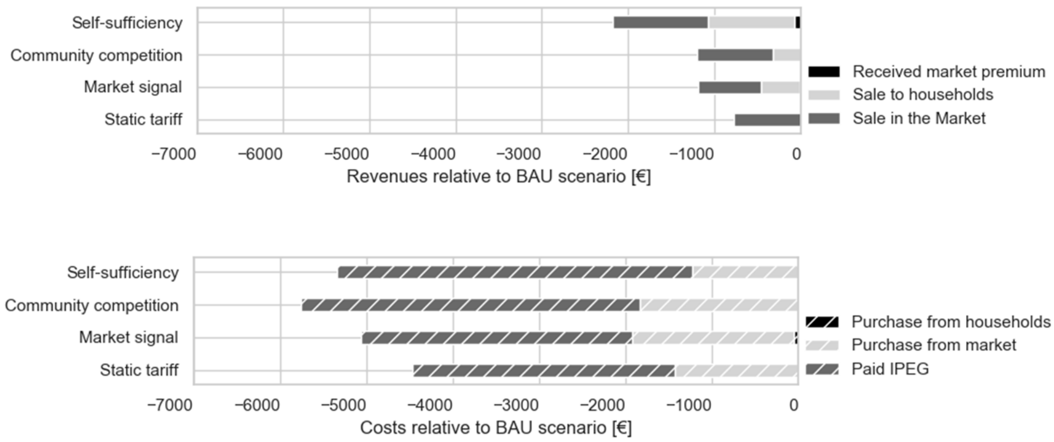

Figure 9. Retailer's cost and revenue streams relative to the BAU scenario; negative values show the reduction of each stream relative to the corresponding stream in the BAU scenario.

- The most prominent change in the retailer's cost and revenue streams belongs to the imposed costs due to IPEG. These savings are proportional with reduced electricity imports to the community energy system (Table 7). The exemption from IPEG inside the community energy system gives the retailer an incentive to balance the electricity generation and consumption inside the community and reduce the exchange with the higher-level energy system.

Table 7. Changes in the community energy system's import and export [1].

Scenario	Relative Import (%)	Relative Export (%)
Static tariff	−9.6	−45.0
Market signal	−9.9	−46.3
Community competition	−12.4	−53.1
Self-sufficiency	−13.0	−59.5

[1] Relative electricity import and export refers to the purchased and sold electricity in the market by the retailer relative to the corresponding values in the BAU scenario.

- The higher level of self-consumption inside the community lowers the retailer's cost for electricity acquisition as well as the revenues from selling the electricity in the market. The lower accrued costs due to acquiring electricity from the market also results from the use of flexibility options for efficient market trading, i.e., purchasing electricity at lower prices. Besides CES, in the market signal and community competition scenarios, the flexibility of households is also used for more efficient electricity acquisition.
- From the retailer's perspective, the purchase prices offered to the prosumagers did not seem to have a significant effect on the performance of different scenarios. Similar results were observed when the range for $p_{proc,p}$ and $p_{proc,s}$ in the *C-RTP* tariff is expanded to [0, 10] cents/kWh. The reason for this observation is the high difference between the electricity tariff and purchase prices in this electricity tariff (due to community grid charges and value-added tax) that makes the self-consumption using the PV-storage system for the prosumagers more attractive than selling it to the retailer.

- The retailer's revenue from electricity sales to the households in all scenarios that involve real-time pricing is reduced. These losses can be traced back to the changes in the electricity consumption of flexible households in response to real-time pricing tariffs. The optimization of real-time prices by the profit-maximizing retailer in the community competition scenario reduces these revenue losses in comparison to the market signal scenario. The highest revenue losses appear in the self-sufficiency scenario, since the real-time prices in this scenario are optimized to minimize the interaction with the market and the prices are lower on average than in other scenarios (see Table 6).

The additional net income the retailer gains from using the CES should be weighed against the costs of investment in the battery system. The result of the performed Net Present Value (NPV) analysis for two different battery module prices is given in Table 8 (see Appendix G for the details of the NPV calculations). The NPV analysis demonstrates that, depending on the battery module prices, the operational profits of using CES may justify an investment in the CES.

Table 8. NPV for different aggregation scenarios [1].

Scenario	Unit	NPV_510	NPV_250
Static tariff	€	−17,280.1	16,512.9
Market signal	€	−13,795.8	19,997.2
Community competition	€	−11,671.7	22,121.4
Self-sufficiency	€	−27,043.5	6749.5

[1] NPV_510 and NPV_250 refer to the NPVs for battery prices of 510 and 250 (€/kWh) respectively.

To analyze the added value of each scenario for the community as a whole, the relative social welfare of the community energy system in each scenario has been investigated. Defined by Equation (7), the relative community welfare represents the sum of received utilities for all actors relative to the BAU scenario. Figure 10 illustrates this value as well as the contributions of the retailer's and households' net income to the changes for all scenarios. The results show that the relative welfare of the community in the community competition scenario is highest (12.2%), whereas it is lowest in the static tariff scenario (9.2%). While the inflexible households in the self-sufficiency scenario have a positive contribution, they have a negative impact on the community welfare in the market signal scenario. Note that the increase in community welfare happens analogously to lower exchanges in the market. This is due to the fact that high taxes and levies on the end-user electricity prices (in this case retailer) means that self-consumption is feasible.

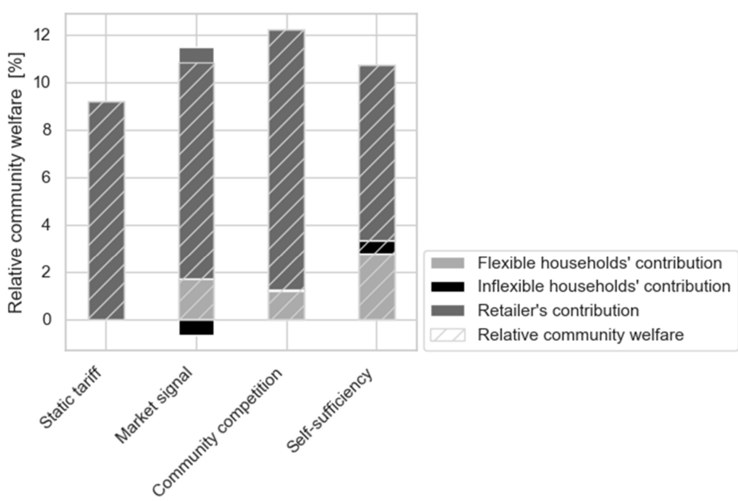

Figure 10. Community welfare in comparison to the BAU case.

4.2. System Perspective

In the next step of our analysis, we investigate the performance of the aggregation scenarios from the perspective of the higher-level energy system. In Figure 11, two indicators are compared: the first indicator is the relative market alignment indicator, with 1 being aligned as the benchmark case and 0 representing the performance of the BAU case (see Section 2.3.2). Secondly, we compare the relative exchanged electricity in the market as an indicator of the "degree of self-sufficiency".

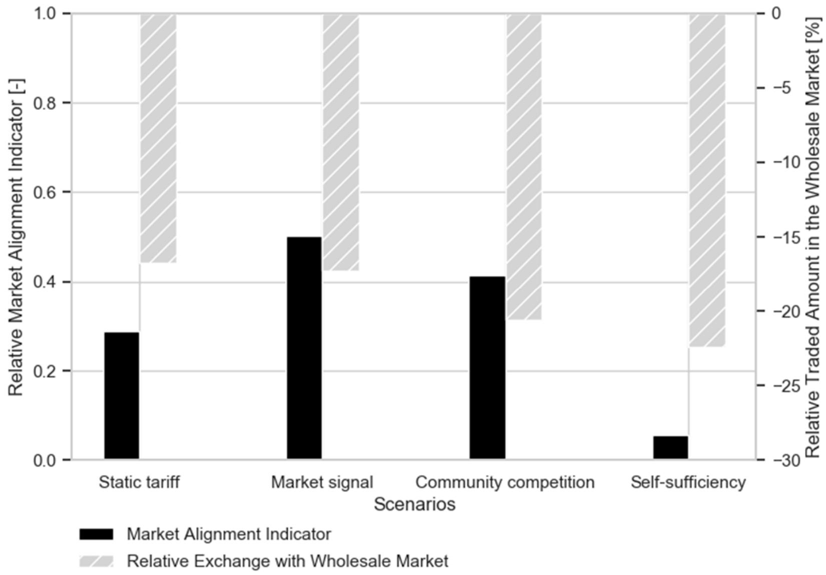

Figure 11. Relative market alignment indicator and reduced exchange with market compared to the BAU scenario.

As explained in Section 2.3.2, the electricity load and feed-in of the community energy system in scenarios with higher *MAI* values are more aligned with signals from the market. The value of *MAI* in our analysis encompasses two competing effects. On the one hand, more efficient market participation by the retailer increases its welfare and consequently the *MAI* indicator. On the other hand, a greater degree of self-consumption in the community reduces the overall exchange with the market. Thus, the *MAI* indicator of a completely self-sufficient community will adopt a negative value. According to the results depicted in Figure 11, the implementation of CES, despite lower electricity exchange in the market, increases the market alignment of the community energy system with the market. This implies that more efficient trade in the electricity market outweighs the effect of increased self-consumption on the *MAI*. The low *MAI* value in the self-sufficiency scenario can be partially explained, therefore, by the lower trade in the market resulting from the focus on self-consumption within the community under this scenario. However, the disproportional reduction in the *MAI* value in comparison to the community competition scenario indicates inefficiency in the dispatch of flexibility options in the self-sufficiency-oriented scenario. A comparison among static tariff, market signal, and community competition scenarios show that the aggregation of flexibility options using real-time pricing signals simultaneously increases *MAI* and the self-consumption inside the community.

The higher rate of self-consumption in the community energy system reduces the electricity import from the public grid. Since the IPEG are paid on a per-unit basis, the collected taxes, levies, and grid charges by the policy agent are reduced. As can be seen in Table 9, the highest decrease belongs to the self-sufficiency scenario, which also has the lowest electricity import during the simulation period. From the perspective of the policy agent, the simulation results yield a deficit in the earnings from the IPEG with no significant changes in its payments.

Table 9. Collected EEG levy and grid charges by the policy agent relative to the BAU scenario.

Scenario	Grid Charges (€)	EEG Levy (€)
Static tariff	−1202.51	−1120.15
Market signal	−1242.57	−1157.46
Community competition	−1551.29	−1445.03
Self-sufficiency	−1628.25	−1516.72

5. Discussion and Conclusions

Aggregation of the distributed generation and the flexibility offered by households in the community energy systems can offer opportunities and challenges to the future energy system. To investigate these impacts from the actors' and market perspectives, in this paper a bottom-up model of a community energy system is presented. We carried out an analysis for the case of Germany and a community energy system located in a private grid. The developed model is used to study various scenarios for the aggregation of electricity load and generation in a community energy system. Next to Community Energy Storage (CES) technology, electricity tariff structure and aggregation goals are the main components in these scenarios. By considering static and Real-Time Pricing (RTP) tariffs, three tariff structures, each of which contain a set of hourly tariffs and purchase prices, are constructed. In the case of the RTP tariff, we distinguished between the Market RTP *(M-RTP)* and Community RTP *(C-RTP)* tariffs. While the *M-RTP* contains uninterrupted signals from the market as the real-time element of the tariff, the hourly varying component in the *C-RTP* is the optimal price determined by the retailer. To obtain the optimal prices in the *C-RTP*, the interactions between the retailer and households are modeled as a Stackelberg game. The second component in the studied scenarios is the retailer's aggregation goal. Here we differentiate between the retailer's profit maximization and community self-sufficiency maximization as the goal of the aggregation. In order to assess the impact of community energy systems on the market prices, we defined the *Market Alignment Indicator (MAI)*. The value of this indicator shows how close the operation of a community energy system resembles the behavior of a benchmark community energy system, which operates in complete alignment with the market signals.

5.1. Policy Interpretation

The analysis above shows that the usage of a storage system in a community, which is located in a private grid, can have a major impact on the operational profit of the retailer. The gained additional profit may justify an investment in CES. At the same time, in all studied scenarios in which CES is used, the value of *MAI* for the community energy system is increased. The usage of CES for the aggregation of households can absorb the electricity load and feed-in peaks that are misaligned with the market signals. Analog to higher *MAI* values, in the scenarios using a CES, the amount of exchanged electricity in the market drops. The greater level of self-consumption that also lead to higher community welfare can be traced back to high end-user prices due to the regulations in Germany and the implemented exemptions from taxes and levies in the community grid. For a community energy system that uses the public grid, however, the self-consumption on the community level is charged by grid charges, taxes, and levies. The regulations for the self-consumption of generated electricity by households in Germany are currently limited to the behind-the-meter self-consumption in residential buildings. An example of such regulations is the German tenant electricity law (Mieterstromgesetz), which promotes the consumption of generated electricity from PV rooftop systems by several consumers in a building [51]. According to the regulations in Germany, a CES that is connected to a public grid, similar to other storage systems, is considered to be an end consumer when charging. Therefore, the stored electricity is charged with taxes, levies, and grid charges [52]. This regulatory burden on CES in many pilot projects such as [46] is indicated as the main source of unprofitability.

In case the aggregation goal of the retailer is profit maximization, the analysis of *MAI* demonstrates that both RTP tariffs improve the alignment of the community energy system with the signals from the market. The perfect alignment of the households' flexibility options with market signals due to other distortions such as the constant community grid charges that do not reflect the market price fluctuations is not achieved. The authors in [10] have shown that in the case of a PV storage system, even by implementing fixed network charges, time-varying feed-in tariffs and the combination of both a complete alignment with market signals is not possible. The low *MAI* value in a self-sufficiency-oriented scenario depicts one source of inefficiency in terms of exchange with the higher-level energy system. Such inefficiency can be justified, for instance, if the reduced exchange with the higher-level energy system lessens the required grid expansion. Otherwise, the self-consumption can lead to the loss of the potential efficiency gain from balancing supply and demand over a larger area by using the existing grid infrastructure [53].

From the actors' perspective, real-time tariffs bring financial benefits to flexible households. Analogous to these benefits, the *M-RTP* tariff imposes extra costs on inflexible households. Although the debate on the fairness of dynamic prices is part of a bigger discussion [54], we want to point out that the implementation of novel tariff schemes may have negative impacts on the inflexible electricity consumers, who are not able or are unwilling to shift their load. Among the studied tariffs in this paper, the *C-RTP* tariff yields the highest profit for the retailer, without increasing the costs of any household. Despite these promising results, the implementation of such tariffs requires the communication infrastructure that is currently not available in Germany. For instance, households need be equipped with smart meter gateways (a device that automatically communicates measurements from connected smart meters to external market participants, and it allows them to send incentives or commands for load adjustments to local control boxes such as energy management systems [55]), which can measure and transfer data to the retailer. According to the German Metering Point Operation Law ("Messstellenbetriebsgesetz"), the roll-out of smart meter gateways in Germany will follow a step-wise plan, which ultimately obliges the consumers with consumption over 6000 kWh/year or for prosumers with renewable peak feed-in above 7 kW to install these devices [56]. The profitability of real-time tariffs for flexible households, however, can be an incentive for the voluntary investment in such devices.

The monetary benefits of RTP tariffs for the prosumagers imply that future business models may incentivize the investment in PV storage systems even more. Since the costs of energy system infrastructure is paid by consumers on a per unit basis, by becoming prosumager, the household contributes less to maintaining the system, while still benefiting the security supply by being connected to the grid. This can raise distributional problems, since the increase in the number of prosumagers may lead to higher costs for households who cannot invest in self-sufficiency [57]. Moreover, this will lead to a spiral because there is more incentive to invest in self-sufficiency [6]. The self-consumption in a community energy system using a private grid (such as the one studied in this work) can lead to a similar problem, since the retailer always has access to the public grid. As observed in the results, such a community energy system not only results in lower payment for maintenance costs on the public grid, but also contributes less to the existing support schemes, for example by paying the EEG levy. To tackle these issues, several solutions, such as capacity price components, are introduced in the literature [58,59].

5.2. Limitations and Outlook

Our model-based analysis incorporates a trade-off between the level of details and the comprehensiveness of the model. In our modeling approach, we focused on actors' plurality in the community energy system and modeled various types of households. A general assumption of our modeling approach is the perfect foresight of all the actors. The households have a perfect estimation of their energy demand and generation one day ahead. It is assumed that households are able and willing to share these forecasts with the retailer. Correspondingly, the retailer has exact knowledge of the market prices of the following day. How the uncertainties in the prediction of these data will impact the performance of different aggregation scenarios should be a topic of further research.

In our model, we assumed the households of each type to be similar, meaning the electricity demand and generation profiles and the technologies they use are similar. For a small community, the aggregation of the resulting identical behaviors may lead to unrealistic patterns, e.g., electricity peaks. When modeling the households' electricity consumption, we considered their electricity demand to be inelastic in response to price signals. Thereby, we drew our focus merely to load-shifting potentials due to flexibility options. Moreover, we simplified the dispatch optimization problems of heat pumps and PV storage systems in our model. For instance, we assumed that heat pumps are set to keep the room temperature constant. Here we neglect the building energy losses and gains depending on weather conditions and building isolation. Moreover, in the case of prosumers and prosumagers, we assumed that the generated electricity from PV rooftop systems covers preliminary the electricity demand of the household. According to the current regulatory framework in Germany, this is a valid assumption since this behind-the-meter consumption of generated electricity by small PV systems is not charged with taxes, levies and other charges and is, therefore, "free". A more complex model such as the one offered in [10] can, however, offer more exploration potential when analyzing the PV storage system response to different electricity tariffs. The main reason behind reducing the complexity of the optimization models was the high computation load that a combination of the implemented genetic algorithm and these optimization processes would otherwise produce. Last but not least, the sizing of PV systems, PV storage systems, as well as heat pumps and thermal storage systems, are set heuristically.

When modeling the retailer, the main limitation of our work is dismissing other costs and revenue streams that may have a major impact on the overall feasibility of the aggregation scenarios. We reduced our analysis to the CES that is located in a private grid. Hence, the imposed charges on CES operations as a decisive cost stream are disregarded in our analysis. Apart from this, additional revenues from participation in other markets such as reserve markets or incentives for offering ancillary grid services can boost the profitability and consequently the community welfare that a CES can produce. A comprehensive feasibility study of CES business models that takes these costs and revenue streams into account can be the subject of future studies. Moreover, the optimal sizing and technology of the CES systems, similar to the approach used in [60], should be explored in subsequent researches. Such a study should include an investigation into the impact of alternative community setups, i.e., the number of each household category in the community, on the optimal CES sizing.

One important constraint of our approach in presenting *MAI* is that it neglects the influence of community energy systems on the prices. The value of *MAI* is therefore only properly defined if the impact of the electricity exchange with the market does not have a significant impact on prices [10]. To address this weakness, coupling the community energy system model with an electricity market model can be suggested for further research works. In doing so, the performance of *MAI* as a proxy for the "system-friendliness" of the community energy systems by investigating the indicators of the larger system (e.g., system costs or CO_2 emissions of the electricity sector) can be examined. Another limitation of the *MAI* is that it does not consider the grid, especially the distribution grid [10]. For instance, the contribution of the community energy systems to alleviate stress on the distribution grid cannot be the current approach.

In this paper, we distinguished between different electricity tariffs by varying the price component that covers the retailer's electricity procurement costs. In this context, we suggest that the modifications of these tariffs that take alternative regulations into account should be studied further. For example, the introduction of capacity-based price components offered in the literature (for instance in [59]) can contribute to debates about the distribution effects of increasing self-consumption. Moreover, by increasing the number of community energy systems, the impact of different tariffs on the larger systems should be examined. Such a study could contribute, for example, to the discussion about a potential overreaction of flexibility options when they are exposed to the signals from the market (also called "avalanche effect" [61]).

We modeled the hierarchical interplay between the retailer and the households as a one-leader and multi-follower Stackelberg game. This approach is widely used in the literature to model the energy management systems in energy communities and microgrids [25,27,28,62]. While Stackelberg games fit the characteristic of the investigated community energy system very well, other methods, such as double auction, can also be used to model the community energy market [63]. In our model, we assumed that households are obliged to trade with one retailer (implying an imperfect competition). In the absence of competition, we used an exogenous constraint (Equation (29)) to limit the negative impacts on consumer welfare and efficiency losses. The expansion of this model to a multi-leader and multi-follower (such as the model in [64]) can tackle this limitation of our work in neglecting the competition among different retailers. Moreover, we did not consider any collusive behavior among the households in our lower-level problem. To the best of our knowledge, such behavior among German households is not a real concern.

Last but not least, we acknowledge the limitations of the genetic algorithm in searching for the Stackelberg equilibrium. The main drawback of our approach is the uncertainty regarding the optimality of the solution and the possibility of a convergence with a local optimum. Parameterization of the genetic algorithm in this work was based on a heuristic approach and incorporated a trade-off between the fitness of the utility function and the required computation time. This approach, however, allowed us to cope with the non-linearities in the game-theoretic modeling. We wish to emphasize that the analytical approaches in modeling the actors' decision-making behavior can deliver solid results for many research questions in the energy system analysis. In bottom-up modeling of the actors' behavior in the energy system, however, actors' rationales are not always reducible to functions, which can be solved with conventional optimization tools. Therefore, the applications of artificial intelligence, such as evolutionary algorithms and machine learning, in solving game-theoretic problems in the energy system analysis should be followed in future works.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Table of Notation

Table A1. Table of notation.

Parameter	Meaning
$\mathbf{I}$	Set of actors: retailer (ret), consumers (cs), flexible consumers (fcs), prosumers (ps) and prosumagers (psg)
$\mathbf{H}$	Set of households: consumers, flexible consumers, prosumers and prosumagers
$\mathbf{P}$	Set of households with generation potential: prosumers and prosumagers
$\mathbf{R}$	Retailer
N^h	Number of households in the category $h \in \mathbf{H}$
$l^h_{BD}(t)$	Base electricity demand of the households $h \in \mathbf{H}$ at time t [kWh]
$l^{fcs}_{HD}(t)$	Heat demand of the flexible consumers at time t [kWh]
$g^p_{PV}(t)$	Electricity generation of the households $p \in \mathbf{P}$ at time t [kWh]
$s^p(t)$	Residual load of the households $p \in \mathbf{P}$ at time t [kWh]
$e^i_{G\rightarrow\partial}(t)$	Electricity flow by actor $i \in \mathbf{I}$ at time t from grid to ∂ with ∂={Demand: D, Heat pump: HP, Battery: B, Electricity market: M} [kWh]
$e^i_{\partial\rightarrow G}(t)$	Grid feed-in by actor $i \in \mathbf{I}$ from at time t from ∂ with ∂={Battery: B, PV systems: PV, Electricity market: M} [kWh]

Table A1. *Cont.*

Parameter	Meaning
$e^{fcs}_{HP\rightarrow TS}(t)$	Energy inflow from heat pumps to thermal storage systems at time t [kWh]
$e^{\mathbf{P}}_{PV,B\rightarrow G}(t)$	Total grid feed-in by all prosumers and prosumagers at time t [kWh]
$e^{\mathbf{H}}_{G\rightarrow D}(t)$	Total grid usage by all households at time t [kWh]
$r^i_x(t)$	Revenue of actor $i \in \mathbf{I}$ in the scenario x at time t [cents]
$c^i_x(t)$	Costs of actor $i \in \mathbf{I}$ in the scenario x at time t [cents]
$u^i_x(t)$	Net income of actor $i \in \mathbf{I}$ in the scenario x at time t [cents]
U^i_x	Net income of actor $i \in \mathbf{I}$ in the scenario x for the simulation period [cents]
$U^{i,rel}_x$	Net income of actor $i \in \mathbf{I}$ in the scenario x relative to BAU scenario for the simulation period [-]
$a(t)$	Amount of traded electricity in the market by the retailer at time t [kWh]
S^{max}_{PV}	Peak power of PV system [kW]
PR_{PV}	Performance ratio of PV system [-]
K^{psg}_B	Battery storage capacity in PV storage systems [kWh]
S^{max}_{HP}	Peak power of heat pump [kW]
cop_{HP}	Heat pump COP [-]
K^{fcs}_{TS}	Thermal storage capacity in the heat pump systems [kWh]
K^{ret}_{CES}	CES capacity [kWh]
η_d	Battery discharge efficiency in CES and PV storage systems [-]
η_c	Battery charge efficiency in CES and PV storage systems [-]
$E2P$	Battery energy to power ratio in CES and PV storage systems [-]
$C^{O\&M}_{CES}$	CES operation and maintenance costs expressed as a ratio of initial investment costs [%]
I^0_{CES}	CES-specific investment cost [€/kWh]
r_{dis}	Discount rate [%]
L_{CES}	Battery lifetime [years]
FiT	Feed-in tariff [cents/kWh]
p_{levies}	EEG and other support levies [cents/kWh]
p_{GC}	Public grid charges [cents/kWh]
p_{CGC}	Community grid charges [cents/kWh]
p_{taxes}	Electricity tax [cents/kWh]
p_{VAT}	Value added tax [cents/kWh]
VAT	Value added tax [%]
p^{ave}_m	Annual mean value of market prices [cents/kWh]
$p_m(t)$	Market price in time t [cents/kWh]
$p_{MP}(m)$	Market premium in the month m [cents/kWh]
$mv_{PV}(m)$	Market value of PV electricity in the month m [cents/kWh]
$p^{ret}_s(t)$	Retailer's electricity tariff in time t [cents/kWh]
$p^{ret}_p(t)$	Retailer's electricity purchase price in time t [cents/kWh]
$p_{proc,s}(t)$	Electricity procurement price component in $p^{ret}_s(t)$ [cents/kWh]
$p_{proc,p}(t)$	Electricity procurement price component in $p^{ret}_p(t)$ [cents/kWh]
W^{ret}_x	Welfare of retailer in the scenario x for the simulation period [cents]
W^{com}_x	Welfare of community in the scenario x for the simulation period [cents]
$W^{com,rel}_x$	Welfare of community in the scenario x for the simulation period relative to BAU scenario [cents]
MAI^{rel}_x	Market alignment indicator for scenario x relative to BAU scenario [-]
MAI_x	Market alignment indicator for scenario x [-]
T_{opt}	Optimization period [Hours]
T_{sim}	Simulation period [Hours]
$\mathbf{E}^h$	Strategy set of households $h \in \mathbf{H}$ in time t
Q	Strategy set of the retailer in time t

Appendix B. Dispatch Optimization

The following section describes the constraints to the flexible consumers, prosumagers and CES dispatch optimization models. The equations are to be seen as complementary to the formulations of utility functions in Section 3.2.

Appendix B.1. Constraints for Flexible Consumers' Optimization Model

The optimization problem of flexible consumers is performed for every optimization period until the whole simulation period is covered. For an optimization period starting at $t_{initial}$, the problem described in Equation (17) subjects to the following constraints:

$$0 \le e^{fcs}_{G\to HP}(t) \le \; S^{Max}_{HP} \tag{A1}$$

$$e^{fcs}_{HP\to TS}(t) = e^{fcs}_{G\to HP}(t).cop_{HP} \tag{A2}$$

$$e^{fcs}_{charge}(t) = \; e^{fcs}_{HP\to TS}(t) - \; l^{fcs}_{HD}(t) \tag{A3}$$

$$e^{fcs}_{TS}(t) = \begin{cases} e^{fcs}_{TS,initial} & t = t_{initial} \\ e^{fcs}_{TS}(t-1) + e^{fcs}_{charge}(t) & t_{initial} < t < t_{initial} + T^{opt} \\ e^{fcs}_{TS,final} & t = t_{initial} + T^{opt} \end{cases} \tag{A4}$$

$$0 \le e^{fcs}_{TS}(t) \le \; K^{fcs}_{TS} \tag{A5}$$

where $e^{fcs}_{G\to HP}(t)$ is the heat pump input electricity load at the time t that is limited by the constraint in Equation (A1). The value of cop_{HP} in Equation (A2) is assumed to be independent of the ambient temperature and therefore constant during the whole simulation time. In the calculation of $e^{fcs}_{charge}(t)$, which represents the changes in the thermal storage energy content, the storage energy losses are neglected (Equation (A3)). $e^{fcs}_{TS}(t)$ in Equation (A4) denotes the energy content of the thermal storage that is considered to be $e^{fcs}_{TS,initial}$ and $e^{fcs}_{TS,final}$ at the beginning and end of each optimization period. In our simulation, we assumed $e^{fcs}_{TS,initial}$ and $e^{fcs}_{TS,final}$ to be 0. The energy content of the thermal storage always adopts a positive value and cannot exceed the maximum storage capacity. This constraint is described in Equation (A5).

Appendix B.2. Constraints for Prosumagers Optimization Model

Similar to the case of flexible consumers, here we explain the constraints to the optimization problem described in Equation (20) for the optimization period starting at $t_{initial}$. In the prosumagers' model, we assumed that the generated electricity is preliminary used to cover the electricity demand. The residual load of the prosumagers (s^{psg}), calculated from Equation (A6), can adopt positive and negative values indicating deficit and excess of electricity, respectively. In case of deficit, the remaining electricity demand is supplied from the grid ($e^{psg}_{G\to D}$) and/or from the battery ($e^{psg}_{B\to D}$). Correspondingly, the electricity excess is fed-in to the grid ($e^{psg}_{PV\to G}$) and/or stored in the battery. To this end, the complexity of the prosumagers model is reduced. The first assumption is the direct consumption of generated solar energy and the definition of residual load and generation. If the residual load is positive, the load will be covered by the grid and/or battery storage. In summary:

$$s^{psg}(t) = l^{psg}_{BD}(t) - \; g^{psg}_{PV}(t) \tag{A6}$$

$$s^{psg}(t) = \begin{cases} \partial(t).e^{psg}_{G\to D}(t) + (1-\partial(t))\cdot e^{psg}_{B\to D}(t) & s^{psg}(t) > 0 \\ -\partial(t).e^{psg}_{PV\to G}(t) - (1-\partial(t))\cdot e^{psg}_{PV\to B}(t) & s^{psg}(t) \le 0 \end{cases} \tag{A7}$$

where the variable $\partial(t)$ in Equation (A7), which adopts discrete values between 0 and 1, defines the portion of the residual load that is covered from or fed-in to the grid at time t. In this optimization, the ∂ can adopt a value from {0, 0.1, 0.2, ..., 0.9, 1}. For each value of ∂, the battery storage is optimized using the following constraints:

$$e^{psg}_{charge}(t) = e^{psg}_{G\rightarrow B} + e^{psg}_{PV\rightarrow B} - e^{psg}_{B\rightarrow D} - e^{psg}_{B\rightarrow G} \tag{A8}$$

$$e^{psg}_{B}(t) = \begin{cases} e^{psg}_{B,initial} & t = t_{initial} \\ e^{psg}_{B}(t-1) + e^{psg}_{charge}(t).\eta & t_{initial} < t < t_{initial} + T^{opt} \\ e^{psg}_{B,final} & t = t_{initial} + T^{opt} \end{cases} \tag{A9}$$

$$\eta = \begin{cases} \eta_c & e^{psg}_{charge}(t) \geq 0 \\ \frac{1}{\eta_d} & e^{psg}_{charge}(t) < 0 \end{cases} \tag{A10}$$

$$\left| e^{psg}_{charge}(t) \right| \leq K^{psg}_{B}.\ \mathrm{E2P} \tag{A11}$$

$$0 \leq e^{psg}_{B}(t) \leq K^{psg}_{B} \tag{A12}$$

where $e^{psg}_{charge}(t)$ in Equation (A8) is the energy flow to/from battery at time t. Equation (A9) describes the dependency of the energy content of the battery (e^{psg}_{B}) to the corresponding value in the last time step and the amount of charged or discharged energy in each time step. The battery is assumed to be empty at the beginning and the end of the optimization period, i.e., $e^{psg}_{B,initial}$ and $e^{psg}_{B,final}$ is set to 0. The battery losses are taken into account by a charge or a discharge efficiency, η_c and η_d respectively. The amount of charged or discharged electricity in each time step cannot exceed the power rating of the battery calculated in Equation (A11). Last but not least, the energy content of the battery is always positive and is limited by the battery capacity (K^{psg}_{B}), as indicated in Equation (12).

Appendix B.3. Constraints for Community Energy Storage Optimization Model

The optimization problems in the Equations (26) and (28) involve finding the optimal dispatch of CES. This model for an optimization period starting at $t_{initial}$ has the following constraints:

$$e^{ret}_{charge}(t) = e^{P}_{PV,B\rightarrow G}(t) + e^{ret}_{M\rightarrow G}(t) - e^{H}_{G\rightarrow D}(t) - e^{ret}_{G\rightarrow M}(t) \tag{A13}$$

$$e^{ret}_{CES}(t) = \begin{cases} e^{ret}_{CES,initial} & t = t_{initial} \\ e^{ret}_{charge}(t-1) + e^{ret}_{charge}(t)\cdot\eta & t_{initial} < t < t_{initial} + T^{opt} \\ e^{ret}_{CES,final} & t = t_{initial} + T^{opt} \end{cases} \tag{A14}$$

$$\eta = \begin{cases} \eta_c & e^{ret}_{charge}(t) \geq 0 \\ \frac{1}{\eta_d} & e^{ret}_{charge}(t) < 0 \end{cases} \tag{A15}$$

$$\left| e^{ret}_{charge}(t) \right| \leq K^{ret}_{CES}\cdot E2P \tag{A16}$$

$$0 \leq e^{ret}_{CES}(t) \leq K^{ret}_{CES} \tag{A17}$$

where $e^{ret}_{charge}(t)$ in Equation (A13) denotes the energy input or output from the CES, which is the sum of the traded electricity with households and in the market. The rest of the constraints are analogous to the prosumagers' optimization model (Equations (A9) to (A12)).

Appendix C. Dynamic Programming Model

In order to solve the optimization problem of flexible consumers, prosumagers, and CES, we adopt the Bellman theory of optimality and use the dynamic programming approach. This approach is widely used in finding the optimal storage charging strategies ([34] as an example). According to this theory, "an optimal policy must only contain optimal sub-policies" [65]. In the case of storage charging, the optimal and sub-optimal policies refer to the optimal charging strategy for the whole optimization period and any other smaller given period, respectively.

For the implementation of this model, as shown in Figure A1, we divide the solution space in each time step to discrete states, each of which represents the state of charge of the storage, as expressed in the Equations (A4), (A9), and (A14). These states in each time step are defined by the optimization constraints, such as storage capacity and energy-to-power ratio. For the sake of simplification, the states in Figure A1 are limited to SOC_{Min} and SOC_{Max}. The possible strategies that connect each of the two states represent a charging or discharging strategy during one time step.

To find the optimal strategy, two calculation steps are required. In the first step, moving backwards from the last time step (T^{opt}), the optimal sub-strategy and cost of that strategy is calculated and recorded for all the states in each time step. An example of such a calculation is shown in Figure A1, where the cost of the optimal sub-strategy for the state SOC_{Max} in the time step $T^{opt}-2$ is calculated ($cost_{T^{opt}-2}^{SOC_{Max}}$). After this calculation is done for all the time steps, we move forward from the first time step and the initial state of the storage and use the recorded strategies to determine the optimal strategy for the whole optimization period.

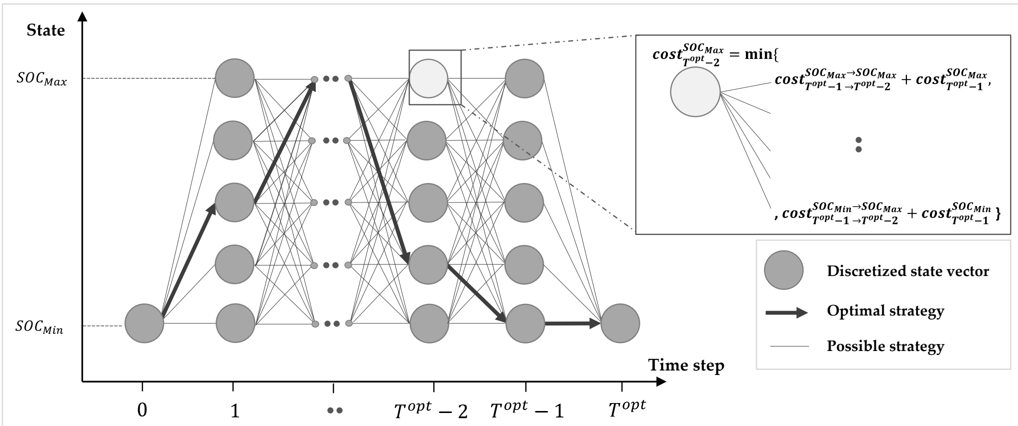

Figure A1. Schematic sketch of the dynamic programming model and an exemplary calculation of the cost of the optimal sub-strategy ($cost_{T^{opt}-2}^{SOC_{Max}}$) for the state SOC_{Max} in the time step $T^{opt}-2$.

Appendix D. Preparation of the Model's Input Data

In this paper, the households in each category are modeled as a single aggregated household. Therefore, we scale up the input time series and technologies for each household model linearly. Considering the l_{BD}^{s} to be the standard demand profile for each household, the aggregated base electricity demand of all the households in the category $h \in \mathbf{H}$ at time t is calculated by Equation (A18). Similarly, as shown in Equation (A19), the heat demand of the flexible consumers' model is obtained by a linear scale-up of the heat demand of a single household (l_{HD}^{s}):

$$l_{BD}^{h}(t) = N^{h} \times l_{BD}^{s}(t) \tag{A18}$$

$$l_{HD}^{fcs}(t) = N^{fcs} \times l_{HD}^{s}(t) \tag{A19}$$

The actual electricity generation of the households in the category $p \in \mathrm{P}$ is determined using the following equation:

$$g^{p}_{PV}(t) = N^{p} \times g^{s}_{PV}(t) \times S^{Max}_{PV} \times PR_{PV} \tag{A20}$$

where g^{s}_{PV} is the share of generated electricity per kWh installed PV capacity in the year 2018 in Germany. S^{Max}_{PV} and PR_{PV} are the peak power and performance ratio of PV systems, respectively. The rest of the parameters, i.e., the peak power of the heat pump as well as the capacity of the thermal storage and PV storage systems are also multiplied by the number of households available in each category.

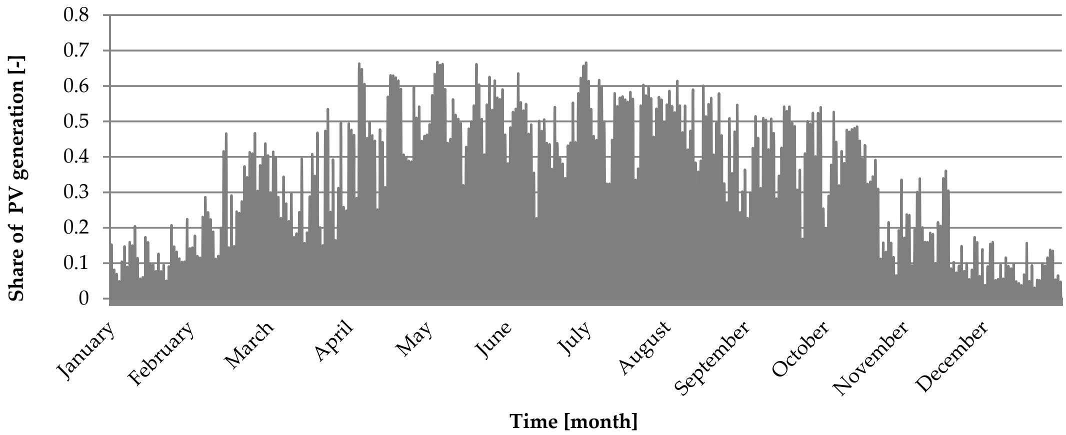

Figure A2. Share of total PV electricity generation to installed PV capacity in Germany in the year 2018 (own presentation based on the data from [35]).

In Figure A3, the day-ahead spot market prices for the year 2018 [35] together with the monthly market values of PV, which are from [36], is presented.

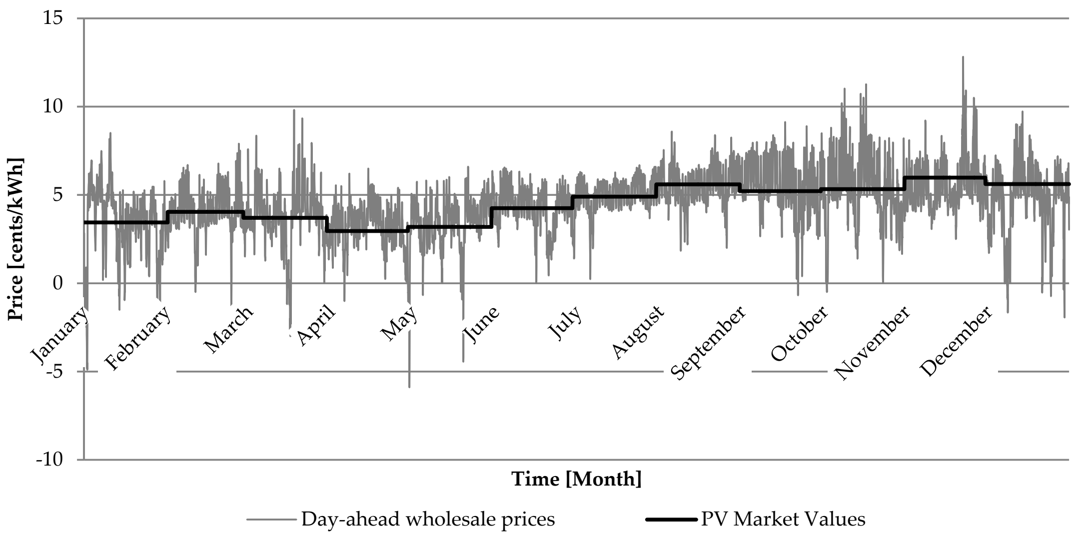

Figure A3. Day-ahead spot market prices and market values for the year 2018 (own presentation based on the data from [35,36]).

Appendix E. Electricity Prices in Different Tariffs

Figure A4 presents the electricity tariffs in the investigated scenarios for an exemplary 24 h.

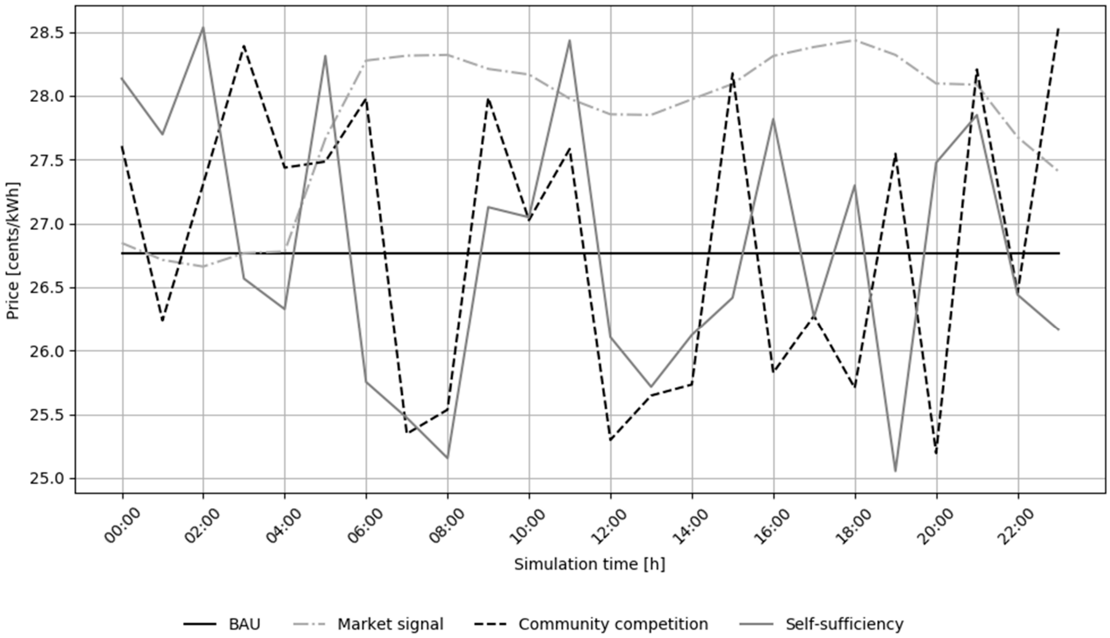

Figure A4. Electricity tariffs in the investigated scenarios for an exemplary 24 h.

The mean value and standard deviation of the electricity tariffs in different seasons are presented in Tables A2 and A3, respectively. Since the electricity prices in the BAU scenario do not change over time, the statistics for the BAU scenario are not presented. In comparison with the community competition and self-sufficiency scenarios, the mean value and standard deviation of the electricity prices in the market signal scenario show a strong seasonality. This seasonality, which reflects the characteristics of the market prices, among others, results from the changes in the availability of renewable energy resources such as wind and sun.

Table A2. Mean values of electricity tariffs during different seasons.

Scenario	Jan–Mar	Apr–Jun	Jul–Sep	Oct-Dec
Market signal	25.85	25.77	27.80	27.66
Community competition	26.86	26.84	26.82	26.83
Self-sufficiency	26.60	26.58	26.61	26.59

Table A3. Standard deviation of electricity retail prices during different seasons.

Scenario	Jan–Mar	Apr–Jun	Jul–Sep	Oct–Dec
Market signal	1.98	1.81	1.48	2.19
Community competition	0.92	0.95	1.04	0.90
Self-sufficiency	0.98	1.00	1.03	1.01

Appendix F. Exemplary Dispatch Optimization Results

Appendix F.1. 48 h Flexible Consumers' Schedule in Response to M-RTP Tariff

In the following, a closer observation of flexible consumer's behavior in reaction to real-time pricing signals is given. Figure A5 shows the optimization results for flexible consumers during the first two days of January in response to the *M-RTP* tariff. It can be seen that as the heat pump shifts the load to the hours with low electricity prices, the total households' electricity load is lower when peak prices occur. Note that the plotted data are aggregated for 10 flexible consumers.

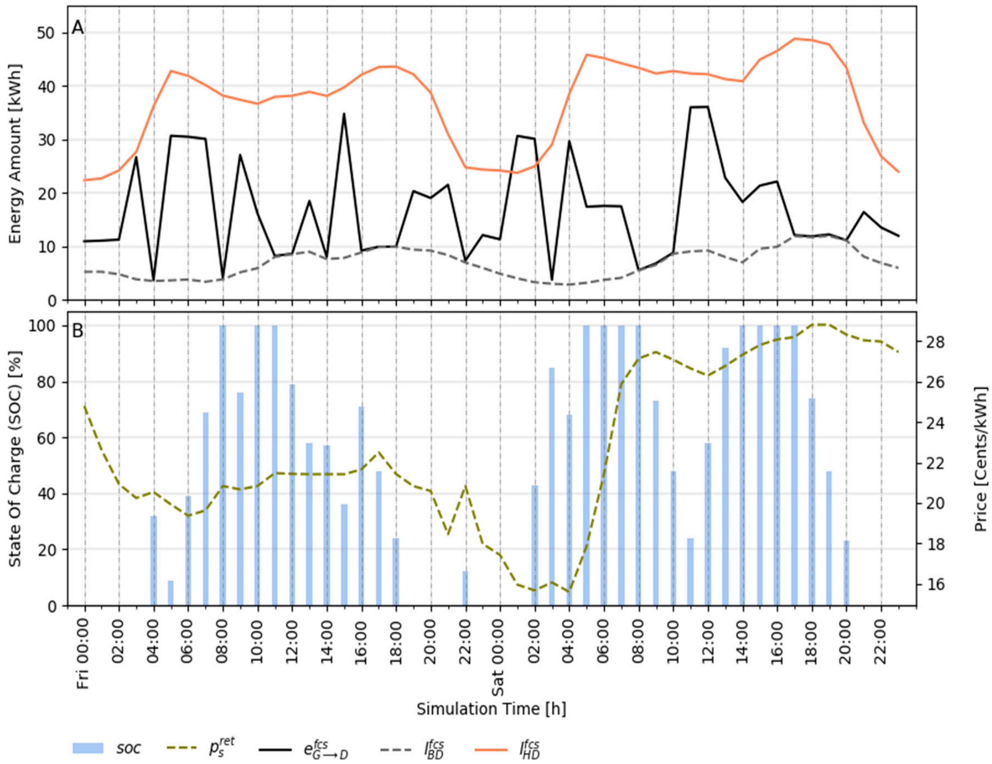

Figure A5. Flexible consumers' response to the *M-RTP* tariff for the first 48 h in January. (**A**) Flexible consumers' heat demand and electricity load; (**B**) state of charge of the thermal storage and electricity tariffs.

Appendix F.2. 48 h Prosumagers' Schedule in Response to M-RTP Tariff

Figure A6 shows the prosumagers' optimization results of the first two days of January in response to the *M-RTP* tariff. The battery dispatch results, depicted in sub-figure B, shows that the battery during these two days did not sell electricity to the grid. When the electricity tariffs were low, the battery was used to buy electricity for later use. This can be seen clearly, for instance, on Sat 4:00. The sub-figure C demonstrates that the residual generation of the prosumagers is not fed into the grid but is rather stored in the battery (see for example Fri 12:00). Note that according to the optimization assumption, the generated electricity is first used to cover the load, and the residual generation may be sold to the grid or stored in the battery.

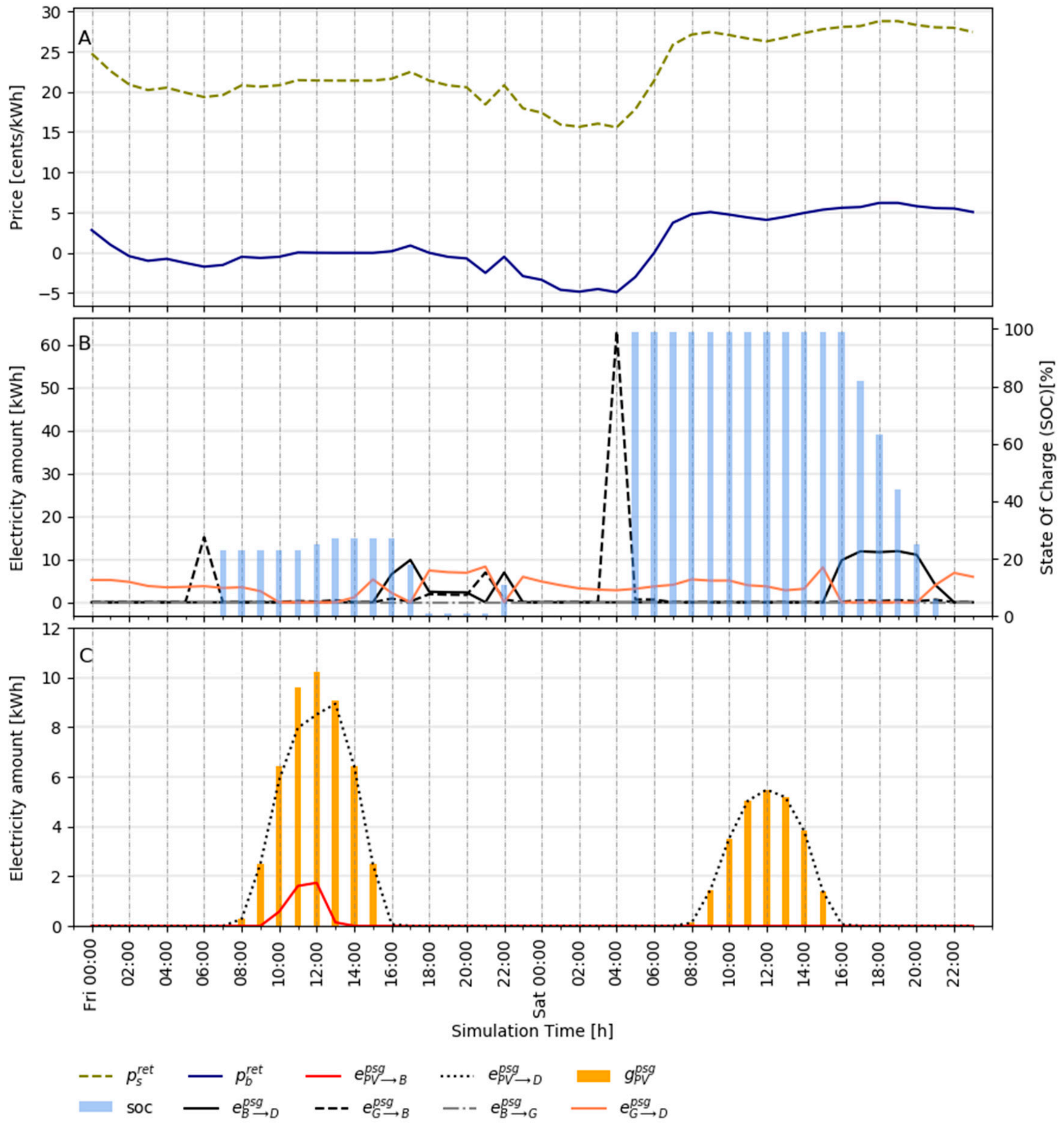

Figure A6. *Prosumagers'* reaction to *M-RTP* tariff: (**A**) 48h electricity tariffs and purchase prices (**B**) schedule details of battery systems (**C**) 48h usage of PV generated electricity.

Appendix G. NPV Calculations

For the NPV calculations, the initial investment in CES can be formulated as:

$$C_0 = I_{CES} \times (1 + VAT) \tag{A21}$$

$$I_{CES} = K_{CES}^{ret} \times I_{CES}^{0} \tag{A22}$$

where I_{CES} is derived from the battery module price multiplied by the size of the CES. In this calculation, we neglect the scaling effect that accounts for the lower specific cost for larger battery systems. Since in retailer's costs and revenue streams, the operation and maintenance costs of the CES are not taken into account, we obtain the retailer's net profit for the scenario x from the following equation:

$$F_x^{ret} = U_x^{ret} - I_{CES} \times C_{CES}^{O\&M} \tag{A23}$$

The operation and maintenance costs in this equation are considered to be a percentage ($C_{CES}^{O\&M}$) of the initial investment costs. The NPV for the scenario x is then calculated as follows:

$$NPV_x = -C_0 + \sum_{y=1}^{L_{CES}} \frac{F_x^{ret} - U_{BAU}^{ret}}{100 \times (1 + r_{dis})^y} \tag{A24}$$

where r_{dis} is the discount rate and L_{CES} is the battery lifetime that assumed to be the project lifetime. To isolate the effect of CES in the cash flows, in the NPV calculations the retailer's net income in the BAU scenario is subtracted from F_x^{ret}. The amount of cash flows are divided into 100 to convert the units from cents to euros.

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3.2 Paper 2: An optimal real-time pricing strategy for aggregating distributed generation and battery storage systems in energy communities: A stochastic bilevel optimization approach

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Authors' contribution: This article presents the outcomes of a collaborative research project with the division of electric power and energy systems at KTH Royal Institute of Technology. I initiated and led the project, and played a key role in conceptualizing the paper. In terms of methodology, I formulated the mathematical problem, developed the model, and implemented the solution algorithm using GAMS. I also collected the data, conducted the formal analysis, and created visualizations of the results. I wrote the initial manuscript and subsequently revised it during the publication process. SM made valuable contributions to the methodology by providing support with the mathematical formulation, model development, and algorithm implementation. SM also assisted with the analysis and visualizations. At the early stages of the project, DK contributed to the selection of the appropriate methodology. MRH and VB provided valuable supervision throughout the research, and SM, MRH, VB, and DB contributed to the manuscript by conducting thorough reviews and editing.

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An optimal real-time pricing strategy for aggregating distributed generation and battery storage systems in energy communities: A stochastic bilevel optimization approach

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ABSTRACT

The expansion of distributed electricity generation and the increasing capacity of installed battery storage systems at the community level have posed challenges to efficient technical and economic operation of the power systems. With advances in smart-grid infrastructure, many innovative demand response business models have sought to tackle these challenges, while creating financial benefits for the participating actors. In this context, we propose an optimal real-time pricing (ORTP) approach for the aggregation of distributed energy resources within energy communities. We formulate the interaction between a community-owned profit-maximizing aggregator and the users (consumers with electricity generation and storage potential, known as "prosumagers", and electric vehicles) as a stochastic bilevel disjunctive program. To solve the problem efficiently, we offer a novel solution algorithm, which applies a linear quasi-relaxation approach and an innovative dynamic partitioning technique. We introduce benchmark tariffs and solution algorithms and assess the performance of the proposed pricing strategy and solution algorithm in four case studies. Our results show that the ORTP strategy increases community welfare while providing useful grid services. Furthermore, our findings reveal the superior computational efficiency of our proposed solution algorithm in comparison to benchmark algorithms.

1. Introduction

1.1. Motivation

The lower levelized cost of electricity from photovoltaic (PV) systems compared to residential retail tariffs has incentivized households in many countries to invest in rooftop PV systems [2]. Similarly, developments in battery storage systems (BSSs) are making them economically viable for use by electricity consumers. Thus, a combination of home energy storage (HES) and rooftop PV systems has been shown to be profitable under various regulatory schemes, leading to the emergence of so-called "prosumagers" (consumers with electricity generation and storage potential[3]) as new market actors [3]. Furthermore, improved charging infrastructures and policy support measures have made electric vehicles (EVs) more competitive for mobility and introduced them into the mix of distributed energy resources (DERs) [4]. However, this growth of DERs poses significant challenges for the electricity system; For economic efficiency, end-user activities should be aligned with market signals [5] and provide system benefits [6].

With the expansion of smart-grid infrastructure, several innovative demand response (DR) business models are seeking to meet these challenges. Ideally, the focus of these business models should be the

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3 In this paper, we adopt the naming convention suggested in [1] and refer to an electricity consumer with generation potential as a prosumer (producer and consumer). A prosumager additionally operates an energy storage system to increase self-consumption (producer, consumer and storage).

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Nomenclature

Parameters

$\Gamma^{\mathrm{S}}, \Gamma^{\mathrm{B}}$	Aggregator's sale and purchase margin in benchmark tariffs
θ_i^{B}	Battery capacity of user i
M^{B}, M^{S}	Sufficiently large constants
P_i^{Q}	Marginal operational cost of charging/discharging the BSS for user i
$\eta_i^C, \eta_i^{\mathrm{D}}$	Battery charge and discharge efficiencies for user i
$\overline{W}_t$	Maximum available line capacity behind the PCC in t
CW	Community welfare
C'	Total cost of all users
G_{itv}, L_{itv}	Electricity generation and load of user i in v and t
N	Last discrete step
P_{tv}^{M}	Wholesale electricity market price in t and v
$\overline{Z}_i^{\mathrm{C}}, \overline{Z}_i^{\mathrm{D}}$	Battery charge and discharge power limits for user i
$\overline{G}_i, \overline{L}_i$	Nominal power limits for user i
$\underline{P}^{\mathrm{B}}, \overline{P}^{\mathrm{B}}$	Aggregator's purchase price limits
$\underline{P}^{\mathrm{S}}, \overline{P}^{\mathrm{S}}$	Aggregator's sale price limits
μ_c, σ_c	Mean value and standard deviation of data in cluster c
$\overline{T}$	Last optimization step
C_{iv}	Cost of user i in v
$P^{\mathrm{S}}, P^{\mathrm{B}}$	Aggregator's discrete sale and purchase prices
ϕ_v	Probability of scenario v
Λ_i	Battery self-discharge rate for user i
U_{it}	Battery availability of user i in t
$\underline{A}_i, \overline{A}_i$	Battery state of charge limits for user i
$\underline{H}_t^{\mathrm{X}}, \underline{H}_t^{\mathrm{X}}, \underline{p}_t^{\mathrm{X}\star}, \overline{p}_t^{\mathrm{X}\star}$	Intermediary parameters of the MBB algorithm in t
S^{X}	Size of each discrete step in the MBB algorithm
LB	Problem's lower bound in the MBB algorithm

Sets

χ	Set of user's decision variables in (1)
ξ	Set of decision variables in (9)
ϱ	Set of decision variables in (15)
C	Set of clusters in k-method
Υ	Set of user-specific model parameters

Indices

c	Cluster in the scenario generation algorithm
k	Discretization step
X	Trade direction: Sale or purchase in t
t	Optimization time
v	Scenario index
i	User index

Variables

r	Aggregator's total profit
r_{itv}	Aggregator's profit considering user i in v and t
$\alpha, \beta, \lambda, \gamma, \tau, v, \mu$	Lagrangian dual variables
Ψ_{itv}	Binary variable for user i to avoid simultaneous charge and discharge in v and t
$b_{tvk}^{\mathrm{S}}, b_{tvk}^{\mathrm{B}}$	Binary variables in the MILP formulation for t, v and k
$z_{itv}^{\mathrm{C}}, z_{itv}^{\mathrm{D}}$	Charged and discharged power for user i in v and t
h_{itkv}^{X}	Continuous variables in the MILP formulation
d_t^{B}, d_t^{S}	Spanning variables in t
$\pi_{itv}^{\mathrm{S}}, \pi_{itv}^{\mathrm{B}}$	Bilinear terms after single level reduction for user i in v and t
c_{itv}	Cost of user i in v and t
$e_{itv}^{\mathrm{S}}, e_{itv}^{\mathrm{B}}$	Grid usage and feed-in of the user i in t and v
$e_{itv}^{\mathrm{S}(0)}, e_{itv}^{\mathrm{S}(1)}, e_{itv}^{\mathrm{B}(0)}, e_{itv}^{\mathrm{B}(1)}$	Non-negative intermediary variables in the quasi-relaxed formulation for user i in v and t
$p_t^{\mathrm{S}}, p_t^{\mathrm{B}}$	Aggregator's sale and purchase prices
s	Silhouette value in the k-mean clustering method
a_{itv}	Battery state of charge for user i in t and v
$\underline{p}_t^{\mathrm{X}}, \overline{p}_t^{\mathrm{X}}$	Dynamic lower and upper bounds of aggregator sale prices in t

provision of incentives that are compatible with the needs of the system. The most common DR schemes instruct consumers to change their consumption patterns upon request or according to a contractual agreement [7]. However, a lack of customer privacy and system scalability are major drawbacks of these directive approaches [8]. Alternatively, in price-based schemes, consumers are exposed to time-varying prices that reflect the cost of electricity and grid conditions. Furthermore, these price-based schemes do not suffer from the same privacy and scalability issues [7]. Real-time pricing (RTP) is perhaps the best-known example of this approach [9]. Although RTP can increase the alignment of BSS dispatch with wholesale market signals [5], it does not usually reflect the local level of generation and the constraints of the grid; achieving this requires more comprehensively specified optimal real-time pricing (ORTP).

This paper considers an energy community (EC) that is not isolated from the wholesale market and is managed by a community-owned aggregator (real-world examples of such ECs can be found in [10] and [11]). We have developed a methodology for the aggregator to set ORTP and show how this can improve the EC's welfare in comparison to an RTP strategy. The economic profitability of ORTP is subjected to many uncertainties associated with wholesale electricity prices as well as the power demand and supply. Therefore, such local aggregators operate under conditions of bounded rationality. Therefore, we also provide a solution for the aggregator to deal with its limited knowledge regarding the market prices, the level of local power generation, and users' electricity demands.

In the remainder of this section, we provide an overview of the background research in this context and thereby identify the research gap to which we contribute.

Table 1
Drawbacks of the reviewed single-level DR studies compared to the chosen bilevel approach.

Approach	Examples	Focus	Drawbacks
Single user optimization	[15,16,24]	Detailed modeling of the user-side reaction to dynamic prices	• Lack of energy-sharing potential • Ignores the aggregator-side strategy
User coordination	[17]	Coordination of multiple users in reaction to external prices	• Interests of the higher-level actors are neglected
Local power markets	[20–22]	Distributed trading of electricity	• Internal prices do not reflect the state of the larger energy system
Retailer-side strategy	[12–14]	Creating dynamic prices for users	• Simplified modeling of the user-side strategy • Internal prices do not reflect the state of DERs

1.2. Background research and contributions

The contributions of this paper can be broadly embedded into two bodies of literature: On the one hand, we contribute to the research area of modeling price-based DR measures for end users in energy communities. In Section 1.2.1, we provide an overview of relevant publications and highlight the novelties of our proposed model. On the other hand, our methodology contributes by proposing a relaxation technique and an algorithm to solve the resulting bilevel optimization problem. In Section 1.2.2, we review the common approaches to solving the bilevel problems that emerge in modeling the hierarchical interactions between an aggregator and users and show the advantages of our proposed approach.

We summarize contributions of this paper in Section 1.2.3.

1.2.1. Price-based DR in energy communities

Residential DR programs in the context of the smart-grid have been extensively studied in recent years [7,9]. A significant fraction of this body of literature has examined efficient dynamic pricing strategies for electricity consumers [12]. Considering consumer adoption barriers, the authors of [13] designed and analyzed dynamic tariffs that can provide considerable cost savings for households. Similarly, the authors of [14] proposed a day-ahead and real-time pricing strategy for a smart-home community to benefit the consumers while reducing their power peak-to-average ratio.

A growing body of literature has focused on the demand-side implementation of DR measures and studied optimization strategies for individual users. For example, the authors of [15] proposed a scheduling optimization model for smart-home appliances to reduce the peak load value and electricity cost. The price-based DR presented in [16] is implemented through control algorithms for different types residential consumer appliances. With a broader perspective, the authors of [17] suggested an autonomous and distributed demand-side energy-management system for efficient coordination of multiple users in reaction to external dynamic prices. The demand-side management design in [18] includes a group of passive consumers and active users with DERs.

DR has also been studied in the context of peer-to-peer markets with little or no interaction with a central energy system [19]. For example, in [20] a two-stage energy sharing strategy for a building cluster with distributed transaction was proposed. Considering a similar setup, buildings in [21] can directly share their energy supplies and demands within the community. The authors of [22] used an agent-based model to study the implementation of DR measures in a local energy market that is not isolated from the public grid.

Although all the works noted above offer beneficial features for both the users and the grid, they generally fail to take the (often conflicting) interests of the actors of the higher-level energy system (e.g., retailers) into account. In this regard, the hierarchical nature of different decision levels can be captured using bilevel optimization models [23]. Table 1 summarizes the reviewed single-level solutions and compares them with the bilevel approach chosen in this work.

There is an extensive body of research that applies game-theoretic frameworks or bilevel optimization models, in which the users follow the pricing strategy of the aggregator [25,26]. However, many of the existing models do not consider the load-shifting potential that results from storage systems such as BSSs. For example, in an uncertain environment, the EV aggregator in [27] offers selling prices to the EV owners. In a similar setup, the decision-making variables of the DR clients in [28] choose the most competitive aggregator. Without load-shifting potential, the EV owners switch to rival aggregators to minimize their energy procurement costs. In other models, users must adapt their preferred electricity demand under strong pricing incentives. For example, in the models of [29] and Yu and Hong [30], users adjust the amount of electricity they consume based on a satisfaction function. In the time-and-level-of-use scheme studied in [31], consumers must book an energy capacity within each optimization time frame. In the pricing process, the electricity consumption of the consumers is unknown to both the supplier and the consumer themselves. The proposed two-stage optimization model presented in [32] consists of a real-time optimization stage, in which the microgrid operator generates separate buy and sell RTPs, and the prosumers decide on the amount of their hourly electricity consumption. Alternatively, in our context, because users may own a BSS, they are not required to reshape their desired demand profiles.

Among the studies that have considered load-shifting with BSSs, in the model of [33] a competitive community energy storage (CES) operator trades with the grid and offers RTP to trade with users. The users in this model decide on the electricity they trade with the grid and the CES operator. From a social planner's perspective, the retailer in [34] interacts with a CES operator and provides RTP for users to minimize their total costs. In these studies, user-owned energy storage systems are neglected. The aggregator in [35] also operates a CES and can adopt either a profit-maximizing or self-sufficiency-maximizing strategy. With full knowledge of market prices, electricity generation, and power demand, the aggregator generates buy and sell RTPs for the users in the EC to elicit a desired load and feed-in pattern. The presented model of the interplay between users with BSSs and a social-welfare-optimizing aggregator in [36] can be effectively used to size the EC. The aggregator agent in [37] provides sale prices for self-optimizing EVs for optimal bidding in the day-ahead reserve market.

None of the above formulations have considered uncertain input parameters, and do not include a more generally applicable scenario-generation algorithm. In our bilevel optimization model, we take these three sources of uncertainty into account. The stochastic bilevel framework presented in [28,38] determines the optimal involvement in the wholesale market and its trading with the wind-generation units while anticipating the reaction of the EVs and responsive loads. The authors of this work showed that the implemented regret-based bidding strategy is effective for hedging the risks of uncertainties. However, the presented model, unlike our model, does not consider bilateral trading with the clients and does not take prosumagers into account. Herein, we take the EC grid restrictions into account and include a novel scenario-generation approach for stochastic optimization. Table 2 compares the existing bilevel models in comparison to our model.

Table 2
Comparative overview of the bilevel RTP models in the literature.

Papers	BSS optimization	User-owned BSS	Prosumager	EV	EC grid restrictions	Bi-directional trading	Uncertain parameters
[29,30,39–43]	✗	✗	✗	✗	✗	✗	✗
[31]	✗	✗	✗	✗	✗	✗	✓
[32–34,44,45]	✓	✗	✗	✗	✗	✗	✗
[28]	✗	✗	✗	✗	✗	✗	✓
[27]	✗	✗	✗	✓	✗	✗	✓
[38]	✓	✓	✗	✓	✗	✗	✓
[36]	✓	✓	✓	✗	✗	✓	✗
[37]	✓	✓	✗	✓	✗	✗	✗
[46]	✓	✓	✗	✗	✗	✗	✗
[35]	✓	✓	✓	✗	✗	✓	✗
This paper	✓	✓	✓	✓	✓	✓	✓

1.2.2. Solution to DR bilevel problems

Bilevel optimization is widely used to solve consumer's DR problems arising in the power sector [23]. Bilevel problems are generally hard to solve; even linear bilevel problems are shown to be NP-hard problems [47]. Different approaches have been used to solve bilevel optimization problems in the literature.

Several studies have used heuristics algorithms [48]. For example, the bilevel problem in the modeled energy-sharing solution in [49] is solved with a closed-loop iterative algorithm based on the Brouwer fixed-point-theorem. Moreover, the authors of [35,42,43,50] used genetic algorithms to iterate between the upper- and lower-level problems and search for the optimal solution. However, heuristic algorithms have the drawback that they cannot guarantee that the global solution is actually found [51].

If the lower-level problem is modeled as a differentiable function, one can derive the optimal solution mathematically and replace it in the upper-level problem. This leads to a single-level problem, which is solvable using commercial solvers. This approach has been used extensively in the context of DR modeling. For example, in [29,32,41] the utility of consumers is modeled in a logarithmic relationship with consumed energy. To model the objectives of the users, the authors of [33,34,44,46] employed quadratic cost functions as strictly convex and increasing functions of demand. Although this method can be used to solve bilevel problems to their global optimum in an efficient manner, the required underlying assumptions for the problem formulation make it impractical for many real-world applications [35].

Another common approach to solving bilevel problems is using mathematical techniques such as the Karush–Kuhn–Tucker (KKT) optimality conditions to transform the problem into an equivalent mathematical program with equilibrium constraints that is solvable with commercial solvers [52]. Under certain conditions, the emerging complementary slackness constraints can be replaced by the strong duality condition to eliminate the bilinear terms. These two approaches for single-level reduction are employed in [53] to solve the microgrid investment and operation planning bilevel problem. Among the literature reviewed in Section 1.2.1, the authors of [27,28,36,38] used this methodology. In many cases, the resulting single-level problem contains many binary variables and requires a high computational effort to solve [54]. In this paper, we propose a quasi-relaxation technique and an innovative solution algorithm to eliminate the binary variables that appear in the single-level reduction process and correspondingly solve the problem efficiently.

1.2.3. Contributions

Against this background, this paper makes the following research contributions:

1. We propose a bilevel stochastic nonlinear programming model to find the buy–sell ORTP for a community-owned profit-maximizing aggregator that manages for users (including prosumagers and EVs) in a smart EC. We show that the profit-maximizing operation also maximizes the welfare of the EC. In two transformation steps, we derive a stochastic disjunctive program from the original bilevel stochastic nonlinear program. To enable this transformation, we first apply a single-level reduction technique using KKT optimality conditions and strong duality conditions and then discretize the aggregator's prices. We use a multi-parameter cluster-based (MPCB) scenario-generation approach to produce the required representative scenarios for the key uncertainties in the stochastic optimization problem.
2. We provide an efficient solution to the reformulated disjunctive program. We apply a linear quasi-relaxation approach to eliminate the nonlinear terms and propose a novel modified branch-and-bound (MBB) algorithm that imposes the relaxed constraint. Moreover, we extend the algorithm used in [54] and [55] by employing a dynamic partitioning approach, which disentangles the optimization results from the disjunctive parameters and reduces the computational effort needed to solve the problem.
3. We present a comprehensive analysis, regarding the effectiveness of the proposed ORTP scheme and solution algorithm. For this analysis, we compare the ORTP tariff with two benchmark tariffs: average pricing and RTP. Moreover, we demonstrate the superior computational performance of the proposed MBB algorithm in comparison with the branch-and-bound algorithm suggested in [54] and a standard mixed-integer linear programming (MILP) formulation that is used extensively in the literature. We parameterize the model with real data, examine several case studies, and evaluate the effectiveness of the proposed ORTP strategy against two benchmark tariffs.

The remainder of this paper is organized as follows. The methodology is described in Section 2, where we present our EC model and the proposed bilevel problem. In this section, we reformulate the mathematical problem into a quasi-relaxed stochastic disjunctive program and describe the developed MBB algorithm to solve the resulting problem. Section 2 also contains the definitions of the benchmark models and tariffs used to assess the results as well as a description of the data used in our analysis. This section ends with the explanation of the developed MPCB scenario-generation algorithm and the used data in the case studies. In Section 3, we introduce four case studies and demonstrate the performance of the ORTP tariff and the MBB algorithm. In Section 4, we compare the results of the case studies with those of the benchmark cases. The limitations of our methodology and the transferability of our results to real-world cases are critically discussed in 5. Section 6 concludes.

2. Methodology

2.1. Model structure

ECs represent multifaceted sociotechnical systems that, depending on their context and purpose, can have numerous definitions and diverse forms [56]. The bottom-up model developed in this work adopts the following definition: *"An EC is a group of electricity users (whether with or without DERs) that are connected to the same distribution network. Each user is metered separately and operates under a contract with a community-owned aggregator. The aggregator manages the electricity*

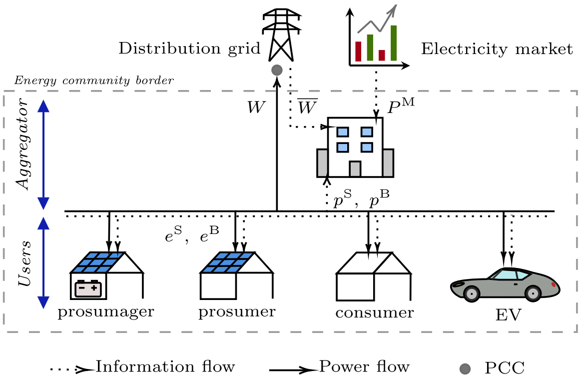

Fig. 1. Schematic illustration of the modeled energy community.

demand and generation of the EC by trading within the community and in the electricity market". Note that in our definition, we do not consider the possibility of collective self-consumption or virtual sharing of the electricity in the EC. The EC modeled according to this definition is schematically illustrated in Fig. 1.

The EC aggregator is an agent that maximizes its profit (r) by optimizing its hourly trading in the day-ahead electricity market (henceforth referred to as the market) and with the users in the EC, while considering the predicted EC grid limitations over the next day. For this optimization, the aggregator receives a forecast of the upcoming market prices (P^{M}) and the maximum available line capacity behind the point of common coupling (PCC) ($\overline{W}_t$). It also sets the real-time sell and buy prices (p^{S}, p^{B}) to trade with the users within the community. To isolate the effects of the ORTP, we consider a case in which the aggregator does not operate a BSS. Therefore, the aggregator's demand and supply bids to the market correspond to the EC's residual load and generation, respectively.

Users within the EC can be parameterized as consumers, prosumers, prosumagers, or EVs. For the case of a prosumager, the user's model and the interaction with the aggregator is schematically shown in Fig. 2. Users with BSS optimize their interactions with the EC grid, i.e., their power consumption and feed-in ($e^{\mathrm{S}}, e^{\mathrm{B}}$) to minimize their costs (C). We assume that the users are equipped with the processing and controlling systems required for this optimization. Since the user's bidirectional grid interaction is measured with a single smart meter, the actual interaction with the grid is unidirectional in each time step ($e^{\mathrm{S}} = 0$ if $e^{\mathrm{B}} > 0$ and vice versa).[4] Moreover, the considered metering scheme allows a behind-the-meter consumption of the self-generated electricity. Due to the near-zero marginal cost of the rooftop PV systems, we assume that the electricity generated by the users is primarily used to cover their electricity demand. If the electricity generated by the user (G) is less than demand (L), the difference must be covered by the BSS or from the grid. Similarly, if the electricity generation exceeds the demand, the user will feed the residual generation into the BSS or sell to the grid. We also assume that the electricity consumption of the users is price inelastic, and the only source of flexibility is the load-shifting potential with the BSS. The parameter Λ_i considers the self-discharge rate, while η_i^C and η_i^{D} account for charge and discharge efficiency of the BSS. The state of charge (SOC) of the BSS (modeled as a) has an initial value of $\underline{A}_i$ and is limited by its lower and upper limits ($\underline{A}_i$, $\overline{A}_i$). By adding an availability factor (U_{it}), we take into account the inability or unwillingness of the users to charge their BSSs. This is particularly important in the case of EVs, as these users may not be connected to the grid during the whole day.

[4] Note that the metering scheme in our model differs from the gross-metering scheme, in which the electricity consumption and generation are metered separately. Furthermore, unlike net-metering schemes, the users cannot consume the electricity fed into the grid at a later time free of charge.

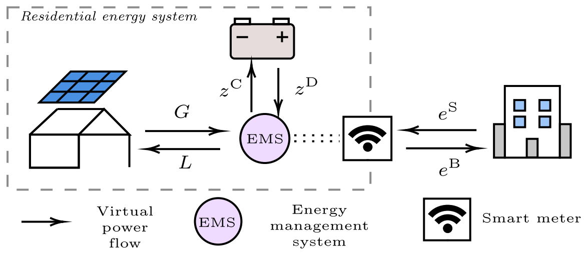

Fig. 2. Schematic overview of the prosumager's model.

The interplay between the aggregator and users within this model structure leads to a hierarchical decision-making formulation, specified as a bilevel program, in which the aggregator's and users' optimizations are the upper- and lower-level problems, respectively.

2.2. Bilevel program

The stochastic bilevel programming model is formulated in (1), in which the indices i, t, and v refer to each user, optimization time, and probabilistic scenario, respectively:

$$\underset{p_t^{\mathrm{S}},p_t^{\mathrm{B}}}{\text{Maximize}}\ r = \sum_{i,t,v} \phi_v \underbrace{(P^{\mathrm{M}}_{tv}(e^{\mathrm{B}}_{itv}-e^{\mathrm{S}}_{itv})+p^{\mathrm{S}}_t e^{\mathrm{S}}_{itv}-p^{\mathrm{B}}_t e^{\mathrm{B}}_{itv})}_{=r_{itv}} \tag{1a}$$

$$\text{subject to: } \underline{P}^{\mathrm{S}} \le p^{\mathrm{S}}_t \le \overline{P}^{\mathrm{S}},\ \underline{P}^{\mathrm{B}} \le p^{\mathrm{B}}_t \le \overline{P}^{\mathrm{B}}, \tag{1b}$$

$$-\overline{W}_t \le \sum_i (e^{\mathrm{S}}_{itv}-e^{\mathrm{B}}_{itv}) \le \overline{W}_t, \tag{1c}$$

$$\text{where } e^{\mathrm{S}}_{itv}, e^{\mathrm{B}}_{itv} \in \underset{\chi}{\operatorname{argmin}}\ C_{iv} = \sum_t \underbrace{(p^{\mathrm{S}}_t e^{\mathrm{S}}_{itv}-p^{\mathrm{B}}_t e^{\mathrm{B}}_{itv}+P^{\mathrm{Q}}_i(z^{\mathrm{C}}_{itv}+z^{\mathrm{D}}_{itv}))}_{=c_{itv}}, \tag{1d}$$

$$\text{subject to: } a_{itv} = \Lambda_i a_{i(t-1)v} + \frac{\eta^{\mathrm{C}}_i z^{\mathrm{C}}_{itv}}{\theta^{\mathrm{B}}_i} - \frac{z^{\mathrm{D}}_{itv}}{\eta^{\mathrm{D}}_i \theta^{\mathrm{B}}_i} : (\lambda^a_{itv}), \tag{1e}$$

$$z^{\mathrm{C}}_{itv} = e^{\mathrm{S}}_{itv} - e^{\mathrm{B}}_{itv} + G_{itv} - L_{itv} + z^{\mathrm{D}}_{itv} : (\lambda^z_{itv}), \tag{1f}$$

$$\underline{A}_i \le a_{itv} \le \overline{A}_i : \left(\underline{\tau}_{itv}, \overline{\tau}_{itv}\right), \tag{1g}$$

$$a_{itv} = \underline{A}_i : \left(\alpha^a_{i0v}\right), t = 0, \tag{1h}$$

$$0 \le e^{\mathrm{B}}_{itv} \le \overline{G}_i : (\underline{\mu}_{itv}, \overline{\mu}_{itv}), \tag{1i}$$

$$0 \le e^{\mathrm{S}}_{itv} \le \overline{L}_i : \left(\underline{v}_{itv}, \overline{v}_{itv}\right), \tag{1j}$$

$$0 \le z^{\mathrm{C}}_{itv} \le U_{it} \overline{Z}^{\mathrm{C}}_i \psi_{itv} : (\underline{\beta}_{itv}, \overline{\beta}_{itv}), \tag{1k}$$

$$0 \le z^{\mathrm{D}}_{itv} \le U_{it} \overline{Z}^{\mathrm{D}}_i (1-\psi_{itv}) : (\underline{\gamma}_{itv}, \overline{\gamma}_{itv}). \tag{1l}$$

where χ in (1d) is the set of the user's decision variables $\chi = \{e^{\mathrm{S}}_{itv}, e^{\mathrm{B}}_{itv}, a_{itv}, z^{\mathrm{C}}_{itv}, z^{\mathrm{D}}_{itv}\}$. The symbols in parentheses (i.e., λ^a_{itv}, λ^z_{itv}, $\overline{\beta}_{itv}$, $\underline{\beta}_{itv}$, $\overline{\gamma}_{itv}$, $\underline{\gamma}_{itv}$, $\underline{\gamma}_{itv}$, $\overline{\mu}_{itv}$, $\underline{\mu}_{itv}$, $\overline{\tau}_{itv}$, $\underline{\tau}_{itv}$, α^a_{i0v}, $\overline{v}_{itv}$, and $\underline{v}_{itv}$) are the Lagrangian dual variables of the corresponding constraint in the lower-level problem. Eq. (1a) represents the utility function of the aggregator and ϕ_v is the probability of each scenario. Eq. (1b) sets bounds to ensure that the aggregator's prices in the EC are no worse than those of the public grid ($\underline{P}^{\mathrm{S}}$, $\overline{P}^{\mathrm{S}}$, $\underline{P}^{\mathrm{B}}$, and $\overline{P}^{\mathrm{B}}$ are the lower and upper limits for the aggregator's sell and buy prices). We make these assumptions in the absence of competition among different aggregators and retailers. The total power imported/exported through the line that connects the EC to the PCC is limited in Eq. (1c), where $\overline{W}_t$[5] is the maximum available capacity of this line at time t. The user's objective in Eq. (1d) is to minimize the total operation costs for the given optimization period ($\overline{T}$). Therefore, the lower-level objective is unique for each pair of i and v. The parameter P_i^{Q} is a strictly positive value representing the marginal operation cost of the BSS. Eq. (1e) describes the SOC of the BSS, which depends on the SOC in the previous time step, the self-discharge rate (Λ_i), and the charged and discharged amount (z_{itv}^{C} and z_{itv}^{D}). The constraint in (1f) guarantees that the incoming and outgoing power flows for each user and time step are balanced. Constraint (1g) makes sure that the SOC of the BSS stays within an acceptable range. Eqs. (1i) and (1j) consider the users' nominal power constraints ($\overline{L}_i$ and $\overline{G}_i$). The battery charge and discharge in each step are limited by the maximum allowed power constraints ($\overline{Z}_i^{\mathrm{C}}$, $\overline{Z}_i^{\mathrm{D}}$), the availability of the battery, and the binary variable ψ_{itv}, which prevents simultaneous charging and discharging of the BSS. In the proposed stochastic model, the aggregator considers the uncertainty of market prices as well as the users' electricity generation and load when deciding the hourly sell and buy prices. To cope with these uncertainties and achieve the best solution, the aggregator must solve the bilevel problem for various scenarios. This means that, for a set of scenarios and for each step, a unique solution (p_t^{S} and p_t^{B}) is delivered to the users. The problem of the users also incorporates uncertainties regarding their demand and generation.

Note that the fact that the aggregator maximizes its profit does not compromise its fiduciary obligation to the EC, since the welfare of the EC is, in this case, maximized (see Proposition 1). The actual redistribution of the aggregator's profit among the EC users can be done in several ways to reflect their respective interests, but these considerations are subsidiary and outside the scope of this analysis.

Proposition 1. *Solving (1) is equivalent to maximizing the community welfare (CW):*

$$\left\{\begin{array}{c} \underset{p_t^{\mathrm{S}},p_t^{\mathrm{B}}}{\mathit{Maximize}}\ r(p_t^{\mathrm{S}},p_t^{\mathrm{B}}) \\ \textit{s.t.}\ (1\mathrm{a}),\ (1\mathrm{b}) \\ \textit{where}\ e_{itv}^{\mathrm{S}}, e_{itv}^{\mathrm{B}} \in \underset{\chi}{\mathit{argmin}}\, C_{iv}(\chi) \\ \textit{s.t.}\ (1\mathrm{e})\text{–}(1\mathrm{l}) \end{array}\right\}$$
$$\equiv \left\{\begin{array}{c} \underset{p_t^{\mathrm{S}},p_t^{\mathrm{B}}}{\mathit{Maximize}}\ \sum_{itv}\phi_v\underbrace{\left(r_{itv}(p_t^{\mathrm{S}},p_t^{\mathrm{B}})-C_{iv}(\chi)\right)}_{=CW} \\ \textit{s.t.}\ (1\mathrm{a}),\ (1\mathrm{b}) \\ \textit{where}\ e_{itv}^{\mathrm{S}}, e_{itv}^{\mathrm{B}} \in \underset{\chi}{\mathit{argmin}}\, C_{iv}(\chi) \\ \textit{s.t.}\ (1\mathrm{e})\text{–}(1\mathrm{l}) \end{array}\right\} \tag{2}$$

Proof. Proof of this proposition is given in Appendix A.1.

2.3. Proposed stochastic disjunctive program

We solve the bilevel program in (1) by reformulating the problem into a single-level problem. To be able to represent the lower-level problem, which is currently a MILP problem, by the KKT optimality conditions (which are necessary and sufficient), we propose an equivalent relaxed linear programming (LP) formulation of (1). Using Proposition 2, we can omit the binary variables in the constraints (1k) and (1l) in the formulation of the lower-level problem.

Proposition 2. *If we drop the binary variables ψ_{itv} from the MILP model, the optimal solution of the resulting relaxed LP model and its original MILP model are the same.*

Proof. We assume that the binary variable ψ_{itv}, (1k), and (1l) do not exist and the BSS unit can charge and discharge simultaneously, i.e., $z_{itv}^{\mathrm{C}} > 0$ and $z_{itv}^{\mathrm{D}} > 0$. Therefore, (1) is an LP problem in this case and the KKT optimality conditions hold. Based on this assumption, the Lagrangian multipliers $\underline{\beta}_{itv}$ and $\underline{\gamma}_{itv}$ are equal to zero. The stationary conditions of the relaxed LP problem are written in (3):

$$p_t^{\mathrm{S}}+\lambda_{itv}^z+\overline{\upsilon}_{itv}-\underline{\upsilon}_{itv}=0:e_{itv}^{\mathrm{S}}, \tag{3a}$$
$$-p_t^{\mathrm{B}}-\lambda_{itv}^z+\overline{\mu}_{itv}-\underline{\mu}_{itv}=0:e_{itv}^{\mathrm{B}}, \tag{3b}$$
$$-\lambda_{itv}^a+\Lambda_i\lambda_{i(t+1)v}^a-\underline{\tau}_{itv}+\overline{\tau}_{itv}=0:a_{itv}, \tag{3c}$$
$$\Lambda_i\lambda_{i1v}^a-\alpha_{i0v}^a=0:a_{itv}, t=0, \tag{3d}$$
$$P_i^{\mathrm{Q}}-\lambda_{itv}^a/\eta_i^{\mathrm{D}}\theta_i^{\mathrm{B}}+\lambda_{itv}^z-\underline{\gamma}_{itv}+\overline{\gamma}_{itv}=0:z_{itv}^{\mathrm{D}}, \tag{3e}$$
$$P_i^{\mathrm{Q}}+\eta_i^C\lambda_{itv}^a/\theta_i^{\mathrm{B}}-\lambda_{itv}^z-\underline{\beta}_{itv}+\overline{\beta}_{itv}=0:z_{itv}^{\mathrm{C}}. \tag{3f}$$

From (3e) and (3f) we can derive:

$$\lambda_{itv}^a/\theta_i^{\mathrm{B}} \overset{(3e)}{=} \eta_i^{\mathrm{D}}(P_i^{\mathrm{Q}}+\lambda_{itv}^z-\underline{\gamma}_{itv}+\overline{\gamma}_{itv}) \overset{(3f)}{=} (-P_i^{\mathrm{Q}}+\lambda_{itv}^z+\underline{\beta}_{itv}-\overline{\beta}_{itv})/\eta_i^C, \tag{4}$$

Based on our assumptions of $z_{itv}^{\mathrm{C}} > 0$ and $z_{itv}^{\mathrm{D}} > 0$, the terms $\underline{\beta}_{itv} = 0$ and $\underline{\gamma}_{itv} = 0$ can be omitted from (4). Therefore,

$$(\frac{1}{\eta_i^C}-\eta_i^{\mathrm{D}})\lambda_{itv}^z=(\eta_i^{\mathrm{D}}\overline{\gamma}_{itv}+\frac{1}{\eta_i^C}\overline{\beta}_{itv})+(\frac{1}{\eta_i^C}+\eta_i^{\mathrm{D}})P_i^{\mathrm{Q}}. \tag{5}$$

While the right-hand side of (5) is strictly positive (P_i^{Q}, η_i^C, $\eta_i^{\mathrm{D}} > 0$ and $\overline{\beta}_{itv}$, $\overline{\gamma}_{itv} \geq 0$) its left-hand side is negative ($\lambda_{itv}^z < 0$ and $\frac{1}{\eta_i^C}-\eta_i^{\mathrm{D}} \geq 0$). From this contradiction, one can conclude that the assumption of simultaneous charge and discharge of the BSS ($z_{itv}^{\mathrm{C}} > 0$ and $z_{itv}^{\mathrm{D}} > 0$) cannot hold.[6] □

Thus, the dual feasibility conditions of the LP formulation can be described as:

$$\underline{\beta}_{itv},\overline{\beta}_{itv},\underline{\gamma}_{itv},\overline{\gamma}_{itv},\underline{\mu}_{itv},\overline{\mu}_{itv},\underline{\tau}_{itv},\overline{\tau}_{itv},\underline{\upsilon}_{itv},\overline{\upsilon}_{itv}\geq 0. \tag{6}$$

The complementary slackness conditions for the lower-level problem result in several nonlinear terms but, according to [57], the complementary slackness conditions can be replaced with the strong duality condition. The strong duality condition for the lower-level problem can be formulated as:

$$-\sum_t(p_t^{\mathrm{S}}e_{itv}^{\mathrm{S}}-p_t^{\mathrm{B}}e_{itv}^{\mathrm{B}}+P_i^{\mathrm{Q}}(z_{itv}^{\mathrm{C}}+z_{itv}^{\mathrm{D}}))=-\alpha_{i0v}^a\underline{A}_i+$$
$$\sum_t(\overline{\tau}_{itv}\overline{A}_i-\underline{\tau}_{itv}\underline{A}_i+\overline{\mu}_{itv}\overline{G}_i+\overline{\upsilon}_{itv}\overline{L}_i-\lambda_{itv}^z(G_{itv}-L_{itv})$$
$$+U_{it}\overline{\beta}_{itv}\overline{Z}_i^{\mathrm{C}}+U_{it}\overline{\gamma}_{itv}\overline{Z}_i^{\mathrm{D}}). \tag{7}$$

The bilinear terms $p_t^{\mathrm{S}}e_{itv}^{\mathrm{S}}$ and $p_t^{\mathrm{B}}e_{itv}^{\mathrm{B}}$ in the strong duality constraint and the upper-level problem make the reformulated problem a nonlinear programming (NLP) problem. We denote these bilinear terms π_{itv}^{S} and π_{itv}^{B}, respectively. To eliminate the nonlinearity, we introduce discrete electricity sell and buy prices that can take values from a feasible set of prices $p_t^{\mathrm{X}} \in \{P_{1t}^{\mathrm{X}},\ldots,P_{kt}^{\mathrm{X}},\ldots,P_{nt}^{\mathrm{X}}\}$. Accordingly, we formulate the bilinear terms in the following disjunctive form:

$$p_t^{\mathrm{X}}e_{itv}^{\mathrm{X}}=\bigvee_{k=1}^{n}P_{kt}^{\mathrm{X}}e_{itv}^{\mathrm{X}}, \tag{8}$$

where the disjunction is represented by the disjunction (OR) operator $\bigvee$. To shorten the expressions in (8) and throughout this paper, the

[5] Availability of the line capacity ($\overline{W}_t$) can vary due to power-system operation issues such as a line outage at time t.

[6] Although we have proved Proposition 2 analytically, the proposition statement is also intuitive. It is not economical for a BSS with charging and discharging efficiencies less than 100% to charge and discharge at the same time.

superscript X represents both sell and buy variables and parameters (instead of the superscripts S and B). The original program can therefore be rewritten as a stochastic disjunctive program:

$$\underset{\xi}{\text{Maximize}}\, r = \sum_{v,i,t\neq 0} \phi_v (P^{\mathrm{M}}_{tv}(e^{\mathrm{B}}_{itv} - e^{\mathrm{S}}_{itv}) + \bigvee_{k=1}^{N} P^{\mathrm{S}}_k e^{\mathrm{S}}_{itv} - \bigvee_{k=1}^{N} P^{\mathrm{B}}_k e^{\mathrm{B}}_{itv})$$

Subject to: (1b), (1c), (1e)–(1l), (3), (6),

(7) rewritten with (8). (9)

where ξ is the set of decision variables. $\xi = \{p^{\mathrm{S}}_t, p^{\mathrm{B}}_t, e^{\mathrm{S}}_{itv}, e^{\mathrm{B}}_{itv}, a_{itv}, z^{\mathrm{C}}_{itv}, z^{\mathrm{D}}_{itv}, \lambda^a_{itv}, \underline{\tau}_{itv}, \overline{\tau}_{itv}, \underline{\mu}_{itv}, \overline{\mu}_{itv}, \underline{v}_{itv}, \overline{v}_{itv}, \underline{\beta}_{itv}, \overline{\beta}_{itv}, \underline{\gamma}_{itv}, \overline{\gamma}_{itv}\}$. Using a binary expansion approach, the disjunctive problem in (9) can be reformulated as a MILP problem. The MILP formulation (presented later in Section 2.5) contains many binary variables, which leads to a high computational effort. Moreover, the performance of the solver depends on the right choice of M^{X}. To improve these shortcomings, authors of [48] suggest an alternative approach to deal with bilinear terms. Similar to [54], we adopt a linear quasi-relaxation to transform this problem to an LP problem and deal with the disjunctive nature of p^{X}_t in our solution algorithm.

To this end, instead of formulating the electricity sell and buy prices as a convex combination of discrete values, we use only their lower and upper bounds. By introducing a continuous variable d^{X}_t, we rewrite p^{X}_t as:

$$p^{\mathrm{X}}_t = \underline{p}^{\mathrm{X}}_t d^{\mathrm{X}}_t + \overline{p}^{\mathrm{X}}_t (1 - d^{\mathrm{X}}_t), 0 \le d^{\mathrm{X}}_t \le 1. \tag{10}$$

Therefore, the aggregator's p^{X}_t always adopts a value between $\underline{p}^{\mathrm{X}}_t$ and $\overline{p}^{\mathrm{X}}_t$. Then, the disjunctive constraints can be enforced by:

$$\bigvee_{k=1}^{N} \left[\underline{p}^{\mathrm{X}}_t d^{\mathrm{X}}_t + \overline{p}^{\mathrm{X}}_t (1 - d^{\mathrm{X}}_t) = P^{\mathrm{X}}_{kt}\right]. \tag{11}$$

To perform the quasi-relaxation method, we rewrite e^{X}_{itv}, which appears in the bilinear term π^{X}_{itv}, as the summation of two non-negative variables:

$$e^{\mathrm{X}}_{itv} = e^{\mathrm{X}(0)}_{itv} + e^{\mathrm{X}(1)}_{itv}. \tag{12}$$

Therefore, the bilinear term π^{X}_{itv} can be formulated as:

$$\pi^{\mathrm{X}}_{itv} = (e^{\mathrm{X}(0)}_{itv} + e^{\mathrm{X}(1)}_{itv}) \left[\underline{p}^{\mathrm{X}}_t d^{\mathrm{X}}_t + \overline{p}^{\mathrm{X}}_t (1 - d^{\mathrm{X}}_t)\right]. \tag{13}$$

We solve the formulated disjunctive program using an MBB algorithm, which branches on the ranges of sell and buy prices instead of branching on binary variables. To obtain the upper bound of the objective value, we apply quasi-relaxation of the problem and drop the disjunctive constraint (11) and replace (13) with (14):

$$\pi^{\mathrm{X}}_{itv} = e^{\mathrm{X}(0)}_{itv} \underline{p}^{\mathrm{X}}_t + e^{\mathrm{X}(1)}_{itv} \overline{p}^{\mathrm{X}}_t, \tag{14a}$$

$$0 \le e^{\mathrm{X}(0)}_{itv} \le M^{\mathrm{X}} d^{\mathrm{X}}_t, \tag{14b}$$

$$0 \le e^{\mathrm{X}(1)}_{itv} \le M^{\mathrm{X}} (1 - d^{\mathrm{X}}_t), \tag{14c}$$

$$0 \le d^{\mathrm{X}}_t \le 1. \tag{14d}$$

As a result, the disjunctive program (9) can be reformulated in the following quasi-relaxed form:

$$\textbf{SDPQ: } \underset{\varrho}{\text{Maximize}}\, r = \sum_{v,i,t} \phi_v (P^{\mathrm{M}}_{tv}(e^{\mathrm{B}}_{itv} - e^{\mathrm{S}}_{itv}) + \pi^{\mathrm{S}}_{itv} - \pi^{\mathrm{B}}_{itv})$$

subject to: (1b), (1c), (1e)–(1l), (3), (6),

(7) rewritten with π^{X}_{itv} from (14), (12). (15)

where $\varrho = \{p^{\mathrm{S}}_t, p^{\mathrm{B}}_t, e^{\mathrm{S}}_{itv}, e^{\mathrm{S}(0)}_{itv}, e^{\mathrm{S}(1)}_{itv}, e^{\mathrm{B}}_{itv}, e^{\mathrm{B}(0)}_{itv}, e^{\mathrm{B}(1)}_{itv}, a_{it}, z^{\mathrm{C}}_{itv}, z^{\mathrm{D}}_{itv}, d^{\mathrm{S}}_t, d^{\mathrm{B}}_t, \lambda^a_{itv}, \underline{\tau}_{itv}, \overline{\tau}_{itv}, \underline{\mu}_{itv}, \overline{\mu}_{itv}, \underline{v}_{itv}, \overline{v}_{itv}, \underline{\beta}_{itv}, \overline{\beta}_{itv}, \underline{\gamma}_{itv}, \overline{\gamma}_{itv}\}$ is the set of decision variables. For simplicity, we will refer to the quasi-relaxed formulation of the stochastic disjunctive program in (15) as SDPQ.

2.4. MBB solution algorithm

We now explain the different steps of the MBB algorithm in solving the SDPQ. Having imposed the dropped constraint in the quasi-relaxation, we partition the disjunctive steps dynamically to find the solution of (1) efficiently. The dynamic partitioning feature addresses the limitation of the disjunctive formulation in having a fixed number of discrete steps.

Fig. 3 illustrates the different steps of the algorithm in detail.

Initialization: The algorithm starts by initializing the parameters $\underline{p}^{\mathrm{X}}_t$, $\overline{p}^{\mathrm{X}}_t$, $\underline{H}^{\mathrm{X}}_t$, and $\overline{H}^{\mathrm{X}}_t$ as well as the algorithm hyperparameters LB and S^{X}:

$$\underline{p}^{\mathrm{X}}_t \leftarrow P^{\mathrm{X}}_{1t},\ \overline{p}^{\mathrm{X}}_t \leftarrow P^{\mathrm{X}}_{nt}, \tag{16a}$$

$$\underline{H}^{\mathrm{X}}_t \leftarrow \underline{P}^{\mathrm{X}},\ \overline{H}^{\mathrm{X}}_t \leftarrow \overline{P}^{\mathrm{X}}, \tag{16b}$$

$$\mathrm{LB} \leftarrow -\infty,\ S^{\mathrm{X}} \leftarrow (\overline{P}^{\mathrm{X}} - \underline{P}^{\mathrm{X}})/(|k|-1), \tag{16c}$$

$$P^{\mathrm{X}}_{kt} = \underline{H}^{\mathrm{X}}_t + k(\overline{H}^{\mathrm{X}}_t - \underline{H}^{\mathrm{X}}_t)/|k|. \tag{16d}$$

where $\underline{H}^{\mathrm{X}}_t$ and $\overline{H}^{\mathrm{X}}_t$ are intermediary lower and upper levels of disjunctive values in each time step, and S^{X} is the disjunction step size and LB is the lower bound of the solution that represents the best solution so far. In (16d), the disjunctive values P^{X}_{kt} for each time step are calculated.

Solving SDPQ and generating new branches: In each iteration (itr in short), the algorithm solves the quasi-relaxed formulation of the problem (SDPQ) in (15). If the problem is infeasible or the upper bound of the objective function (r) is less than LB, the nodes are fathomed. For the cases with r higher than LB ($r \ge$ LB), the algorithm checks the condition (17) to make sure that the result of the SDPQ is identical to (1) and the relaxed constraint in (11) is imposed.

$$d^{\mathrm{X}}_t \in \{0,1\} \vee \underline{p}^{\mathrm{X}}_t = \overline{p}^{\mathrm{X}}_t. \tag{17}$$

If condition (17) is valid for all the optimization time steps, the node is fathomed, LB is updated ($LB \leftarrow r$), and the values of $\underline{p}^{\mathrm{X}}_t$ and $\overline{p}^{\mathrm{X}}_t$ are stored in intermediary parameters $\underline{p}^{\mathrm{X}\star}_t$ and $\overline{p}^{\mathrm{X}\star}_t$. The results with $d^{\mathrm{X}}_t \notin \{0,1\}$, $\underline{p}^{\mathrm{X}}_t \neq \overline{p}^{\mathrm{X}}_t$ indicate that p^{X}_t is not discrete (i.e., $p^{\mathrm{X}}_t \notin \{P^{\mathrm{X}}_{1t}, \dots, P^{\mathrm{X}}_{kt}, \dots, P^{\mathrm{X}}_{nt}\}$) and therefore does not satisfy constraint (11). In these cases, we keep the nodes active and **generate new branches**. According to (18a), the algorithm finds the closest disjunctive value and generates two new branches on either side of the p^{X}_t (18b):

$$P^{\mathrm{X}}_{kt} \le \underline{p}^{\mathrm{X}}_t d^{\mathrm{X}}_t + \overline{p}^{\mathrm{X}}_t (1 - d^{\mathrm{X}}_t), \tag{18a}$$

$$\overline{p}^{\mathrm{X}}_t = P^{\mathrm{X}}_{kt} \text{ and } \underline{p}^{\mathrm{X}}_t = P^{\mathrm{X}}_{(k+1)t}. \tag{18b}$$

After creating new branches, the algorithm evaluates all the nodes and selects the one with the largest LB as the next node to assess. We chose this branching method as it creates fewer sub-problems and, therefore, reduces the computational time required [58]. The next node is evaluated by repeating this step.

Dynamic partitioning: Each optimization "round" is terminated when all the created nodes have been investigated. Once there are no branches left to solve, if LB is equal to its initial value (i.e., $-\infty$), the problem is infeasible. If not (i.e., the algorithm has found at least one solution to the problem), we discretize the solution range further to search for values that may lie between the first disjunctive steps and we start a new round of optimization. Changes in the solution range ($\underline{p}^{\mathrm{X}}_t$ to $\overline{p}^{\mathrm{X}}_t$) are schematically visualized in Fig. 4. To perform the dynamic partitioning, we update $\overline{H}^{\mathrm{X}}_t$ and $\underline{H}^{\mathrm{X}}_t$ with the lower and upper values of the best solution:

$$\overline{H}^{\mathrm{X}}_t \leftarrow \overline{p}^{\mathrm{X}\star}_t, \underline{H}^{\mathrm{X}}_t \leftarrow \underline{p}^{\mathrm{X}\star}_t \tag{19}$$

If $\underline{p}^{\mathrm{X}}_t$ and $\overline{p}^{\mathrm{X}}_t$ have adopted the same value ($\underline{p}^{\mathrm{X}}_t = \overline{p}^{\mathrm{X}}_t$), at least one of them is moved by the size of one step S^{X}:

$$\text{If } \underline{p}^{\mathrm{X}}_t = \overline{p}^{\mathrm{X}}_t = \underline{P}^{\mathrm{X}} \text{ then } \overline{H}^{\mathrm{X}}_t \leftarrow \underline{p}^{\mathrm{X}}_t + S^{\mathrm{X}}, \tag{20a}$$

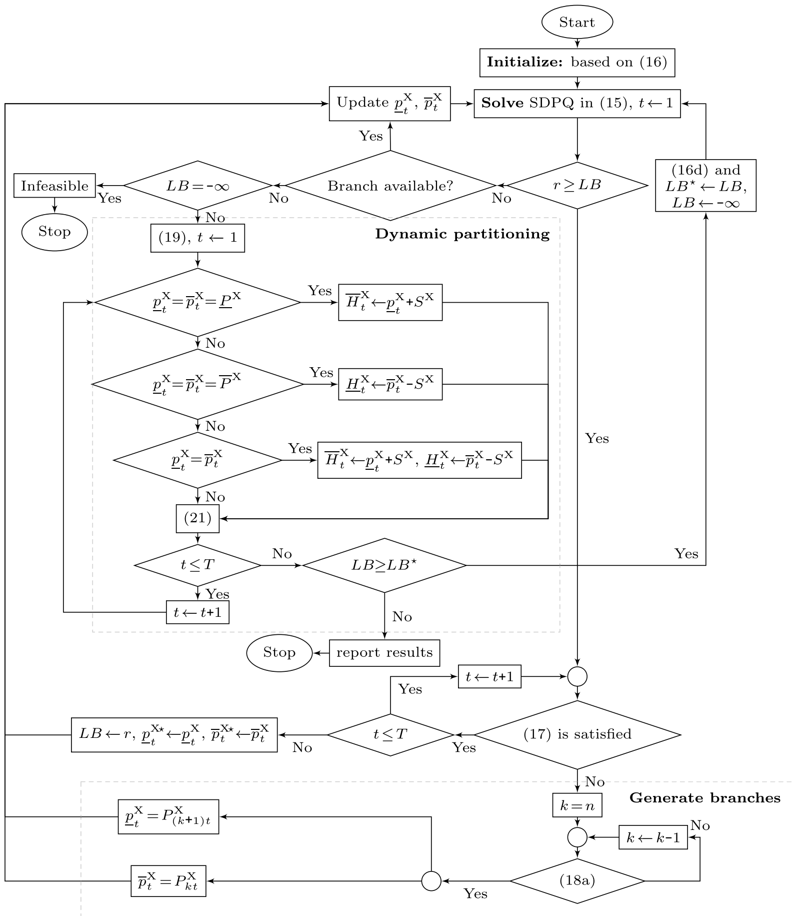

Fig. 3. Our proposed modified branch-and-bound (MBB) algorithm.

$$\text{Else if } \underline{p}_t^X = \overline{p}_t^X = \overline{P}^X \text{ then } \underline{H}_t^X \leftarrow \overline{p}_t^X - S^X, \tag{20b}$$

$$\text{Else } \{\overline{H}_t^X \leftarrow \underline{p}_t^X + S^X \text{ and } \underline{H}_t^X \leftarrow \overline{p}_t^X - S^X\} \tag{20c}$$

Finally, we update the values of $\underline{p}_t^X$ and $\overline{p}_t^X$ once more, set the LB to $-\infty$, update the disjunctive values according to (16d), and solve the problem again.

$$\overline{p}_t^X \leftarrow \overline{H}_t^X, \underline{p}_t^X \leftarrow \underline{H}_t^X \tag{21}$$

If the solution (LB) is improved, the algorithm continues. Otherwise, the optimal solution is reported.

2.5. Benchmark models

To assess the performance of the proposed MBB algorithm, we solve the bilevel program with two alternative algorithms, as described in Sections 2.5.1 and 2.5.2.

2.5.1. MILP

To reformulate the disjunctive problem in (9) as a MILP problem, we use a binary expansion approach. For the disjunctive term $\bigvee_{k=1}^{n} P_{kt}^X e_{itv}^X$, we introduce binary variables $\sum_{k=1}^{N} b_{tvk}^X = 1$ and rewrite the disjunctive constraints as:

$$-M^X b_{tvk}^X \leq h_{itkv}^X \leq M^X b_{tvk}^X, \forall itvk, \tag{22a}$$

$$-M^X(1 - b_{tvk}^X) \leq h_{itkv}^X - P_{kt}^X e_{itv}^S \leq M^X(1 - b_{tvk}^X), \forall itvk, \tag{22b}$$

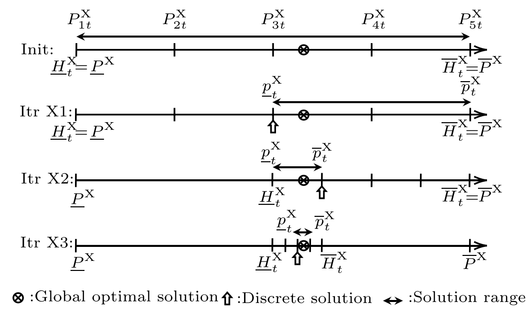

Fig. 4. Change of the solution range ($\overline{p}_t^X$ to $\underline{p}_t^X$) in our proposed MBB algorithm. Itr X1, X2 and X3 respectively refer to the iterations with the best solutions in the first, second, and third rounds of optimization.

where M^X is a sufficiently large number, and h_{itkv}^X are continuous variables that are enforced to take the values of the binary terms for a single step k. The disjunctive term and the prices can then be written as:

$$\bigvee_{k=1}^{N} P_{kt}^X e_{itv}^X = \sum_{k=1}^{N} h_{itkv}^X, \tag{23a}$$

$$p_t^{\mathrm{X}} = \sum_{k=1}^{N} P_{kt}^{\mathrm{X}} b_{tvk}^{\mathrm{X}}. \tag{23b}$$

The disjunctive problem in (9) together with additional constraints derived in (22) and (23) can be solved using standard commercial MILP solvers and branch-and-bound algorithms.

2.5.2. Special branch-and-bound (SBB) algorithm

To demonstrate the improvements resulting from the MBB algorithm, we also solve SDPQ using the SBB algorithm proposed in [54].

2.6. Benchmark tariffs

As shown in Proposition 1, we expect that the competition between the aggregator and users in the proposed ORTP strategy increases the CW of the EC, defined as CW $= r - C'$, where $C' = \sum_{itv} \phi_v C_{iv}$ is the total cost of users. Note that, in the calculation of CW, the terms with p_t^{X} are eliminated. Therefore, CW $= \sum_{itv} \phi_v P_{tv}^{\mathrm{M}}(e_{itv}^{\mathrm{S}} - e_{itv}^{\mathrm{B}}) + P_i^{\mathrm{Q}}(z_{itv}^{\mathrm{C}} + z_{itv}^{\mathrm{D}})$. To validate our hypothesis regarding the impact of competition on the CW, we compare the resulting CW values from the ORTP with those gained from the two benchmarks.

- *Average pricing* (AP) uses the mean value of the market prices during the simulated period to calculate p_t^{X}. Therefore, the tariff does not contain any real-time element and the price is constant over time, similar to the retail price in many countries:

$$p_t^{\mathrm{X}} = (\sum_{t}^{\overline{T}} P_{tv}^{\mathrm{M}})/|t| + \Gamma^{\mathrm{X}}. \tag{24}$$

- *Real-time pricing* (RTP) includes the market price signals in p_t^{X}:

$$p_t^{\mathrm{X}} = P_{tv}^{\mathrm{M}} + \Gamma^{\mathrm{X}}. \tag{25}$$

While the aggregator's margin in the ORTP is optimized and may change in real time, the parameters Γ^{X} in Eqs. (24) and (25) are exogenous model assumptions that do not vary over time. We assume that $\Gamma^{\mathrm{S}} = -\Gamma^{\mathrm{B}}$, and this is set at 0.5 ¢/kWh. Since, in the calculation of CW, the terms with p_t^{X} are eliminated, the choice of Γ^{X} does not have any impact on the community's welfare.

2.7. Data and model parameterization

For the household demand profiles, we use the data from [59]. This dataset contains high-resolution measured load profiles of 74 different German households. Data regarding the load and availability profiles of EVs were obtained using the open-source tool VencoPy [60], based on the mobility data available in [61]. The translation of the mobility data into the EV electrical demand and charging availability profiles for this analysis is described in Appendix A.2. The electricity generation profile of the PV systems is scaled based on the share of generated electricity from the installed PV capacity in 2018 in Germany (PV capacity data was collected from [62]). For P_{tv}^{M}, we use the day-ahead electricity market prices for Germany in [62]. The aggregator's maximum (minimum) sell price $\overline{P}^{\mathrm{S}}$ ($\underline{P}^{\mathrm{S}}$) is 8 (3) ¢/kWh, while the maximum (minimum) buy price $\overline{P}^{\mathrm{B}}$ ($\underline{P}^{\mathrm{B}}$) is 7 (2) ¢/kWh. The marginal cost of charging and discharging the battery (P_i^{Q}) is 1 ¢/kWh. The SOC of the BSSs cannot drop below 0 or exceed a maximum value of 1 ($0 \leq \overline{A}_i \leq 1$). For the user-specific model parameters (Υ), we assume the values listed in Table 3. The big-M parameters (M^{S} and M^{B}) in the MILP and LP formulations are set to 100000. Other parameters will be introduced for each case study in the next section.

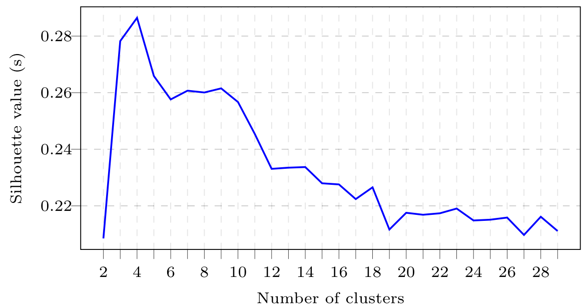

Fig. 5. Silhouette values for different numbers of clusters.

2.8. MPCB scenario generation

The uncertain *attributes* in SDPQ are the market price, demand and PV generation of each user. Since these attributes vary continuously over time and with temperature, wind speed, cloud cover, etc., the aggregator needs to take their associated uncertainties into account. One approach to generating the required scenarios for the optimization is the so-called direct-sampling method, which samples directly from the historical data. Using this approach, if we increase the size of the sample, the distribution of the scenarios will converge to the actual distribution of the data. However, performing the optimization for many scenarios requires excessive computational resources and is impractical. To provide a **practical** number of scenarios that are **representative** of the historical data, we propose the following MPCB scenario-generation algorithm:

Step 1: The time series for all attributes is specified according to year, month, week, day of the week and hour of the day. Then, the data for all attributes are scaled to the range [−1,1] so that we can use the Euclidean distance to compare similarities between different data points. The vector of attributes $\mathbf{x}$ has a probability distribution function $f(\mathbf{x})$.

Step 2: The data for the attributes are divided into $|\{C\}|$[7] clusters. We employ the well-known k-means method to group the dim($\mathbf{x}$) data into clusters. To decide on the suitable number of clusters, we perform a sensitivity analysis by applying the k-means method for different numbers of clusters and choose a value of $|C|$ that demonstrates the highest silhouette value. The silhouette value $s(\mathbf{p})$ is calculated in (26), in which $d(\mathbf{p})$ is the average Euclidean distance between point $\mathbf{p}$ and all the points in its cluster. In this equation, $d'(\mathbf{p})$ is the smallest average Euclidean distance between point $\mathbf{p}$ and all the points in other clusters [63]. A larger average silhouette value, i.e., $\sum_{\mathbf{p}} s(\mathbf{p})/\dim(\mathbf{x})$, indicates better cohesion within and separation between the clusters.

$$s(\mathbf{p}) = \begin{cases} 1 - d(\mathbf{p})/d'(\mathbf{p}), & \text{if } d(\mathbf{p}) < d'(\mathbf{p}) \\ 0, & \text{if } d(\mathbf{p}) = d'(\mathbf{p}) \\ d'(\mathbf{p})/d(\mathbf{p}) - 1, & \text{if } d(\mathbf{p}) > d'(\mathbf{p}) \end{cases} \tag{26a}$$

$$-1 \leq s(\mathbf{p}) \leq 1 \tag{26b}$$

The average silhouette values for different numbers of clusters are plotted in Fig. 5. We select $|\{C\}| = 4$, which results in the highest silhouette value, as the optimal number of clusters for the k-means clustering. Moreover, we only retain the attributes that improve the silhouette value. These attributes are the hour of day, day of the week, market prices, load, and solar generation profiles.

[7] The expression $|\{Q\}|$ is used for cardinality of the set $\{Q\}$.

Table 3
Users' technical parameters.

Y [−]	θ_i^{B} [kWh]	η_i^{C} [−]	η_i^{D} [−]	Λ_i [−]	$\overline{Z}_i^{\mathrm{C}}$ [kW]	$\overline{Z}_i^{\mathrm{D}}$ [kW]	$\overline{G}_i$ [kW]	$\overline{L}_i$ [kW]	P_i^{Q} [¢/kWh]	θ_i^{PV} [kW]	BSS [−]
1	20	1	1	1	20	20	20	20	1	20	HES
2	0.01[a]	0	0.01[a]	0	0	0	20	20	0	0	✗
3	10	0.95	0.95	0.99	10	10	20	20	1	10	HES
4	6	0.90	0.90	1	6	6	20	20	1	7	HES
5	50	0.98	0.98	1	50	50	11	11	1	0	EV

[a]User 2 does not own a BSS. To avoid division by zero, a very small number is chosen for its θ_i^{B} and η_i^{D}.

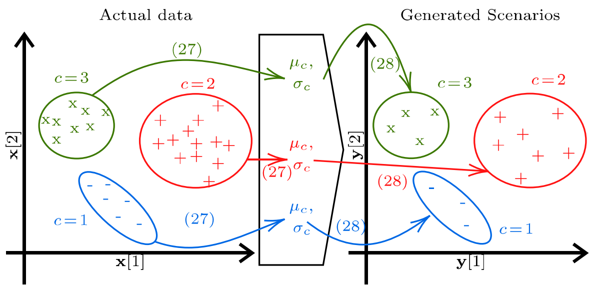

Fig. 6. Illustrative representation of the scenario-generation algorithm.

Step 3: The mean (μ_c) and standard deviation (σ_c) of the data in each cluster $c \in C$ are calculated as:

$$\mu_c = E(\mathbf{x}) = \int \mathbf{x} f(\mathbf{x})\mathrm{d}x \tag{27a}$$

$$\sigma_c = \sqrt{E((\mathbf{x}-\mu_c)^2)} = \sqrt{\int (\mathbf{x}-\mu_c)^2 f(\mathbf{x})\mathrm{d}x}. \tag{27b}$$

We then use these values are to generate scenarios in each cluster separately. Using the calculated means and standard deviations for each cluster, we generate a vector of random numbers $\mathbf{y}$ with a normal distribution:

$$\mathbf{y} = [\mathbf{y}_c] \text{ and } g(\mathbf{y}_c) \equiv N(\mu_c, \sigma_c). \tag{28}$$

Here, $N(\mu_c, \sigma_c)$ is a normal distribution function with a mean value of μ_c and a standard deviation of σ_c. The data within each cluster show significantly higher cohesion compared to the alternative of not using these clusters, e.g., direct sampling. Fig. 6 shows a simplified representation of the scenario-generation algorithm for three clusters ($|\{C\}| = 3$) in two dimensions. Note that, depending on the number of attributes, the actual number of dimensions $\dim(\mathbf{x})$ could be greater than 2.

Fig. 7 shows a comparison of the means and standard deviations of the actual data (described in Section 2.7) with the scenarios generated by the direct-sampling and the MPCB approaches. It can be seen that the distribution of the generated scenarios using the MPCB algorithm for all attributes are closer to the actual data when compared to the direct-sampling approach.

3. Case studies

In this section, we consider four case studies to demonstrate the performance of the methodology. The first three are illustrative examples to show how the algorithm and pricing work. The fourth is a larger-scale example to demonstrate computational scalability. Table 4 gives an overview of the model setups of the different case studies.

Table 4
Overview of model setups in the case studies.

Case study	$\overline{T}$	i	υ	Y	Demonstration goal
I	2	1	1	1	Convergence of the solution algorithm
II	4	1	1	1	Determination of ORTP
III	4	2	1	1,2	Internal balance of load and generation
IV	8	5	9	1,2,3,4,5	Large-scale stochastic optimization

3.1. Case study I

In the first example, we consider a single prosumager ($i = 1$), parameterized with $Y = 1$, an optimization period of 2 h ($t \in \{1, 2\}$), one scenario with probability of 1 ($|\{\upsilon\}| = 1$, $\phi_\upsilon = 1$), and three discretization steps ($k = 3$). The prosumager has a constant demand of 5 kWh ($L_{it\upsilon}|_{(t=1)} = L_{it\upsilon}|_{(t=2)} = 5$ kWh), and the power generation is 7 kWh and 3 kWh in the first and second time steps, respectively ($G_{it\upsilon}|_{(t=1)} = 7$ kWh, $G_{it\upsilon}|_{(t=2)} = 3$ kWh). The market price changes from 0 ¢/kWh in $t = 1$ to 8 ¢/kWh in $t = 2$ ($P_{t\upsilon}^{\mathrm{M}}|_{t=1} = 0$ ¢/kWh, $P_{t\upsilon}^{\mathrm{M}}|_{t=2} = 8$ ¢/kWh). The BSS is available all the time ($U_{it} = 1$). The discrete options for sell and buy prices are $p_t^{\mathrm{S}} \in \{3, 5.5, 8\}$ and $p_t^{\mathrm{B}} \in \{2, 4.5, 7\}$, respectively. Detailed results for the performance of the proposed solution algorithm are shown in Table 5.

The proposed MBB algorithm changes $\underline{p}_t^{\mathrm{S}}$, $\overline{p}_t^{\mathrm{S}}$, $\underline{p}_t^{\mathrm{B}}$, and $\overline{p}_t^{\mathrm{B}}$ at each iteration. In iterations 1 to 7, condition (17) is not satisfied (status A). Iteration 8 is the first iteration in which all solutions are discrete for all time periods (status B: condition (17) is fulfilled). Since $r \geq$ LB and all the solutions are discrete, LB is updated for the first time from −1000 to −14 in iteration 9. Similarly, $\underline{p}_t^{\mathrm{X}}$ and $\overline{p}_t^{\mathrm{X}}$ are changed until better solutions are found in iterations 25, 48, and 53 and the lower bound updates to 72 (LB=72). After 56 iterations, the algorithm has checked all the branches and this round is ended (status C). Therefore, the highest profit for the aggregator with the current discretization steps is 72 ($r = 72$ ¢). Thus, if we use the SBB algorithm proposed in [54] with fixed discrete steps, the optimal solution will be 72 in iteration 53, and the algorithm will stop after iteration 56. In contrast, in the proposed MBB algorithm, we modify the discrete steps inside the algorithm to find a solution that is closer to the global optimal point. In iteration 57, we apply the dynamic partitioning technique and start a new round in our algorithm (status D). Based on the best discrete result of the last round, the new discrete options for sale and purchase prices in the new round are $p_1^{\mathrm{B}} \in \{2, 3.25, 4.5\}$, $p_2^{\mathrm{B}} \in \{4.5, 5.75, 7\}$, $p_1^{\mathrm{S}} \in \{3, 4.25, 5.5\}$, and $p_2^{\mathrm{S}} \in \{5.5, 6.75, 8\}$.

As the choices are changed, the LB is initialized again with −1000. Then, $\underline{p}_t^{\mathrm{X}}$ and $\overline{p}_t^{\mathrm{X}}$ are changed until a better discrete solution is found at iterations 71, 83, and 84 with the aggregator's profit r and LB equal to 0, 94, and 94.5. Round 2 of the algorithm is finished after iteration 92. After this, the discrete options are updated once more: $p_1^{\mathrm{B}} \in \{2, 3.25, 4.5\}$, $p_2^{\mathrm{B}} \in \{5.75, 6.375, 7\}$, $p_1^{\mathrm{S}} \in \{3, 4.25, 5.5\}$ and $p_2^{\mathrm{S}} \in \{6.75, 7.375, 8\}$. In round 3, the lower bound of the problem updates twice, in iteration 99 and 101, to 0 and 105.75, respectively. Fig. 8 shows the transformation of the solution range for the purchase price (p_t^{B}) in the time step $t = 2$ in iterations 53, 84, and 101. The remaining

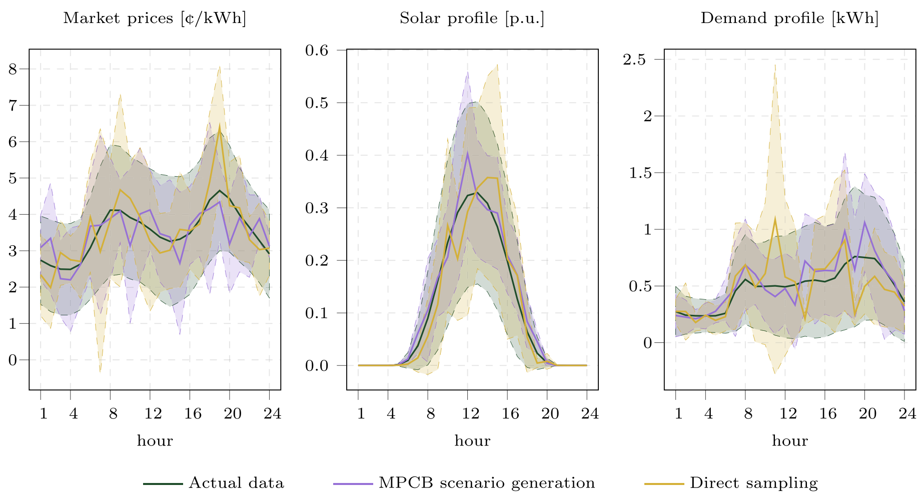

Fig. 7. Comparison of means and standard deviations between MPCB scenario generation, direct sampling, and actual data (sources: [59,62]). Mean values are illustrated with continuous lines. Standard deviations are shown with dashed lines as confidence intervals.

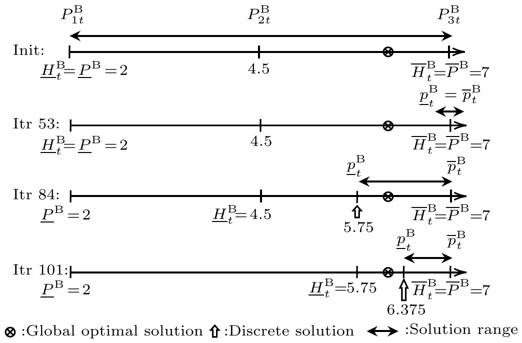

Fig. 8. Change of solution range ($\overline{p}_t^{\mathrm{B}}$ to $\underline{p}_t^{\mathrm{B}}$) in Case I for $t = 2$.

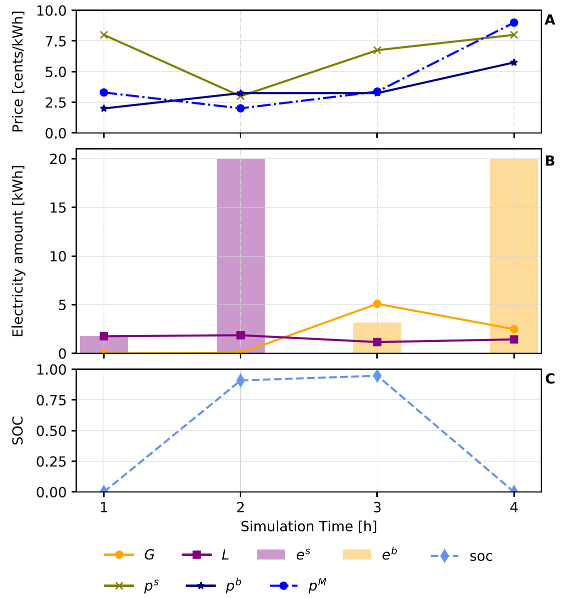

Fig. 9. Optimization results for Case study II. A: Aggregator's and market prices. B: Prosumager's electricity demand and generation, as well as grid usage and feed-in. C: Battery SOC of the prosumager.

options for $\underline{p}_t^{\mathrm{X}}$ and $\overline{p}_t^{\mathrm{X}}$ are investigated until iteration 104, after which the MBB algorithm for this problem is ended. To reach this objective value with the SBB algorithm, a larger number of discretization steps (k) and correspondingly more iterations are required.

3.2. Case study II

In the second example, the bilevel problem for a simple setup with one prosumager ($i = 1$), parameterized with $\Upsilon = 1$, is solved. For a time period of 4 h ($\overline{T} = 4$) and a single scenario, the model results, electricity prices, and prosumager's grid interactions, as well as the input time series, P^{M}, $G_{itv}|_{(\Upsilon=1)}$, and $L_{itv}|_{(\Upsilon=1)}$, are shown in Fig. 9.

In time steps $t = 3$ and 4, the prosumager uses its generation to cover its load. Note that in our model, the self-consumption of electricity by prosumagers is considered to be free of charge. Therefore, it is profitable for the users to use the generated electricity mainly to cover the own load in most cases. Since the storage is full in this hour, the residual generation at $t = 4$ is fed into the grid. As the highest market price occurs at $t = 4$ ($P_{tv}^{\mathrm{M}}|_{(t=4)} = 9$ ¢/kWh), the aggregator increases the purchase price to $p_t^{\mathrm{B}}|_{(t=4)} = 5.75$ ¢/kWh and incentivizes the prosumager to discharge the storage. The prosumager completely discharges the BSS in this time step and feeds 20 kWh into the grid ($e_{itv}^{\mathrm{B}}|_{(t=4)} = \overline{G}_i = 20$ kWh).

3.3. Case study III

In Case study III, we demonstrate how the ORTP reacts to market prices, limited available line capacity, and the availability of local generation and storage. Two users with the technical specifications of $\Upsilon = 1$ and 2 (see Table 3) are considered. User 2 ($\Upsilon = 2$) does not have a PV system or BSS. Therefore, this user does not have electricity generation and cannot have a flexible interaction with the

Table 5
Detailed results of Case I.

Iteration [−]	t [h]	r [¢]	LB [¢]	p_t^{S} *	p_t^{B} *	$\underline{p}_t^{\mathrm{S}}$ *	$\overline{p}_t^{\mathrm{S}}$ *	$\underline{p}_t^{\mathrm{B}}$ *	$\overline{p}_t^{\mathrm{B}}$ *	Round [-]	Status
1	1 2	108	−1000	3 4	2 2.0005	3 3	8 8	2 2	7 7	1	A
2	1 2	106	−1000	3 3	2 2.0006	3 3	8 3	2 2	7 7	1	A
3	1 2	108	−1000	6 8	6 2.0005	3 5.5	8 8	2 2	7 7	1	A
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
8	**1** **2**	**−14**	**−1000**	**8** **3**	**2** **2**	**3** **3**	**8** **3**	**2** **2**	**2** **2**	**1**	**B**
9	1 2	55.6	−14	7.9990 3	4.5002 2	3 3	8 3	4.5 2	7 2	1	A
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
53	**1** **2**	**72**	**69**	**3** **8**	**2** **7**	**3** **8**	**3** **8**	**2** **7**	**2** **7**	**1**	**B**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
56	1 2	−14	72	5.5 5.5	4.5 4.5	5.5 5.5	5.5 5.5	4.5 2	4.5 4.5	1	C
57	1 2	108	−1000	5.4995 6.9996	4.5 6.9996	3 5.5	5.5 8	2 4.5	4.5 7	2	D
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
71	**1** **2**	**0**	**−1000**	**3** **5.5**	**2** **4.5**	**3** **5.5**	**3** **8**	**2** **4.5**	**2** **4.5**	**2**	**B**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
83	**1** **2**	**94**	**0**	**3** **5.5**	**2** **5.75**	**3** **5.5**	**3** **5.5**	**2** **5.75**	**2** **7**	**2**	**B**
84	**1** **2**	**94.5**	**94**	**3** **6.75**	**2** **5.75**	**3** **6.75**	**3** **8**	**2** **5.75**	**2** **7**	**2**	**B**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
92	1 2	0	94.5	5.5 6.75	4.5 5.75	5.5 6.75	5.5 6.75	3.25 4.5	4.5 5.75	2	C
93	1 2	108	−1000	5.4999 8	4.5 7	3 6.75	5.5 8	2 5.75	4.5 7	3	D
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
99	**1** **2**	**0**	**−1000**	**5.5** **8**	**4.5** **7**	**5.5** **8**	**5.5** **8**	**2** **5.75**	**4.5** **7**	**3**	**B**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
101	**1** **2**	**105.75**	**0**	**4.25** **6.75**	**2** **6.375**	**3** **6.75**	**4.25** **8**	**2** **6.375**	**3.25** **7**	**3**	**B**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
104	1 2	94.5	105.75	3 8	3 5.75	3 6.75	3 8	2 5.75	3.25 5.75	3	C

*: [¢/kWh]. A: (17) is not fulfilled. B: (17) is fulfilled. LB will be updated. C: All branches are checked. End of this round. D: Dynamic partitioning is applied. Beginning of a new round. Highlighted solution: Best solution in this round.

grid. Moreover, we assume that the available line capacity is limited ($\overline{W}|_{(t=1,2,4)}$ = 20 kWh and $\overline{W}|_{(t=3)}$ = 0.6 kWh). The optimization results and the input series for Case III are presented in Fig. 10. As a result of a low market price at $t = 2$, the aggregator offers a low sale price to the users. However, due to the restricted available line capacity, user 1 cannot charge the BSS completely ($e^{\mathrm{S}}_{itv}|_{(t=2)}$ = 17.526 kWh, $a_{itv}|_{(t=2)} = 0.78$). In hour 3 ($t = 3$), user 1 feeds enough electricity into the community grid to cover the load of user 2 and therefore the load and generation of the EC can be balanced locally in this hour. At $t = 4$, the market price reaches its highest value ($P^{\mathrm{M}}_{tv}|_{(t=4)} = 8.9$). Therefore, the aggregator increases the purchase price to $p^{\mathrm{B}}_t|_{(t=5)}$ = 5 ¢/kWh and user 1 is encouraged to discharge its battery completely.

3.4. Case study IV

In Case study IV, we increase the problem size and analyze an EC with a larger number of users and a longer optimization period compared to the previous illustrative examples. Five users ($|\{i\}| = 5$) and eight optimization periods (i.e., $|\{t\}| = 8$) are considered. These users are relatively diverse and adopt the parameters shown

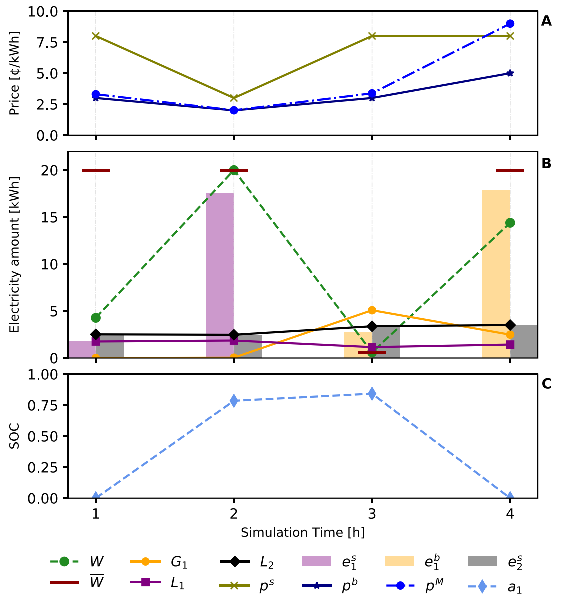

Fig. 10. Optimization results for Case study III. A: Aggregator's and market prices. B: Users' electricity demand and generation, as well as grid usage and feed-in. C: Battery SOC of the prosumager.

in Table 3. For this case, we study the sensitivity of the aggregator's expected profit to the scenarios. In a simulation experiment, we vary the number of scenarios ($|\{v\}|$) from 1 (indicating a deterministic solution) to 50 and solve the SDPQ over 7000 times.[8] We use the MPCB scenario-generation algorithm (introduced in Section 2.8) to provide the required scenarios for this experiment. Note that every scenario is unique and used only once in this analysis. Moreover, as a simplifying assumption, we consider a uniform probability of occurrence for all the scenarios ($\phi_v = 1/|\{v\}|, \forall v$).

The results of this experiment are presented in Fig. 11. Each box plot in this figure displays the distribution of the aggregator's profit (objective value of the optimization problem in SDPQ) for a fixed number of scenarios. In this case, the fluctuation of the profit stems from the variance of the underlying time series in each of the generated scenarios. The trend of the median values indicates that, with an increasing number of scenarios, the aggregator's expected profit tends to drop. We observed that solving the SDPQ with a higher number of scenarios, e.g., larger than 100, the median value falls below 100 ¢. In the formulated stochastic problem, regardless of the number of scenarios, the aggregator chooses a single set of prices for the users (see also (1a)). With an increasing number of scenarios, these prices are less tailored to each individual scenario and therefore the overall efficiency of the ORTP drops. Moreover, the aggregator's profit is more sensitive to the scenarios when the number of scenarios is lower. For instance, in the deterministic solution, i.e., $|\{v\}| = 1$, the profit of the aggregator varies between 104 and 382 ¢ (267% change) depending on the selected scenario. This range is reduced to 121 and 174 ¢ (43% change), when the number of scenarios is 47. Due to the considered uniform probability of scenarios, the impact of extreme scenarios reduces when the number of scenarios increases. This leads to a smaller spread of profit in the cases simulated with high numbers of scenarios.

Due to computational limitations, for the comparative analysis in Section 4, we solved the SDPQ with nine scenarios ($|\{v\}| = 9$). In Section 4.2, we present a sensitivity analysis and elaborate on the dependency of the computational efforts to solve the formulated problem on the numbers of users, optimization time steps, and scenarios.

[8] These cases are optimized using high performance computer Tegner PDC with 24 computational nodes and 32 threads [64].

4. Comparison of results

4.1. CW comparison

The results regarding the aggregator's profit, users' total costs, and the CW of the EC for the proposed ORTP tariff together with those derived from AP and RTP schemes are presented in Table 6 (the contents of this table are plotted in Appendix A.3). With the implementation of the ORTP, the CW of the EC has the highest value relative to the two other tariff strategies. In the setup in which only one flexible user interacts with the aggregator (Case study I), the RTP tariff performs as well as the ORTP tariff. In more complicated setups with multiple users, the ORTP tariff outperforms the RTP tariff. The AP tariff, the current pricing strategy for many small-scale electricity users in Germany, demonstrates the lowest CW value. This tariff does not contain any real-time signals relating to the scarcity or surplus of electricity (in the market or the EC). Note that we did not monetize the achieved grid relief by the ORTP in Case study III. In such a case, we would expect that the achieved CW in the ORTP tariff would outperform the benchmark tariffs by an even higher margin.

In all case studies, the aggregator's profit reveals the highest and lowest values for the ORTP and AP versions, respectively. However, the aggregator's profit in the benchmarks depends on the choice of the aggregator's margin. (Γ^X). Larger Γ^X values will lead to greater profits for the aggregator, which come at higher costs for the users. This will be a policy decision for the EC stakeholders as the aggregator's profit increases the EC's assets; these may be redistributed to users or invested.

4.2. Computational comparison

Table 7 compares the performance of the MBB algorithm and the benchmark algorithms introduced in Section 2.5 for the four case studies (the contents of this table are plotted in Appendix A.3). The model statistics and the number of discretization steps (k) in different cases under investigation are given in 8. We carried out the optimization for both the MILP and LP models on GAMS 25.1.3 platform using the CPLEX 12.8 solver. The case studies I–IV are optimized on a laptop with Intel Core i7-8650U CPU running at 1.90 GHz with eight nodes and 16 threads. Note that our algorithm does not use parallel computation and therefore, even though multiple processors were available, all the calculations were carried out on a single CPU node.

The optimal solution of SDPQ (the profit of the aggregator) depends substantially on the level of discretization (k); a larger number of discretization steps will converge closer to the optimal solution of the original problem in (1).

The results in Table 7 clearly show that the MBB algorithm outperforms the SBB algorithm (from [54]) and the MILP model, as it is able to reach a better objective value with fewer iterations and less computation time. These improvements increase in more complex cases. For example, in Case study IV, the MBB algorithm converges to an objective value, which is respectively 9.2% and 11% higher than those from the SBB algorithm and MILP model with 83.1% and 91.8% less solver execution time. This indicates the efficient performance of our proposed MBB algorithm, especially for solving large-scale problems.

A convergence plot of the proposed MBB and the benchmark SBB algorithms for Case study III is presented in Fig. 12. Starting with a lower value k, the MBB algorithm converges to the objective value of 76.49 after 768 iterations for the first time. After this step, the discretized prices are dynamically modified, and LB is set back to $-\infty$. After five more rounds, the algorithm converges to the objective value of 123.25 in iteration 2189. In contrast, with $k = 5$, the SBB

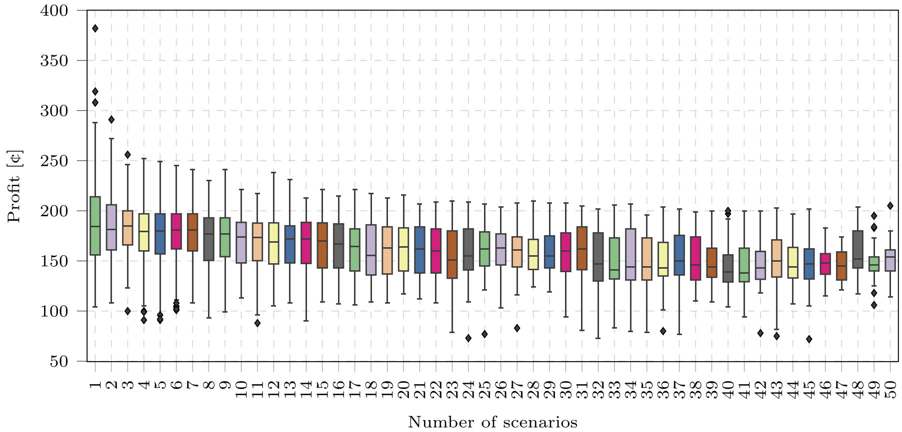

Fig. 11. Sensitivity analysis of the impact of the number of scenarios on the aggregator's profit in Case study IV. Box plots show the distribution of profit with the corresponding quartiles (25%, 50%, 75%).

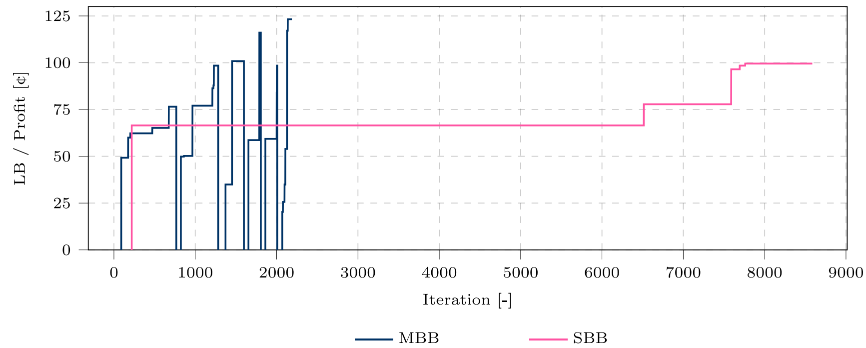

Fig. 12. Convergence plot of the benchmark SBB and MBB algorithms for Case study III. The LB values lower than zero are not shown in the figure.

Table 6
Comparison of aggregator's profit, users' costs and CW under different tariff strategies.

Tariff	Case study I			Case study II			Case study III			Case study IV		
	r [¢]	C' [¢]	CW [¢]	r [¢]	C' [¢]	CW [¢]	r [¢]	C' [¢]	CW [¢]	r [¢]	C' [¢]	CW [¢]
ORTP	**105.7**	**1.7**	**104**	**93.36**	**−13.31**	**106.67**	**99.6**	**52.3**	**47.3**	**181.1**	**−2.7**	**183.8**
AP	−14	2	−16	12.59	−0.67	13.26	4.3	199.9	−195.6	23.5	−31.3	54.8
RTP	18	−86	104	22.45	−84.22	106.67	28.4	338.6	−310.2	50.2	−56.1	106.3

Table 7
Comparison of the computational performance.

Case	Number of iterations [–]			Nodes explored [–]			CPU time [s]			Profit (r) [¢]		
	MILP	SBB	**MBB**	MILP	SBB	**MBB**	MILP	SBB	**MBB**	MILP	SBB	**MBB**
I	1226	306	**104**	203	296	**102**	5.12	0.69	**0.37**	105.75	105.75	**105.75**
II	70439	5959	**1701**	19945	5610	**1608**	35.39	18.22	**5.85**	93.36	91.17	**102.34**
III	876382	8586	**2188**	141848	7761	**2138**	347.2	26.83	**6.9**	99.55	99.55	**123.25**
IV	50227324	41254	**6086**	190145	30058	**4021**	10935	5270	**924.3**	181.08	184.18	**201.14**

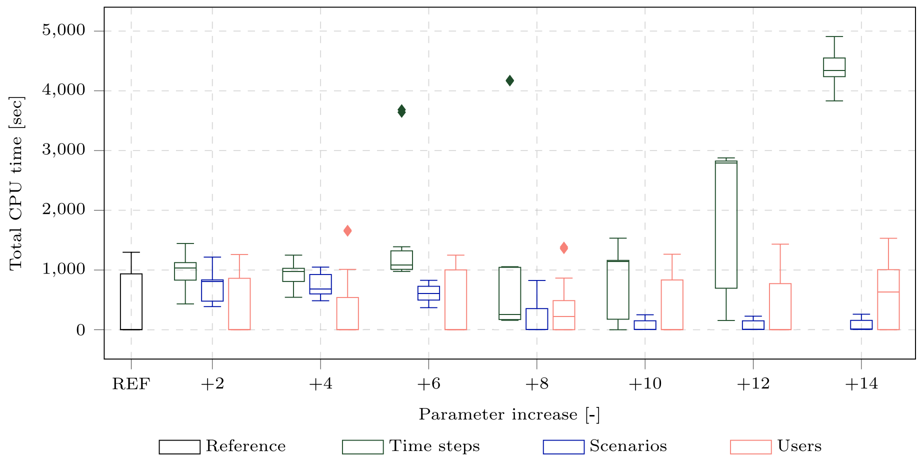

Fig. 13. Sensitivity analysis regarding the impact of optimization time steps, number of users, and scenarios on the computation time. The numbers on the x-axis indicate the increased value of the parameters under study relative to the reference case.

Table 8
Model statistics.

Case	Bin.	Con.	Const.	$\lvert k\rvert_{MILP}$	$\lvert k\rvert_{SBB}$	$\lvert k\rvert_{MBB}$
I	38	115	198	9	9	3
II	44	163	264	5	5	3
III	48	277	495	5	5	3
IV	819	8799	16035	4	4	3

Bin.: Number of binary variables. Con.: Number of continuous variables. Const.: Number of constraints.

algorithm, achieves the optimal value of 99.55 after 8587 iterations. This shows that a significant efficiency improvement is made by the MBB algorithm. Note that each round of optimization is finished, when the termination criteria (see Section 2.4) are fulfilled.

To assess the sensitivity of the computation effort to three key model parameters, i.e., number of optimization time-steps, users, and scenarios, we perform another simulation experiment. The starting point of our sensitivity analysis is a reference case, which is parameterized identically to Case III (i.e., with five time steps, one scenario, and two users). In three parallel analyses (one for each parameter), we increase the parameters and carry out more than 600 simulations with unique scenarios. The required CPU time for the simulated cases is presented in Fig. 13.[9] The x-axis in Fig. 13 shows the increased number of time steps, scenarios, and users (with the maximum value of 14) in each analysis.

The computation time of the reference case (black box in Fig. 13) varies between 0.6 and 1297 s. This fluctuation indicates a strong dependency of the computation effort to the input time series (electricity demand, generation, and market prices). The findings of the simulation experiment reveal that the required computation time rises significantly when prolonging the optimization period. Simulations with 19 time steps (14 steps more than REF) require an average computation time of 4370 s. In contrast, optimizing the formulated problem with a larger number of users does not increase the needed solution time substantially. When increasing the number of scenarios, we observed that stochastic optimizations with larger $|\{v\}|$ were solved faster than deterministic optimizations. For instance, the maximum recorded computation time for the cases with 13 and 15 scenarios (12 and 14 scenarios more than REF) is 226 and 259 s. These findings indicate that the proposed model scalable with respect to the number of scenarios and users in the EC. In contrast, increasing the optimization period above 14 time steps seem to have a strong impact on the required computation effort.

5. Discussion of limitations and implications for external validity

The results of our analysis demonstrate that the implementation of DR in ECs with the help of smart real-time pricing strategies can potentially lead to technical and economic benefits. Our evaluation did not assess the practical implementation of this pricing strategy. The following are pointers to future research needs.

Concerning the economic benefits of the proposed pricing strategy, a question arises about how the generated welfare is redistributed among the stakeholders; i.e., what are the financial incentives for the users to participate in this business model, rather than switching to another retailer. In this regard, the absence of competition among aggregators is a limitation of our model that should be addressed in future research. Moreover, the observed actor behavior in this analysis could be distorted by the addition of regulatory-induced charges to the electricity consumer price.[10] Expensive electricity consumer prices generally

[9] For this simulation experiment, we used the processor AMD EPYC 2.25 GHz and 16 GB memory from the recent KTH Dardel system [65].

[10] These regulatory-induced charges do not contain any time-varying signal and comprised more than 70% of the end-user electricity price in Germany in the year 2021.

incentivize a higher level of behind-the-meter self-consumption for the prosumagers [66]. Because we neglected the impact of these consumer-price components, future research should assess the adaptability of such real-time pricing schemes in different regulatory environments.

With an efficient operation, ECs can support the power network and enhance the integration of renewable energies. In this paper, we demonstrated that the ORTP strategy can incentivize an operation that contributes to power-grid relief. Quantifying the value of the delivered flexibility requires a more comprehensive study with the help of a distribution grid model. Along with these benefits, the establishment of ECs can arouse concerns regarding inefficient investments and increasing overall energy-system costs. For instance, if sharing the electricity across the EC reduces the revenues of the distribution grid, raising the grid charges for other consumers is likely. This effect may exacerbate inequalities and incentivize local self-consumption even further. In this case, solutions such as distribution-network tariffs are suggested in the literature [67]. Therefore, further studies are required concerning the impact of the (collective) self-consumption in ECs on the larger energy system. A useful approach for such analysis is the coupling of models with different perspectives (e.g., local and national perspectives) [68].

Regarding the technical implementation, this paper assumes that the bidirectional communication infrastructure and the required measuring and control equipment for an efficient and secure transmission of data is available in the EC. Therefore, we have neglected the investment costs in our calculations. For the case of Germany, users need to be equipped with smart-meter gateways, which are devices that automatically communicate measurements from connected smart meters to external market participants; these allow them to send incentives or commands for load adjustments to local control boxes such as energy-management systems [69]. While a general advantage of the price-based DR measures is respecting users' privacy [8], a limitation of the single-level reduction approach in solving bilevel optimization problems (compared to distributed algorithms such as [35]) is the necessity for sharing information about users with the aggregator. The technical evaluation of the technologies and algorithms that enable an efficient and secure transmission of the necessary data is part of another field of research [70]. Concerning our proposed methodology, we demonstrated that the presented modeling approach and solving technique can significantly contribute to a more effective solution of the bilevel problem when compared to the benchmark solving approaches. Real-world applications, however, can lead to optimization problems with longer durations and more heterogeneous users. Improving the performance of the proposed methodology to satisfy real-world-scale problems should be the focus of future research. In this context, one direction to improving the scalability potential of the algorithm is the simultaneous evaluation of the created branches on multiple processors using parallel computing [71].

6. Conclusion

The expansion of distributed electricity generation and storage potential poses challenges for the efficient technical and economic operation of the power system. Smart-grid infrastructure has opened the door to many innovative DR business models that can contribute to meeting these challenges while creating financial benefits for the participating actors. In this context, we have proposed an ORTP methodology for a profit-maximizing community-owned aggregator in an EC, that is not isolated from the wholesale market. In our model, the aggregator trades bilaterally with users in the EC (e.g., prosumagers and electric vehicles) while coping with restrictions regarding the maximum available line capacity behind the point of common coupling. Moreover, the stochastic formulation of the problem provides a solution for the aggregator to deal with uncertainties regarding the wholesale market prices as well as users' electricity demand and generation. The required representative scenarios for these sources of uncertainty are produced by developing a multi-parameter cluster-based scenario-generation approach. To capture the hierarchical nature of the decision-making process in the considered setup, the interplay between the users and the aggregator is formulated as a bilevel optimization problem. To solve the resulting problem efficiently, we reformulated the original stochastic bilevel program as a stochastic disjunctive program and proposed a novel MBB algorithm that applies a linear quasi-relaxation approach and a dynamic partitioning technique. We assessed the effectiveness of our proposed methodology in four cases studies.

Our results show that the derived ORTP leads to higher community welfare for the EC. Furthermore, if necessary, the ORTP can provide useful grid services by creating incentives to offset the EC's demand and supply locally. The comparison of the ORTP with the average pricing strategy (with no time-varying component) shows a significant improvement in all studied cases. However, the effectiveness of the ORTP against a simple real-time pricing strategy (including only signals from the wholesale market) becomes evident when the diversity of users increases. Moreover, our proposed algorithm outperforms the benchmark algorithms both in computational performance and community welfare. These enhancements were found to be more substantial in the large-scale case studies. There are two major drivers for the achieved improvements: first, by applying the quasi-relaxation approach a large number of binary variables are eliminated; second, the implemented dynamic partitioning technique disentangles the optimization results from the disjunctive parameters. Our simulation experiments show that the computational effort is sensitive to the number of optimization time steps. In contrast, the proposed model is observed to be scalable in terms of the number of users and scenarios. One direction of future studies includes assessing the impact of ECs on the German electricity market. Another objective of the subsequent studies will be the further development and enhancement of the proposed EC model and the solution algorithm.

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CRediT authorship contribution statement

Seyedfarzad Sarfarazi: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Saeed Mohammadi:** Methodology, Formal analysis, Writing – review & editing, Visualization. **Dina Khastieva:** Methodology. **Mohammad Reza Hesamzadeh:** Supervision, Writing – review & editing. **Valentin Bertsch:** Supervision, Writing – review & editing. **Derek Bunn:** Writing – review & editing.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

Appendix

A.1. Proof of Proposition 1

We start with the objective on the left-hand side of (2), which is defined in (29a). In (29), $\{p_t^{\mathrm{S}}, p_t^{\mathrm{B}}\}$ and χ are sets of decision variables for the user and the aggregator, respectively and $\chi = \{e_{itv}^{\mathrm{S}}, e_{itv}^{\mathrm{B}}, a_{itv}, z_{itv}^{\mathrm{C}}, z_{itv}^{\mathrm{D}}\}$. The expression $-\sum_{iv}\phi_v C_{iv}(\chi)$ is not a function of p_t^{S} and p_t^{B}. Therefore, it can be added to the objective function in (29a) without changing the optimal solution, i.e., (29a) and (29b) are equivalent. From (1), the expression $r(p_t^{\mathrm{S}}, p_t^{\mathrm{B}})$ can be replaced with its equivalent $\sum_{itv}\phi_v r_{itv}(p_t^{\mathrm{S}}, p_t^{\mathrm{B}})$, as done in (29c). Then, we can extract ϕ_v in (29d); this has the term $(r_{itv}(p_t^{\mathrm{S}}, p_t^{\mathrm{B}}) - C_{iv}(\chi))$, which is the CW. The terms $r(p_t^{\mathrm{S}}, p_t^{\mathrm{B}})$ and $-C_{iv}(\chi)$ indicate profit of the aggregator and user i, respectively. CW can be defined as a summation of revenue of all the participants in the EC (users and the aggregator). Therefore, CW $= r_{itv}(p_t^{\mathrm{S}}, p_t^{\mathrm{B}}) - c_{itv}(\chi)$. Note that ϕ_v is a fixed parameter that does not change with the decision variables.

$$\underset{p_t^{\mathrm{S}}, p_t^{\mathrm{B}}}{\text{Maximize}}\; r(p_t^{\mathrm{S}}, p_t^{\mathrm{B}}) \equiv \tag{29a}$$

$$\underset{p_t^{\mathrm{S}}, p_t^{\mathrm{B}}}{\text{Maximize}}\; \left(r(p_t^{\mathrm{S}}, p_t^{\mathrm{B}}) - \sum_{iv} \phi_v C_{iv}(\chi) \right) \equiv \tag{29b}$$

$$\underset{p_t^{\mathrm{S}}, p_t^{\mathrm{B}}}{\text{Maximize}}\; \left(\sum_{itv} \phi_v r_{itv}(p_t^{\mathrm{S}}, p_t^{\mathrm{B}}) - \sum_{iv} \phi_v C_{iv}(\chi) \right) \equiv \tag{29c}$$

$$\underset{p_t^{\mathrm{S}}, p_t^{\mathrm{B}}}{\text{Maximize}}\; \sum_{itv} \phi_v \underbrace{\left(r_{itv}(p_t^{\mathrm{S}}, p_t^{\mathrm{B}}) - C_{iv}(\chi) \right)}_{=\mathrm{CW}} \tag{29d}$$

We have started from the left-side of (2) and demonstrated that it is equivalent to the right-side of (2), which is CW. This shows that solving (1) is equivalent to maximizing the CW, as stated in (2). □

A.2. EV parameterization

The optimization of the charging schedule for EVs requires a deliberate consideration of their mobility pattern. Assuming a price-inelastic transport demand, we should know when the EV is available for charging/discharging from/to the grid (the battery storage of the prosumager is connected to the grid the whole time) and what the electricity consumption of the EV is. Due to a lack of suitable empirical open-source data, in this work, the VencoPy tool was deployed to derive these data. VencoPy uses data from the German national travel survey [61] and aims to estimate future electric vehicle fleet charging flexibility [60]. In the first step (trip diary building), the individual trips are consolidated into a user-specific travel diary. In this step, the driven distance and the travel purpose (e.g., shopping, returning home, etc.) are allocated to their respective hour and merged into the daily travel diaries. In the next step, using a basic charging infrastructure model, the charging availability is allocated through a binary True–False mapping of the respective trip purposes. Since we focus on the technical load-shifting potential, and due to lack of sufficient data, user behavior (e.g., state-of-charge dependent plugging decisions) is disregarded. The result of the charging-availability allocation is a binary grid connection profile that describes whether the EV is connected to the grid at a given hour. To calculate the electricity flow from the battery to the electric motor, the driven distance is multiplied by an assumed average specific electricity consumption in 100 kWh/100 km. The two resulting profiles, together with the technical parameters of the storage, are then passed to the EC model. Fig. 14 gives an overview of the described steps to calculate the EV load and availability profiles. The interested reader can refer to [60] for a more detailed explanation of the internal calculations of VencoPy.

A.3. Visualization of the comparative results

In this section, we visualize the comparative results presented in Section 4. Fig. 15 shows the achieved community welfare with ORTP compared to the benchmark tariffs AP and RTP. Fig. 16 compares the computational performance of the MBB with the benchmark approaches SBB and MILP. Figs. 15 and 16 respectively correspond to Tables 6 and 7.

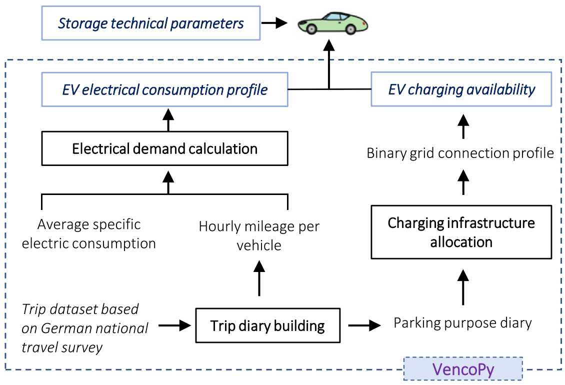

Fig. 14. Data preparation using the VencoPy tool.

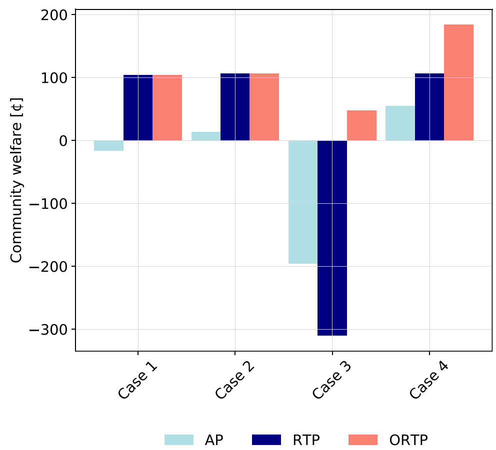

Fig. 15. Community welfare for the studied tariffs in different case studies.

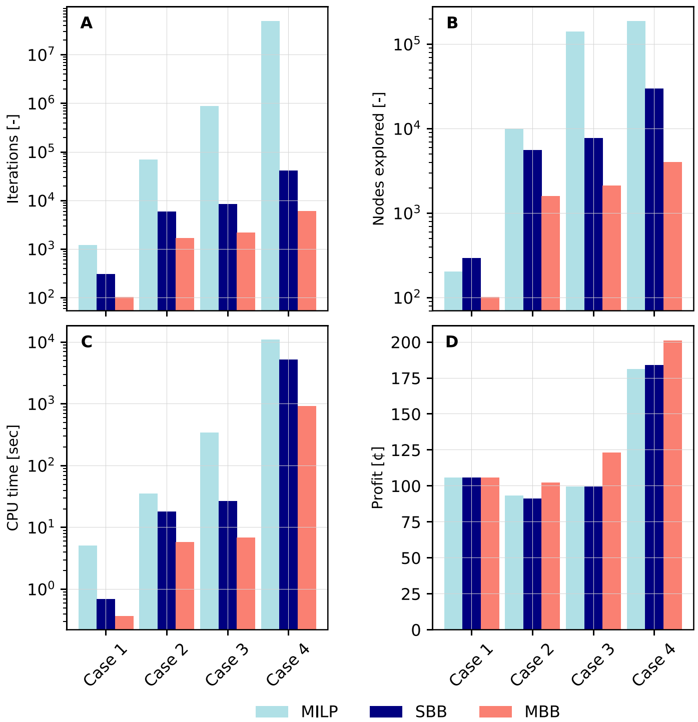

Fig. 16. Computational performance of the benchmark MILP approach compared to the SBB and MBB algorithms. A: Number of iterations. B: Number of explored nodes. C: CPU time. D: Aggregator's profit (r).

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Chapter 4

System integration of distributed energy systems

4.1 Paper 3: Improving energy system design with optimization models by quantifying the economic granularity gap: The case of prosumer self-consumption in Germany

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Authors' contribution: As the lead author, I made significant contributions to the methodology of this paper. Firstly, I developed AMIRIS further and set up the iog2x tool required for automatically reading the REMix results into AMIRIS and vice versa. Additionally, I performed model harmonization and conducted the formal analysis. I was also responsible for visualizing a portion of the results. I wrote the original manuscript and later revised it for publication. SHS contributed to the project by undertaking the REMix-side model developments, parameterization, and simulations. SHS provided support in the formal analysis and contributed to the visualization of results. Moreover, SHS wrote parts of the original manuscript. KKC, who conceptualized the research project, was responsible for funding acquisition and project administration. KKC made contributions to the methodology by supervising the REMix model developments and setting up the RCE tool (an Open Source distributed, workflow-driven integration environment) to fully automate the model-coupling workflow. KKC also wrote sections of the original manuscript and edited it in later stages of the publication.

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Research paper

Improving energy system design with optimization models by quantifying the economic granularity gap: The case of prosumer self-consumption in Germany

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ABSTRACT

Energy system models are widely used to inform the political decisions required to successfully mitigate climate change in the energy sector. The energy system optimization models (ESOMs) used to identify cost-minimal transformation pathways assume the perfect behavior of market participants from a central planner's perspective. Neglecting the decision-making under uncertainties or biased perceptions and attitudes leads to inaccurate assumptions regarding the requirements of a successful energy transition. In particular, ESOMs underestimate the required capacities for power generation, storage, and transmission compared with real-world energy systems, a phenomenon known as the "economic granularity gap". Agent-based models (ABMs) are helpful tools for capturing the behavior of market actors. Hence, attempts have been made to identify and alleviate this phenomenon through the coupling of ESOMs and ABMs. In this paper, we propose an automated workflow for such model coupling and quantify the economic granularity gap for the case of photovoltaic-prosumer self-consumption. Our results show that the current business models and regulatory frameworks affecting prosumer self-consumption patterns require the adaptation of cost-minimal energy system designs. However, if correctly implemented, instruments such as dynamic tariffs could narrow the economic granularity gap, shifting real-world energy systems closer to their ideal counterparts.

1. Introduction

1.1. Background

To successfully mitigate climate change, it is important for the energy sector to understand how future energy supplies can be realized in a secure, affordable, and sustainable manner. In this sense, a multitude of aspects need to be considered, such as the electrification of energy demand sectors (IPCC, 2022), security of supply even in time periods that lack renewable power generation (Lund et al., 2015), and a highly diverse, economically feasible mix of technologies. Hence, identifying suitable policy measures to incentivize the transformation of the energy supply system is a complex task. Models are often applied to gain insights into possible future scenarios for the energy system (e.g., to serve as decision support in energy policy and industry Pfenninger et al., 2014). To investigate the uptake of renewable power generation and the deregulation of power markets from a macro-perspective, a broad variety of so-called energy system models has evolved, each having different strengths for addressing the abovementioned aspects (Ringkjøb et al., 2018; Horschig and Thrän, 2017). One prominent category is energy system optimization models (ESOMs) (Hawker and Bell, 2020), which are applied to observe the possible operation of power plants and technologies for balancing the intermittent power supply of renewable energy sources. Due to the clear specification of an objective function and constraints, they provide an easy-to-use framework for modeling decision processes and simulating investment decisions when multiple solutions are conceivable (i.e., different technologies for load-balancing). Moreover, they are used to design future energy systems subject to the relevant political targets (e.g., greenhouse gas (GHG) mitigation targets) (Sasanpour et al., 2021). The purpose of drafting such ideal system designs is to provide templates for navigating the transformation of the system, e.g., by setting incentives. However, at this point, obvious discrepancies between the ideal scenario

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and the real world occur. We refer to these discrepancies as the granularity gaps that are revealed across several dimensions of a model. For example, Prina et al. (2020) identified four dimensions of interest in this regard, which they refer to as resolution in time, in space, in techno-economic detail, and in sector-coupling. Similarly, we have defined four model dimensions where granularity gaps occur (Cao et al., 2021), but propose, in addition to the distinction of the temporal, spatial, technological scale, the consideration of an economic scale.

1.2. Economic granularity gap

The economic granularity gap comprises different aspects. In general, similar to the well-studied granularity gaps in the spatial, temporal, and technological dimensions (Fleischer, 2020; Poncelet et al., 2016), it includes the error made by abstracting processes and phenomena of the real world in a model (abstraction bias). This may relate to the assumption of perfect and equal information of market participants, thus neglecting decision-making under uncertainty or ignoring distortions due to regulatory framework conditions. The obvious solution for bridging the economic granularity gap in this regard relates to the calibration of a model. This calibration may be based on observations of the real world or, if this is not possible, with models that simulate the real world with greater accuracy. A more specific aspect concerning the economic granularity gap reflects the differences between a hypothetical macroeconomic optimum and the entirety of decisions of heterogeneous actors in the real world. This is particularly important in liberalized energy markets under the absence of large integrated energy utilities (Hawker and Bell, 2020), where a multitude of stakeholders and decision-makers, each having diverging levels of knowledge or economic rationale, may lead to significant economic efficiency losses compared with the desired system optimum (aggregation bias).

The aggregation bias is a notable weakness of the above-mentioned ESOMs. Other modeling approaches are more accurate in this regard, but have drawbacks elsewhere. Consequently, model-coupling frameworks are popular for compensating the weaknesses of different modeling approaches. In this context, it becomes obvious that granularity gaps also exist between modeling approaches, so we can study different gaps depending on our reference point. Maintaining the perspective of a partial-equilibrium model, such as an ESOM, an economic granularity gap exists when compared with a macroeconometric model, which describes the entire economy. Studying this "upper economic granularity gap" is a typical research subject in energy economics. For example, this relates to so-called hybrid modeling (Catenazzi, 2009) (realized by coupling bottom-up and top-down models). In this paper, we focus on the less-studied "lower economic granularity gap", which concerns discrepancies between a central, technology-rich planning approach and the microeconomic decision-making of individuals.

1.3. Research questions

Given the existence of the lower economic granularity gap in the context of transforming the energy system, several questions arise. They concern, for instance, the technological composition of desired energy systems (e.g., in terms of the required expansion of energy storage, power grids, or other so-called flexibility services). As shown by Neumann and Brown, diverse system compositions exist near the macroeconomic optimum (Neumann and Brown, 2021). Accordingly, the two research questions to be answered in this study are as follows:

1. Does the economic granularity gap significantly affect system designs that result from an ESOM?
2. If this is the case, how can the economic granularity gap be bridged?

Answering these questions is relevant because, from a central planner's perspective, it would help improve the quality of an ESOM in terms of the plausibility of ideal system designs. From a policy-making perspective, the answers would offer opportunities for evaluating the system-friendliness of regulatory frameworks or incentives. However, both questions come down to one key requirement: the capability to quantify effects that can be summarized as the lower economic granularity gap.

1.4. How to quantify the economic granularity gap?

To quantify the lower economic granularity gap in the context of energy system design, we seek approaches that extend or complement the capabilities of central planning by modeling real-world processes at greater detail in terms of decision-making in liberalized markets. This includes the possibility to influence these processes by the application of policy measures. Data-driven approaches allow such models to be calibrated according to empirical data (e.g., by comparing investment decisions from before and after the liberalization of power markets). Against the background of fundamental changes in the existing energy system (which are poorly reflected by empirical data), we consider data-driven approaches to be insufficient. In other words, they are limited to effects that are assumed to be crucial in energy futures with unprecedented power generation from renewable energy sources. A large spectrum of different model types can simulate liberalized markets with asymmetric behavior, each having strengths and weaknesses. In the field of decentralized electricity markets, several simulation approaches have been established. For instance, System Dynamics is a suitable approach because it enables the modeling of imperfections and allows the dynamic influencing of individuals' decision-making (Teufel et al., 2013). From a technological bottom-up perspective, agent-based models (ABMs) are similar (Macal, 2010). Accordingly, they are useful when considering the bounded rationality of actors and understanding the impact of self-organized actions on the overall energy system (Deissenroth et al., 2017). In contrast to ESOMs, ABMs have no superior, centrally specified objective function and each actor is modeled as a self-interested agent with the aim of maximizing their own utility. This property enables the evolution of the energy system to be simulated, in which agents act autonomously based on their microeconomic interests, but are affected by external factors such as regulatory frameworks. Compared with ESOMs, simulation approaches have several drawbacks. From a microeconomic perspective, estimating the feedback of the overall system to the multitude of individual decisions and anticipating the behavior of other actors becomes very complex. This requires more profound knowledge about actors on the micro-level, and thus, more data. Accordingly, modeling anticipations across a large diversity of actor groups, and particularly decision-making on investments into competing flexibility options, becomes as challenging as stand-alone microeconomic simulation models. The substantial data demand also complicates the development of energy simulation models with broad system boundaries (i.e., for sector-coupling in an international context) needed to draft comprehensive energy system designs.

To conclude, simulation approaches are a valuable building block for quantifying the lower economic granularity gap. However, simulating aspects that are easily modeled in ESOMs (e.g., investments into competing technologies) is somewhat difficult. Therefore, instead of extending existing models to integrate the strengths of other model types, the coupling of both macroeconomic system optimization and microeconomic simulation provides an alternative means of studying the lower economic granularity gap within broad system boundaries. In the literature, such model setups have been applied by Torralba-Diaz et al. (2020), who coupled the ESOM E2M2 with the ABM AMIRIS to investigate the effect of increasing the share of renewable energy sources on the lower economic granularity gap. They demonstrated the suitability of this methodological approach for the analysis of energy policy instruments, and revealed the importance of a harmonized model-coupling setup. Additionally, Torralba-Díaz and her co-authors recommend bidirectional model couplings for studying the impact of policy measures on the granularity gap. Few studies have examined a combination of macroeconomic system optimization and microeconomic simulation to investigate the effects of different policy measures. One example is the study of Fraunholz et al. who used the ESOM ELMOD for multi-regional dispatch optimization and the ABM PowerACE to analyze the long-term effects of splitting the German electricity market into two zones (Fraunholz et al., 2021). Their key result was the negative welfare effect of splitting into northern and southern price zones from benchmarking against a single price zone. Hence, in a very simplified way, this means that market splitting under the assumptions used by Fraunholz et al. contributes to an increase in the lower economic granularity gap.

1.5. Scope and contribution

Granularity gaps in energy system designs are known. However, in the domain of energy system analysis, they are mainly studied with regard to spatial and temporal model dimensions. The economic dimension has been the focus of economic research, where the granularity gap between macroeconometric and partial-equilibrium models is investigated. However, there are few model-coupling frameworks that quantify the biases between central planning and decentralized decision-making in liberalized energy markets using only bottom-up models. Accordingly, this study considers the question of how to implement an optimal overall energy system in an environment with a multitude of decentralized decision-makers. For this purpose, we set up a modeling framework that combines two bottom-up energy system models: (1) a partial-equilibrium model, represented by an ESOM, for designing future energy systems and (2) an ABM for simulating the individual decision-making behavior of market participants. In this way, we combine the strengths of both modeling approaches: the capability of determining the globally required investment decisions across a broad set of technological options ensures mitigation of GHG emissions for a future target year, while the influence of specific policy measures on decision-makers in a market and the impact on optimal energy system design can be investigated. The framework retains a holistic perspective by ensuring a broad technological and spatial scope. Therefore, our analysis focuses on Germany, which is embedded in the European power system, while pan-European power exchange and hourly operation planning of competing load-balancing technologies are optimized, and further energy demand sectors are interfaced. As an example for a specific policy instrument, we investigate dynamic tariffs for photovoltaic (PV)-prosumers.

To summarize, our contributions are as follows:

1. We present a modeling framework based on the coupling of an ESOM and an ABM implemented via automatized and reproducible workflows. This allows the market alignment (Klein et al., 2019) of defined technologies in interaction with a transforming European energy system to be studied.
2. We quantify the lower economic granularity gap in energy system design in terms of changes in system costs and underlying model-endogenous investment decisions induced by the different modeling perspectives. This answers research question 1.
3. We demonstrate and assess the different effects that cause model-specific deviations in system costs starting from a fully harmonized modeling framework.
4. For an exemplary real-world application, we examine how the implementation of frequently discussed instruments (e.g., real-time pricing) influences the economic granularity gap. This answers research question 2.

We do not claim to study all aspects of the economic granularity gap in detail (i.e., uncertainty or distortions due to changing framework conditions).

The remainder of this paper is structured as follows. Section 2 describes how we quantify the economic granularity gap, and briefly introduces the specific energy system models used. Next, we detail the crucial aspects of how to establish and calibrate a stable model-coupling system and introduce our case-study and the underlying assumptions and data, before presenting our results on the influence of actor behavior and, thus, the operation strategy of PV-prosumers on the economic granularity gap. The corresponding evaluations are presented in Section 3 and critically discussed in Section 4. Section 5 concludes this paper. A list of acronyms and abbreviations used in this paper is presented in Appendix A.

2. Methodology

2.1. Overall workflow

The core of our methodology is the coupling of two existing energy system models, i.e., REMix, an ESOM with a geographical focus on Europe and Maghreb (EUMA), and AMIRIS, an ABM of the German electricity market. These models are introduced in Section 2.2. We perform our analysis in four phases. Fig. 1 schematically illustrates these phases and the proposed model-coupling workflow. We prepare the model-coupling setup in phases A and B of the overall workflow. The complete model-coupling workflow is then applied in phases C and D to investigate the case of PV-prosumers. In the following, we give an overview of the proposed workflows, followed by a more in-depth description in Sections 2.3 and 2.4.

In general, our analysis relies on the definition of an observable deviation Δ that allows us to measure a quantity we refer to as the economic granularity gap Δ^{econ}. In Section 2.4, we propose an indicator for quantifying these deviations (i.e., to calculate Δ). The overall workflow begins with the harmonization of both models. In phase A, we configure the models with a set of equal values for parameters that describe the same quantities in order to produce identical results. This means that if AMIRIS is configured with a macroeconomic ideal energy system expansion and system-cost-minimizing storage dispatch (resulting from REMix), the power system operation of both models will be congruent (no deviation, i.e., $\Delta = 0$). Therefore, the techno-economic input data are unified, and the power generation capacities, cross-border power exchange, and dispatch of all storage technologies are fed from REMix into AMIRIS. To select and process the input parameters for AMIRIS, we use iog2x[2] (see Section 2.4.1 for a detailed explanation of the harmonization phase). In contrast to the harmonization phase, where the operation of all storage

[2] iog2x is a Python-based software tool that uses the open-source workflow manager ioproc (Fuchs et al., 2020).

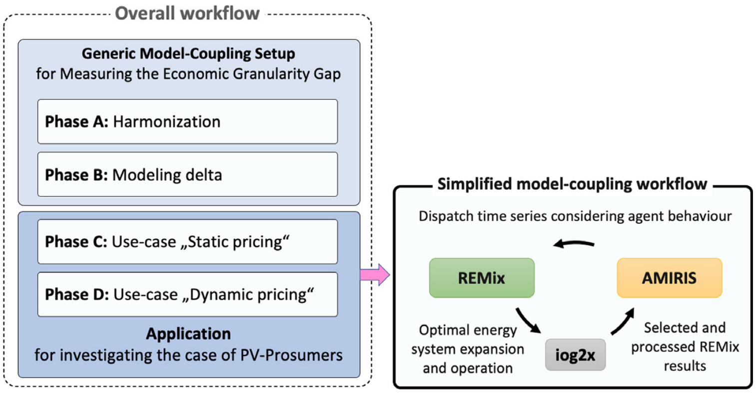

Fig. 1. Schematic overview of the overall and model-coupling workflow. In phase A, both models are harmonized. In phase B, the modeling delta between REMix and AMIRIS is measured. In phases C and D, stakeholder behavior is enabled and different tariffs for prosumers are compared. In the proposed model-coupling workflow (applied in phases C and D), data are exchanged between REMix and AMIRIS through a Python tool called iog2x.

technologies is determined in REMix, phase B optimizes the dispatch of the selected storage technology in AMIRIS. While the storage systems in both models are optimized to minimize the system costs, the resulting deviation is caused by different model implementations of the storage operation in REMix and AMIRIS. In our analysis, we call this deviation the modeling delta Δ^{model}. If Δ^{model} is sufficiently small, we conclude that the Δ observed for the following application of the model-coupling setup mainly represents the economic granularity gap, rather than deviations caused by different real-world abstractions of energy storage ($\Delta^{\text{model}} \ll \Delta^{\text{econ}}$). The derivation of Δ^{model} is further detailed in Section 2.4.2. In phase C, stakeholder behavior is enabled in AMIRIS. For the specific use-case investigated in Section 2.5, this means that instead of minimizing total system costs, storage units mimic actor behavior under current market and regulatory conditions. In particular, AMIRIS simulates PV-battery storage systems in households (PV-prosumers) in Germany. Next, we run REMix for the second time, while constraining the dispatch of the PV-storage system according to the PV-prosumer behavior given by AMIRIS. This allows us to assess the impact of PV-prosumer self-consumption patterns on the optimal system design (i.e., system expansion), and thus on the economic granularity gap ($\Delta \approx \Delta^{\text{econ}}$). How this gap can be influenced is finally demonstrated by exposing the PV-prosumers to different market implementations of dynamic tariffs (phase D). To integrate the required data processing into an automated, executable workflow, the Remote Component Environment (RCE) software is used (Seider et al., 2012).

2.2. Models

This section describes the energy system models used in this study. Table 1 provides an overview of the model scopes and features that are relevant to our methodological approach. Note that the model characteristics listed in Table 1 are limited to their application in this paper.

2.2.1. REMix

REMix is a modeling framework used for setting up ESOMs that optimize the capacity and hourly dispatch of technologies under perfect foresight for one target year by minimizing total system costs. The total system costs are represented by investment (i.e., costs for new renewable power generators, grid and storage technologies) and operational expenditure (e.g., fuel costs). Accordingly, power plants are only built and dispatched if this contributes to a least-cost solution within the operation horizon of one year. The modeled power sector is represented by various power plant technologies, energy storage facilities, and power transmission capacities, and includes the electricity demand for conventional consumers, heat pumps, heat boilers, and electric vehicles. Typical applications of REMix are scenario studies for interconnected countries (Gils et al., 2017). The model input includes techno-economic parameters for each technology, feed-in time series, and potential data for renewable power generation, such as from wind and solar radiation. Besides prescribed and maximal capacities for power generation, storage, and transmission, the costs for CO_2 certificates are part of the scenario dataset (see Section 2.5.2).

2.2.2. AMIRIS

AMIRIS is an ABM that simulates the operational behavior of the actors in the energy-only market with an hourly resolution and uses a merit order model to calculate the electricity prices.[3] In AMIRIS, the power plants offer their generated electricity based on their marginal costs, which are calculated based on power plant-specific techno-economic parameters (such as efficiency and variable costs) as well as fuel and CO_2 prices. Depending on the implemented policy regimes, renewable power generators may be entitled to receive financial support.

Based on information from fossil-fired and renewable power plants, the forecaster agent in AMIRIS provides a prediction of electricity prices for a certain period in the future (e.g., the next 24 h). In the following analysis, we assume that forecasts do not contain any errors. This forecast can then be used by storage operators to optimize the bidding strategy and maximize their utility function. The model setup allows the implementation and strategic optimization of one storage entity. In other words, in our case study (see Section 2.5), one flexibility option is operated according to stakeholder behavior: PV-prosumers (remaining flexibility options mimic the macroeconomic optimal dispatch in REMix). For the purpose of this study, two new agents are modeled and introduced to AMIRIS: prosumers and aggregator agents. The role and functionality of these agents are described in Section 2.5. The structure of AMIRIS and the interactions among agents are schematically illustrated in Appendix B.

[3] A basic version of AMIRIS is open-source. The model developments made in this study are not part of the open-source model at the time of publication. See also Appendix B.

Table 1
Model comparison between REMix and AMIRIS based on the model setups used in this study.

	REMix	AMIRIS
Primary purpose	Planning of large-scale energy systems	Simulation of actors' behavior with limited information
Model type	Linear optimization	Agent-based simulation
Economic scope	System perspective: Central planner minimizes total system cost	Actor perspective: Each actor minimizes its own costs
Temporal scope	One year with hourly resolution	One year with hourly resolution
Spatial scope	Country-specific	Country-specific
Geographical focus	Europe and Maghreb	Germany
Specific features	Investment planning, cross-border power exchange, power sector coupling to heat and transport sector	Actor behavior under different policy regimes

2.3. Model coupling

To perform our analysis, multiple datasets need to be processed and exchanged between REMix and AMIRIS. Depending on the individual phase of our overall workflow, this is done in a unidirectional or bidirectional manner. In the following, we describe the four steps required for bidirectional data exchange in phases C and D of the overall workflow. The unidirectional data exchange in phases A and B require only steps 1–3 of the model-coupling workflow. Note that this model-coupling methodology is independent of the specific use-case analyzed in this paper and can therefore be used to investigate a large variety of policy regimes. Fig. 2 provides a more detailed overview of the corresponding model-coupling workflow implemented in RCE. The advantage of this workflow implementation is that all data processing steps can be executed without specialist knowledge of the models or data processing tools involved.

The model-coupling workflow consists of four data processing steps:

1. The reference energy system (REF) is determined. Therefore, energy system optimization is executed in REMix to provide the optimal expansion and dispatch of power plants, storage technologies, and the electricity grid for a GHG mitigation scenario on the European level. After optimization of REMix, the outputs and input parameters, such as CO_2 and fuel prices, are passed on to iog2x.
2. The iog2x module filters and processes the REMix outputs into AMIRIS inputs. This includes unit conversions, changing data formats, and data aggregation, such as balancing power demand and power exchange time series. We describe the data aggregation process in Section 2.4.1. Appendix C provides a more detailed overview of all technology-specific modifications of the REMix outputs.
   The processed data representing the cost-optimal energy system design are then sent to AMIRIS over a peer-to-peer network connection using RCE.
3. The processed data together with additional parameters that describe the regulatory framework and business model, are used to simulate the electricity market for one year in AMIRIS. In the harmonization phase, the storage agent imitates the determined optimal storage dispatch in REMix. To determine the modeling delta in phase B, the storage agent in AMIRIS minimizes the system costs. In our case study, the AMIRIS market simulation includes PV-storage optimization that minimizes the PV-prosumers' costs.
4. In the last step, we pass the time-series back to REMix. The energy system is then optimized for a second time, with the dispatch of selected technologies constrained according to the AMIRIS results. Regarding the specific case study of this paper (see Section 2.5), we fix the charging and discharging profiles[4] of the batteries that belong to German prosumers with the PV-storage dispatch obtained by AMIRIS. In doing so, we ensure that the corresponding storage technology in REMix reflects the PV-prosumer stakeholder behavior derived from AMIRIS. Concerning generation and storage expansion, the capacity values are directly prescribed according to REF for all regions except that for which dispatch is constrained.

2.4. Setup for measuring the granularity gap

In this section, we describe the measures necessary to achieve a modeling setup that can quantify the economic granularity gap. In particular, we perform model harmonization and measure what we refer to as the modeling delta.

2.4.1. Harmonization

Harmonization requires that, for a certain set of identical input parameters, both involved models produce identical results. However, this is only possible in the absence of model-specific features. Accordingly, in phase A of the overall workflow, the power plants in AMIRIS bid at their marginal costs, and the dispatch of storage systems resembles that from REMix. Furthermore, influences that stem from unequal technological and geographical scopes need to be treated. In particular, this translates into balancing the hourly demand time-series that is input to AMIRIS to consider technologies that are not simulated there. Based on the REMix outputs for Germany, D_t^{total} is calculated as follows:

$$D_t^{total} = D_t^{conv} + D_t^{hp} + D_t^{eBoiler} + D_t^{eCars} + E_t^{export} - E_t^{import} + Z_t^{C,stor} - Z_t^{D,stor} + L_t^{trans}, \forall t, \quad (1)$$

where D_t^{conv} represents the electricity demand of conventional consumers and D_t^{hp}, $D_t^{eBoiler}$, and D_t^{eCars} represent the power consumption of heat pumps, electric boilers, and electric vehicles, respectively. Moreover, electricity imports to Germany E_t^{import}, and the discharging of storage technologies, $Z_t^{D,stor}$, are deducted, whereas electricity export from Germany, E_t^{export}, charging of storage technologies, $Z_t^{C,stor}$, and power transmission losses, L_t^{trans}, are added to the total hourly electricity demand of Germany. Due to the different representations of storage self-discharge in AMIRIS and REMix, this feature is deactivated in both models, i.e., we neglect self-discharge in all storage technologies. Due to the very low self-discharge rate and short charge cycle (less than one day) of the PV-storage systems, this assumption does not significantly impact the results.

To achieve successful harmonization, two indicators that can be directly obtained from the model outputs are useful: electricity prices and costs. The former is the more intuitive choice, but different mechanisms for determining wholesale market electricity prices with REMix and AMIRIS render a direct comparison difficult.[5] Although an appropriate model configuration would allow

[4] In other words, we set the lower and upper bounds of the storage optimization variables, i.e., hourly amounts of charged and discharged electricity, equal to a fixed value.

[5] To derive the electricity prices in REMix, the dual variables of the power-balance constraint (so-called shadow prices) are used. However, this common

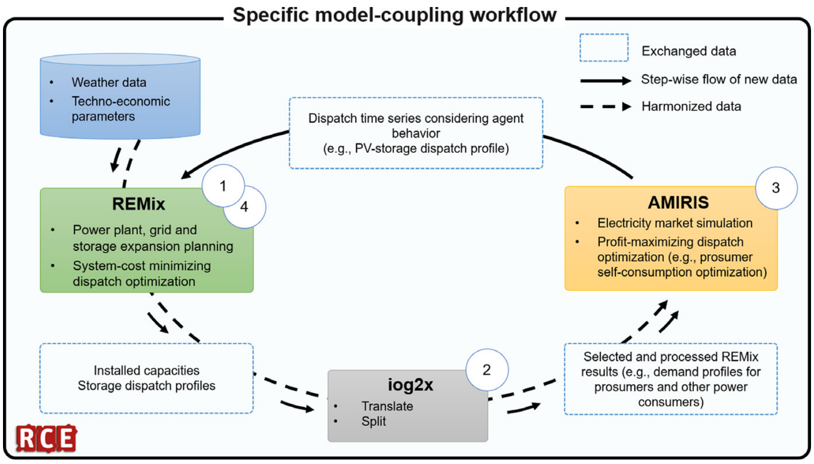

Fig. 2. Data exchange during model-coupling of REMix and AMIRIS. Step 1: Energy system optimization in REMix to determine the REF. Step 2: Filtering and processing the REMix outputs for AMIRIS simulation. Step 3: Electricity market simulation in AMIRIS based on the REF energy system design. Step 4: Second round of energy system optimization in REMix while constraining the dispatch of the selected technologies according to AMIRIS results.

the model harmonization to be assessed, numerical issues still complicate a meaningful comparison. In particular, these issues can be traced back to the non-differentiability of the merit-order curve. Considering a vertical demand curve, the price cannot be precisely determined for supply amounts that lie at the transition between two price levels. At this point, minor numerical differences in demand can cause significant differences in the resulting electricity prices. Unlike the prices, the value of the operational system costs, represented by the area under the price curve, is insensitive to these complications. For this reason, we evaluate the operational system costs of our models instead.[6]

2.4.2. Modeling delta

In phase B of the overall workflow, we determine the modeling delta Δ^{model}. In general, we define the modeling delta as the deviation between results from REMix and AMIRIS that cannot be treated by harmonization. In other words, it is the difference between operational system costs if the dispatch of energy storage is modeled individually in both REMix and AMIRIS (even if storage agents still aim to minimize system costs in AMIRIS).[7] In this phase of the overall workflow, our target is to keep Δ^{model} as small as possible, which calls for additional adjustments of our model-coupling setup. This relates to the reference quantity of a storage component's capacity.[8] To resolve the corresponding discrepancies, the REMix source code adapts the constraints for the capacity cap and storage-balancing so that the converter and storage capacities in REMix represent chemical or potential values, similar to AMIRIS. Additionally, the storage level in REMix is fixed to zero for the last time step of the operational time horizon. This is to replicate the behavior of the storage in AMIRIS, which sees no economic advantage in stored energy at the end of the operation period.

When it comes to modeling energy storage technologies, a further aspect is crucial: the storage operators in AMIRIS use a forecast of the upcoming market prices to optimize the storage dispatch. However, in this model, the competition among storage systems is neglected, meaning that one operator does not anticipate the strategy of other operators. Thus, exposing more than one flexibility option to the same electricity market forecast leads to an overreaction of the storage entities. This model artifact, which is referred to as the avalanche effect in the literature (Ensslen et al., 2018), results in extreme price peaks. Hence, we optimize the operation of only one storage system in AMIRIS and fix the dispatch of all other storage technologies according to the results of REMix.

Nevertheless, the operational system costs vary between the models. The final modeling delta comprises several effects: REMix operates storage technologies with variable costs and has perfect foresight over the whole modeled year, whereas AMIRIS does not consider variable costs for a storage agent's business model. In contrast to REMix, the operation foresight horizon is limited to 48 h, and (dis-)charging is modeled for discrete storage levels.

2.4.3. Granularity gap indicator

As mentioned before, we measure the economic granularity gap in terms of total system costs. The total system costs consist of all expenses for electricity supply in one year of a future scenario, which includes both operational costs (C_k^{OPEX}) and amortization charges (C_k^{CAPEX}) for investments in new infrastructure. Accordingly, we measure Δ^{model} and Δ^{econ} by comparing the total system costs for REF in REMix C_1 (step 1 of the model-coupling workflow, see Fig. 2), with C_4, which is observable after constraining REMix according to the results from AMIRIS in step 4 of the model-coupling workflow:

$$\Delta = C_4 - C_1. \tag{2}$$

The total system costs C_k in step k of the model-coupling workflow are composed of

$$C_k = \underbrace{C_k^{fuels} + C_k^{O\&M} + C_k^{CO_2}}_{=C_k^{OPEX}} + C_k^{CAPEX}, \ \forall k \in \{1, 4\}. \tag{3}$$

interpretation of shadow prices is distorted if the costs for storage operations or capacity expansion are considered in the energy system optimization. A consequence of this circumstance would be additional price levels in the resulting merit-order, which do not formally occur in the real market. In contrast, AMIRIS correctly models the price-building procedure, and thus the merit-order based on individual bids in the day-ahead market.

6 Note that the compared operational system costs for the harmonization of the models are only one part of the total system costs. As we will explain in Section 2.4.3, we use the total system costs as an indicator for quantifying the economic granularity gap.

7 Hence, in phase B, $Z_t^{D,stor}$ and $Z_t^{C,stor}$ are no longer considered in Eq. (1) for the storage technology modeled in AMIRIS.

8 Initially, the capacities of both power converters (e.g., pumps and turbines) and storage (e.g. a water basin) are provided in terms of electricity in REMix. This is not the case for AMIRIS, where converter and storage capacities refer to their chemical or potential values. As the charging and discharging capacities are identical in both models, they cannot be harmonized if one model considers electrical and the other chemical/potential values.

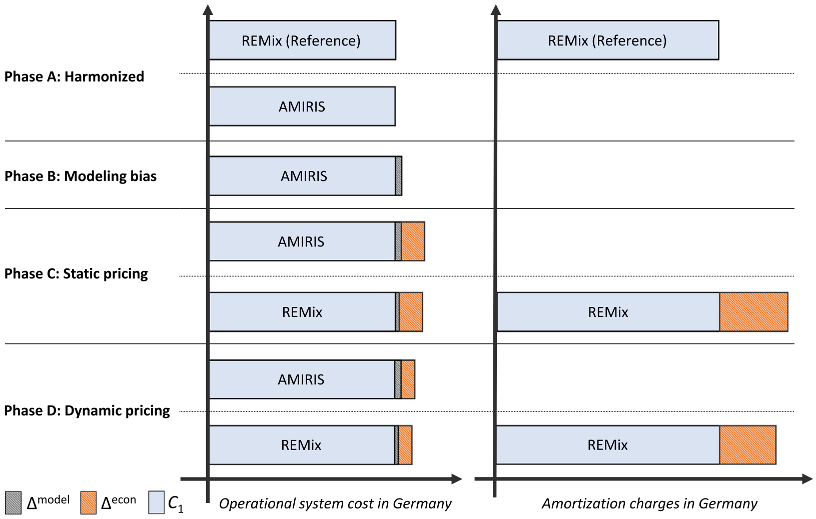

Fig. 3. Schematic overview of qualitative system cost relations: System costs of the reference energy system (C_1, blue bars), the modeling delta (Δ^{model}, gray bars), and the economic granularity gap (Δ^{econ}, orange bars) in the different phases of the overall workflow. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The operational system costs, C_k^{OPEX}, comprise the costs for fuel C_k^{fuels}, operation and maintenance (O&M) costs of the power system components $C_k^{O\&M}$, and costs for emission allowances $C_k^{CO_2}$. Fig. 3 illustrates the different cost components for each phase of our overall workflow. While the operational system costs in AMIRIS and REMix are equal in the harmonization step, a modeling delta (Δ^{model}, shown in gray) can be observed in phase B. The prosumer operation strategy in phases C and D of the overall workflow increases the operational system costs and amortization charges in Germany, resulting in the economic granularity gap (Δ^{econ}, shown in orange).[9]

2.5. Case study

The model-coupling setup is now ready to be applied. Therefore, we consider the battery storage used to moderate the intermittency of the power supply from rooftop PV as the technology to be investigated. In other words, given the successful completion of phases A and B in the overall workflow, we are ready to quantify the impact of stakeholder behavior on energy system design for one particular technology.

2.5.1. PV-prosumers in Germany

The levelized cost of electricity from PV systems has fallen below the retail electricity price in many countries worldwide, a development that has incentivized investment in PV rooftop systems for many households (Lang et al., 2016; Bazilian et al., 2013). Similar to PV systems, battery storage has experienced a significant reduction in system prices. Several studies indicate that this trend will continue in the next few years (Agnew and Dargusch, 2015). As a result, storage systems for rooftop PV (PV-prosumers) have become economically viable for households under certain support schemes and generation potentials (Hoppmann et al., 2014; Bertsch et al., 2017). The available storage capacity gives PV-prosumers the flexibility to store electricity at specific times (e.g., when self-generated PV electricity exceeds the electricity demand or when grid electricity is cheap) and discharge it at later times (e.g., to cover the electricity demand or sell to the grid) (Sarfarazi et al., 2023).

From an overall systems perspective, self-consumption with PV-storage systems is neither desirable nor detrimental (Günther et al., 2021). While the flexibility of PV-prosumers can contribute to the integration of renewable energies, current business models and regulatory frameworks are unable to incentivize a system-beneficial dispatch of PV-prosumers (Sarfarazi et al., 2020; Klein et al., 2019). Moreover, to untap the potential of the residential demand-side flexibility, an entity should undertake the aggregation of the small prosumer capacities (Plaum et al., 2022). Therefore, we investigate how the operation of aggregated PV-prosumers leads to an economic granularity gap under the current regulatory framework and business models in Germany, and how it could be decreased. Accordingly, assessing alternative policy instruments is part of our analysis.

Next, we introduce the energy scenarios and input data used in our case study (Section 2.5.2). In Section 2.5.3, we describe the investigated business models and regulatory framework for two different use-cases: static pricing (phase C of the overall workflow) and several implementations of dynamic pricing (phase D). How PV-prosumers are modeled in AMIRIS is discussed in Section 2.5.4.

2.5.2. Scenarios, input data, and modeling assumptions

The starting point for our analysis is a dataset of the European power system from the year 2020 and the aim for GHG mitigation of 55% compared with 1990. The REMix inputs are based on a previous study by Cao et al. (2020), where the corresponding scenario is referred to as "55% Base: Trend". However, instead of a CO_2 cap, we apply penalties to achieve the emissions reduction target. Therefore, a price of 50 euros per ton of CO_2 is assumed.[10] While the energy system optimization is conducted for EUMA on a national level, the electricity market simulation and the model coupling are carried out for Germany only. According to this scenario, system planning comprises the capacity expansion of wind turbines, PV, pumped-hydro storage, lithium-ion batteries

[9] Note that, for a simple illustration, the operational system cost differences caused by the modeling delta and the economic granularity gap are stacked in this figure. This might not be the case in reality.

[10] In our scenarios, the focus is on the power sector. The study by Cao et al. (2020) shows that, within this model setup, a CO_2 price of 50 euros per ton can achieve GHG mitigation of 55% in the power sector.

and power transmission lines. In addition, the current model setup considers a technology split for both lithium-ion batteries and PV to distinguish rooftop PV with and without storage, utility PV, and stand-alone stationary battery storage, each of which has individual techno-economic parameters. For Germany, this means that the scenario's minimal total generation capacity of PV (46.8 GW) comprises 34.9 GW rooftop PV, which is equally split and assigned to systems with and without storage. In the following, we refer to former as "PV-prosumers". In considering their capacity expansion in REMix, we assume a fixed capacity ratio between PV generators and battery power (factor 2), and for the energy-to-power-ratio of the battery (factor 3).[11] Furthermore, the electricity demand is split to distinguish between PV-prosumers and other power consumers:

- **Aggregated prosumers** (AP) consist of virtually aggregated PV-prosumer households whose hourly power consumption is calculated using typical household demand profiles. These are scaled by the annual electricity demand of PV-prosumers. The former come from a dataset containing measured load profiles of 74 different German households (Tjaden et al., 2015). The annual electricity demand D_t^{AP} is estimated by assuming that a household with an annual demand of 750 kWh installs 1 kW of PV rooftop capacity. Accordingly, the total value for Germany depends on the resulting capacity expansion of rooftop PV systems in step 1 of the model-coupling workflow.
- **Other power consumers** (OPC) represent all electricity demand except that of AP. This includes PV-rooftop systems without integrated battery systems. Accordingly, we calculate the electricity demand by subtracting the electricity demand of the prosumers D_t^{AP} from the total electricity demand of Germany D_t^{total}:

$$D_t^{OPC} = D_t^{total} - D_t^{AP}, \forall t. \tag{4}$$

  In other words, in contrast to model harmonization (phase A of the overall workflow), data for the prosumer systems are treated separately in AMIRIS.

Moreover, we assume that conventional and renewable power plants always bid with their marginal costs, i.e., no mark-ups or mark-downs for conventional power plants and no feed-in incentives for renewable power plants, except for PV-prosumers. Moreover, as mentioned above, large-scale storage systems (e.g., pump storage systems) have the system-optimal dispatch calculated in REMix. Regarding prosumer self-consumption, we consider complete relief from regulatory-induced charges for behind-the-meter use of self-generated electricity.

2.5.3. Use-cases under investigation

In this section, we define the use-cases for phases C and D of our overall workflow. In phase C, the electricity retail price (p_t^s) and the price of purchasing electricity from prosumers (p_t^p) are fixed over a year. In this case, p_t^p adopts the value of the feed-in remuneration (FiT). Taxes and levies, which make up over 70% of the retail electricity price in Germany, are fixed over a year and do not include any time-varying component. This static pricing approach is referred to as the business-as-usual (BAU) use-case. Accordingly, the retail electricity price can be written as

$$p_t^s = (p_t^{elec} + r + p^{tax} + p^{nc} + p^{lev} + p_t^{eeg}) \cdot (1 + VAT), \tag{5}$$

where p_t^{elec} is the cost of acquiring electricity, r is the aggregator's profit margin, p^{tax} are the associated taxes, p^{nc} are the volumetric network charges. p_t^{eeg} and p^{lev} are respectively levies to support the renewable energy feed-in (according to the German renewable energy act, EEG[12]) and other mechanisms. VAT is the value-added tax.

Table 2
Regulatory framework and business model parameters.

Parameter	Symbol	Value	Source
Taxes [¢/kWh]	p^{tax}	2.05	BDEW (2022)
Network charges [¢/kWh]	p^{nc}	7.65	BDEW (2022)
EEG levies [¢/kWh]	p_t^{eeg}	3.72	BDEW (2022)
Other support levies [¢/kWh]	p^{lev}	4.1	BDEW (2022)
Value added tax [%]	VAT	19	BDEW (2022)
Feed-in remuneration [¢/kWh]	FiT	7.69	BSW (2021)
Market price upper cap [¢/kWh]	$\overline{p^m}$	30	o.a.[a]
Aggregator's profit margin [¢/kWh]	r	2	o.a.
Scaling factor in RTP tariff [–]	κ	0.88	o.c.[b]
Scaling factor for $vFiT$ [–]	θ	1.28	o.c.
Scaling factor for dEEG [–]	ι	0.53	o.c.

[a]Own assumption.
[b]Own calculation (see Appendix D).

In phase D of the overall workflow, we study different levels of dynamism in the retail and purchase electricity prices via real-time pricing. The basic idea behind this is that p_t^p or certain components of p_t^s follow the fluctuating market prices and therefore, the demand and supply in the market to better align the distributed decisions made by PV-prosumers. Based on suggestions discussed in the literature, the following instruments are considered:

1. Real-time pricing (RTP) (Hogan, 2014). The resulting dynamic prices include variable procurement costs (p_t^{elec}), which are proportional[13] to the electricity wholesale prices.
2. Variable feed-in tariff (vFiT) (Ossenbrink, 2017; Klein et al., 2019). This instrument denotes remuneration for PV electricity feed-in proportional to the wholesale prices.
3. Dynamic EEG levy (dEEG) (Economics and BET, 2016; Freier et al., 2019). The EEG levy (p_t^{eeg}) in this instrument varies hourly according to the market prices.[14]

For these dynamic instruments, the values of p_t^{elec}, p_t^p, and p_t^{eeg} are determined such that their cumulative monetary effect over the course of a year compared with the static equivalent for a benchmark user is zero (i.e., the instruments do not affect the annual cost or revenue of a benchmark user). The choice of benchmark users and the calculation of the used scaling factors for this calibration, κ (for RTP), θ (for vFiT), and ι (for dEEG), are explained in Appendix D. The assumed values for the parameterization of the electricity tariffs are given in Table 2.

Considering the introduced instruments and their combinations, in addition to BAU, we build three use-cases with the naming conventions given in Table 3. For example, the instrument mix of RTP and vFiT would be called "RTP + vFiT".

2.5.4. PV-prosumer modeling in AMIRIS

As explained in Section 2.5.2, we assume that all PV-prosumers in AMIRIS are virtually aggregated to a single agent. An aggregator is responsible for managing the electricity load and feed-in of PV-prosumers. The aggregation of prosumers without PV-storage

[11] This means, for instance, that a PV-prosumer with a 10 kWp PV system is equipped with 5 kW battery power and 15 kWh battery storage.

[12] Based on the German government' decision, the EEG levy was eliminated recently to lower the cost burden of power consumers.

[13] Read as: wholesale market price times a constant.

[14] Despite the omission of the EEG levy, this instrument is still relevant as it can be applied to other regulated elements of the retail electricity price.

Table 3
Naming convention of the use-cases under investigation.

Use-case	RTP	vFiT	dEEG
BAU	–	–	–
RTP	✓	–	–
RTP + vFiT	✓	✓	–
RTP + vFiT + dEEG	✓	✓	✓

Table 4
Cost components of the EUMA and GER in the Reference energy system.

Cost component	Cost–EUMA [B€]	Cost–GER [B€]
CAPEX	114.73	3.07
O&M cost	27.86	0.55
Fuel cost	18.94	2.57
CO_2 cost	8.19	2.85

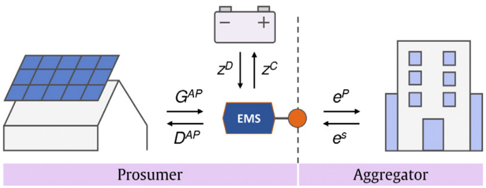

Fig. 4. Schematic overview of the prosumer's model.

systems and using community energy storage systems instead has already been investigated with AMIRIS (Safarazi et al., 2020). For the current analysis, we further develop the aggregator and prosumer agents as follows:

Aggregator: The aggregator agent receives a forecast of the upcoming market prices and related policy-related information, such as electricity price elements induced by the government. Based on the chosen instrument, the aggregator agent creates and sends two sets of prices, i.e., retail and purchase prices (p^s and p^p), to the prosumers. Note that the market price forecasts are generated based on the electricity demand and generation of all market actors except the prosumers.

Prosumer: This prototype agent represents an aggregated PV-prosumer entity[15] with a conventional household load, generation from a PV rooftop system, and battery storage system. In reaction to the aggregator price signals, the PV-prosumer uses a dynamic programming approach to optimize the dispatch of the PV-storage system. Fig. 4 schematically illustrates the virtual power flows in the PV-prosumer model and between the PV-prosumer and aggregator. The prosumer's electricity load and generation are managed by an energy management system (EMS), which determines the amount of battery charge (z^C) or discharge (z^D) as well as grid usage (e^s) and grid feed-in (e^p) on an hourly basis according to the prosumer's generation (G^{AP}) and demand (D^{AP}). In Appendix E, we provide a more detailed explanation of the mathematical model employed for prosumer storage optimization.

3. Results

3.1. Model harmonization and modeling delta

In phase A of the overall workflow, AMIRIS does not operate any PV-storage and adopts the optimized dispatch of its counterparts in REMix. The hourly sum of all discrepancies in operational system costs between REMix and AMIRIS is 26 800 € for Germany, which (considering overall German operational system costs of around 5.96 B€) corresponds to a relative deviation of 0.00045%. The root-mean-square error is 1900 €. With this marginal difference, we consider the models to be harmonized and phase A to be complete.

[15] The model can also be parameterized for individual prosumers. Due to computational impracticality and lack of data, we consider an aggregated prosumer entity.

To calculate Δ^{model}, PV-prosumers operate such that operational system costs are minimized by AMIRIS (phase B).[16] The annual sum of the hourly differences between the operational costs of the first and third steps of the model-coupling workflow is $\Delta^{\text{model}} = 899\,300$ €. The corresponding root-mean-square error is 13 500 €. In other words, due to the modeling delta, our indicator for measuring the granularity gap increases by 0.015% compared with the reference energy system[17] (see Fig. 3). This indicates that the modeling delta is negligibly small.

3.2. Economic granularity gap

In this section, the economic granularity gap is quantified for the case of PV-prosumers in the German electricity market. The indicator used is the difference in total system costs (see Section 2.4.3). We distinguish the system costs for two spatial scopes: (i) EUMA and (ii) Germany (GER). Therefore, based on Eq. (2), the economic granularity gap to be observed in this case-study is

$$\Delta^{\text{econ}}_{c,s} = C_{c,s} - C_{\text{REF},s}, \quad \forall c \in \{\text{BAU, RTP, RTP+vFiT, RTP+vFiT+dEEG}\}, \quad \forall s \in \{\text{EUMA, GER}\}, \tag{6}$$

where c is the set of studied use-cases and s is the spatial scope. $C_{c,s}$ represents the total system costs considering the stakeholder behavior of PV-prosumers and $C_{REF,s}$ is the total system costs for the cost-minimal reference energy system design (REF) (step 1 of the model-coupling workflow, see Fig. 2). By considering EUMA as well as GER, we can differentiate between the impacts of the instruments on the overall and German energy systems. The tariffs are only applied in Germany. However, by modeling the whole EUMA region, we can consider the electricity grid and observe changes in imports and exports. This allows us to analyze the German energy system in a more dynamic setup.

In general, high retail electricity prices in comparison to feed-in remunerations make self-consumption of electricity profitable. However, in the BAU use-case, this self-consumption is scheduled independently from market signals. Therefore, it is likely that the system operation deviates from the macroscopic cost minimum of REF, which may also affect the optimal energy system design. In contrast, introducing instruments such as RTP, vFiT, and dEEG increases the alignment of the operations of PV-prosumers, and should thus decrease the economic granularity gap.

Table 4 lists the cost components on the EUMA level and in Germany for REF. The macroeconomic optimum is at 169.71 B€ of total system costs in REF. For Germany, system costs comprise 0.55 B€ for O&M of the power system, with 2.57 B€ and 2.85 B€ of fuel and CO_2 costs, respectively. Amortization charges (CAPEX) for additional power system components are 3.07 B€.

[16] Note that the modeling delta is determined between REMix (REF) and AMIRIS, but it finally affects the economic granularity gap measured against a second energy system optimization with REMix. Therefore, we estimate an upper bound for the modeling delta because, even if constrained to the AMIRIS output, the operational system costs observed in step 4 of the model-coupling workflow can be further minimized in REMix, e.g., by re-dispatching storage technologies other than PV-prosumers.

[17] If the optimized PV-prosumer dispatch from AMIRIS is implemented in REMix, CAPEX increases by 128 000 €, corresponding to an increase of 0.0042%, and OPEX increases by 54 000 €, an increase of 0.00091%.

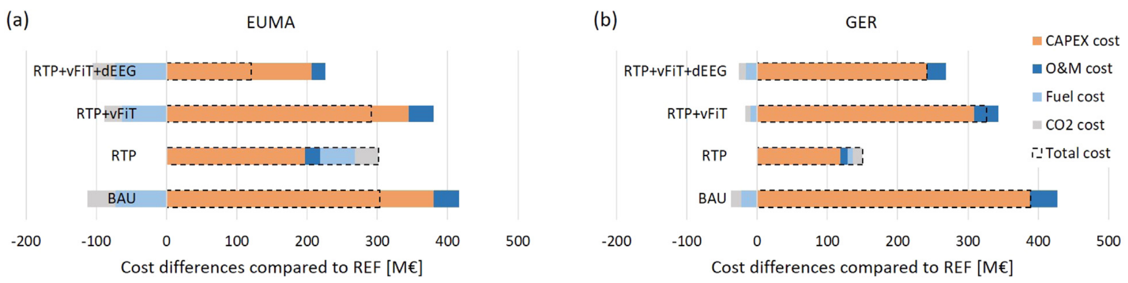

Fig. 5. Differences in the cost components of EUMA and GER compared with REF for different tariff options. In the BAU scenario, the cost increase in Germany is the highest at almost 400 M€. With the RTP tariff, the additional investment cost decreases in Germany by around two-thirds, shifting costs abroad. With a more flexible vFiT the additional costs in Germany increase, while the overall system costs decrease.

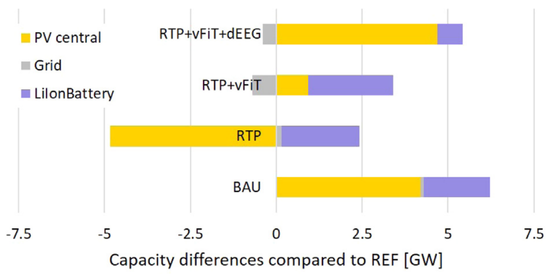

Fig. 6. Capacity differences in GER compared with REF for different tariff options. The BAU scenario leads to the highest additional capacities in GER. In the RTP scenario, the capacity of central PV decreases significantly. With an additional vFiT, the capacity of the grid decreases. The additional flexibility of the EEG results in comparably low additional lithium-ion battery capacities.

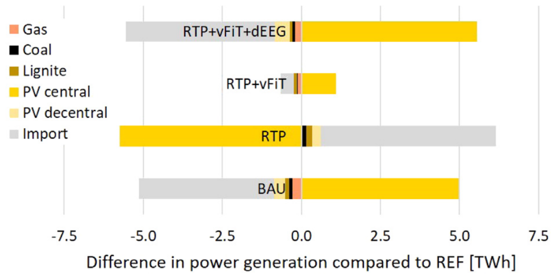

Fig. 7. Differences in power generation in GER compared with REF for different tariff options. In the BAU and RTP+vFiT+dEEG scenarios, the power generation of central PV increases significantly, leading to less power generation and imports from abroad. In the RTP+vFiT scenario, the power generation shifts slightly to Germany. With the RTP tariff, the central PV power generation decreases significantly in Germany, resulting in additional imports from abroad.

Fig. 5(a) shows the economic granularity gaps for the EUMA scope, and thus, the cost components and total system costs in the overall energy system compared with REF. As the power generation and storage capacities are similar to REF in all countries but Germany (see Section 2.3), the relative changes in total system costs on the EUMA level are rather low. However, differences can be observed depending on the tariff implemented for PV-prosumers: higher flexibility of the prosumer tariff produces a smaller economic granularity gap on the EUMA level. For BAU and RTP, similar additional system costs can be observed, while introducing a variable feed-in-tariff leads to a marginal improvement in RTP+vFiT. The additional implementation of dynamic EEG has a rather strong influence on the economic granularity gap. RTP+vFiT+dEEG reduces the deviation of system costs significantly.

For a better understanding of the impact of PV-prosumer behavior on energy system design in Germany, Fig. 5(b) illustrates economic granularity gaps for the German scope and thus, the cost components in Germany compared with the least-cost REF. In all use-cases, the energy system design changes in a way that increases investment costs, which dominates the effect on the total system costs. As expected, this is striking in BAU, where additional investment costs are at 428 M€. In particular, Fig. 6 shows that the economic granularity gap is mainly visible in the form of an additional need for stationary lithium-ion battery capacity in Germany and, for all use-cases but RTP, utility PV. The installed capacities in Germany in the REF are listed in Table F.1.

In general, the above results indicate that, in the case of PV-prosumers, the economic granularity gap is mainly driven by the nonaligned, and thus, inflexible operation of the associated PV-storage systems. They do not fully exploit their capability to balance power supply and demand. This is underestimated in the optimal energy system design of REF, which ignores PV-prosumer behavior. Therefore, the resulting inflexibility needs to be balanced by further installations of technologies having the same capabilities. However, with a sufficiently dynamic electricity retail tariff and feed-in remuneration, and with additional energy storage capacity, the granularity gap in Germany can be reduced, e.g., down to 242 M€ in the RTP+vFiT+dEEG case. If the share of dynamic price components in the prosumer tariff becomes larger, such as in RTP+vFiT+dEEG, the need for temporal energy balancing in the form of lithium-ion batteries is minimized (+0.7 GW compared with REF) and the need for spatial energy balancing is reduced. This is even more significant for RTP+vFit, where the grid transfer capacity between Germany and its neighbors is reduced by 0.7 GW compared with REF.

As shown in Fig. 5(b), RTP gives the smallest economic granularity gap for Germany due to considerably lower investments in additional power generation and storage capacity. Fig. 6 illustrates that considering RTP[18] causes a displacement of 4.9 GW of utility PV compared with REF. However, carbon emission costs decrease across all use-cases except RTP. The reason is that, in the RTP use-case, the cost savings observed for Germany are compensated by shifting power generation to other countries. Although the additional costs in Germany decrease with the RTP tariff compared with the BAU tariff, the additional costs in EUMA are almost the same, indicating higher additional costs abroad. This becomes evident when looking at Fig. 7, which shows the changes in power generation in GER compared with REF. The power generation in REF is listed in Table F.2. Given the significant additional imports of about 5.5 TWh for RTP, it becomes clear that the missing

[18] According to our methodology, only in the German electricity market.

solar power is mainly compensated by both greater renewable and fossil-fired power generation outside Germany. This leads to the most extensive GHG emissions across the analyzed use-cases, even at the EUMA scope, with 33 M€ for additional CO_2 emission allowances compared with REF. At the same time, while the additional costs of the German energy system decrease with the RTP tariff, Germany's import dependency increases.

Furthermore, Fig. 7 shows that BAU and RTP+vFiT+dEEG are very similar in terms of power generation: the power generation from utility PV increases significantly, while imports from abroad decrease and less fossil-fired power plants are operated, both in Germany and abroad, leading to lower fuel and CO_2 costs, as indicated in Fig. 5. However, due to the more efficient usage of PV-storage systems in the RTP+vFiT+dEEG use-case, a decrease in imports to Germany can be achieved with less infrastructure in the form of additional lithium-ion battery capacity.

4. Discussion

4.1. Results summary

Our case-study has quantified the economic granularity gap that arises, from a central planner's perspective, when stakeholder behavior is considered in the optimization of large-scale energy systems. In particular, we studied the case of PV-prosumers aiming to optimize the dispatch of PV-storage systems at the household level in Germany. Under the actual pricing regime, which we refer to as BAU, we observed an economic granularity gap in Germany represented by an increase of 389 M€. To put this into context, designing future energy systems with an optimization model implies an underestimation of costs, whereas the absolute value of 389 M€ is rather interesting from a technical point of view. However, the novelty of our study is that we were able to quantify these costs, which are usually hidden if stakeholder behavior is ignored. In addition, we studied the influence of different prosumer tariffs, which are supposed to increase the alignment of PV-prosumer dispatch decisions according to price signals from the electricity market. We showed that a larger share of dynamic components in electricity retail prices and feed-in remunerations results in lower additional total system costs at the overall system level. Accordingly, the economic granularity gap could be reduced. In the case of variable procurement prices (RTP use-case), the additional cost in Germany decreases to 150 M€, but at the cost of increasing GHG emissions and additional power generation outside Germany, resulting in a higher import dependency.[19] In contrast, for a prosumer tariff that additionally considers variable feed-in-tariffs and a dynamic EEG levy (RTP+vFiT+dEEG use-case), we observed a very similar annual electricity mix as in BAU. However, this could be realized with less investment, and thus at lower total system costs, while also decreasing GHG emissions.

In summary, replacing the static components of the prosumer electricity prices with time-varying elements that contain signals from the wholesale market reduces the total system costs at the overall system level. Looking at Germany, considering only system costs may provide an incomplete picture. Therefore, additional factors such as power exchange with neighboring countries need to be considered when quantifying the economic granularity gap.

[19] In this particular case, a greater utilization of fossil-fired power plants and purchasing emission allowances at 50 €/t turned out to be more cost-efficient than greater investment in new PV plants.

4.2. Limitations

One limitation of our modeling setup is the isolated consideration of stakeholder behavior for a single electricity market (Germany) and solely for one technology. This limits the scope for studying the economic granularity gap from an overall system perspective and causes inaccuracies. In particular, when evaluating system costs in Germany, the profits and expenses of power exchange are not considered because they cannot be directly derived from REMix, which calculates the total system costs across Europe and Maghreb. Additionally, it is clear from the relative cost deviations that the granularity gaps are rather low compared with the absolute total system costs. This effect is a consequence of our methodology, where expenses for power plants and storage outside Germany cannot be changed after determining the reference energy system. In this way, we consider policy instruments to be solely implemented for individual countries. This severe limitation of the solution space fosters more significant changes in the German energy system caused by stakeholder behavior. In our study, this refers to investments in technologies, which are directly affected by the dispatch decisions of PV-prosumers' lithium-ion batteries. Accordingly, further improvements in the context of quantifying the economic granularity gap require the consideration of stakeholder behavior for more than one decentralized actor, necessitating more technologies in the market. This includes the optimization of diverse storage technologies, each of which is suitable for a specific system need.

4.3. Policy implications of the case-study

The implementation of retail prices with dynamic components based on perfect forecasts of wholesale market prices is still largely hypothetical. Despite the associated simplifications, the results of our case-study provide valuable insights into the system impacts of different implementation levels of dynamic pricing instruments for prosumers. In this context, we conclude that dynamic electricity tariffs and remuneration schemes are not a "system-friendly" policy instrument by default. Against our expectations, the total system costs in Germany did not alter consistently with the increasing market alignment of PV-prosumers. Whether dynamic pricing mechanisms are beneficial depends on the specific implementation (i.e., which price components are dynamic) and also where it is introduced. Therefore, we can confirm that the desired effects are possible in terms of both reducing GHG emissions and the need for energy infrastructure. Concerning the observed additional GHG emissions in one of our use-cases, we recommend further research to cross-check our findings with sensitivity analysis of CO_2 costs.

In this context, our results show that replacing more than one component of the electricity retail price with time-varying elements significantly increases the effectiveness of the instrument. However, the remaining distortions caused by other static taxes and levies prevent complete alignment of the prosumer operation with the electricity market, and so complete elimination of the economic granularity gap is not achieved (these findings are similar to the results of Klein et al. (2019) and Sarfarazi et al. (2020)). The implementation of other instruments, such as fixed network charges (Borenstein, 2016), that reduce the share of fixed volumetric components of the electricity retail price may further improve the system impacts of prosumer operations. Moreover, for the "system-friendly" operation of prosumers, besides fluctuations in wholesale market prices, the condition of the physical infrastructure, e.g., congestion in the distribution grid, should also be signaled to the prosumers.

5. Conclusion and outlook

How can a climate neutral overall energy system be implemented in a society with a multitude of decentralized decision-makers? This was the overall research question that motivated the study described in this paper. As an extension to existing research in energy system analysis, we have introduced different economic perspectives with regard to the transformation of large-scale energy systems that affect the potential gains from model-based analyses on energy system design. In particular, we applied the energy system optimization model REMix and the agent-based electricity market model AMIRIS to explore different economic perspectives. We described the economic granularity gap as a metric for bringing these two perspectives closer together. In general, this approach was useful in identifying effective policy measures in terms of system-friendliness. From a technical point of view, we set up an automated and reproducible modeling workflow by coupling the energy system models in a bidirectional manner. This technical implementation is an essential novelty compared with the state-of-the-art. We demonstrated the usefulness of this formulation in a case-study for PV-prosumers, providing an example of how unaligned stakeholder behavior affects energy system designs provided by ESOMs.

In the case-study, we analyzed a set of different policy measures that affect the deviation of simulated operation decisions of PV-prosumers in the German power market and compared them with optimal decisions from the overall system perspective. We found that the developed modeling workflow was capable of investigating the influence of different policy instruments for bridging the economic granularity gap, and was thus able to reduce costs, which are usually underestimated when designing energy systems. From a practical point of view, the strength of the established modeling workflow is its adaptability to a large spectrum of further research questions that go beyond our particular case-study. Therefore, an intuitive next step would be a roll-out to further stakeholder groups, such as operators of other storage technologies. It is expected that, when a large variety of stakeholders are covered, the economic granularity gap will increase. Thus, research on effective policy measures for bridging this gap becomes even more important. Accordingly, examples for further research are analyses of the market premium (Frey et al., 2020), the interaction of markets due to increasing coupling of energy demand sectors, or the impact of the strategic behavior of stakeholders on the economic granularity gap. In this context, an important topic for future research is modeling policy measures that directly influence investment decisions.

CRediT authorship contribution statement

Seyedfarzad Sarfarazi: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Shima Sasanpour:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Visualization. **Karl-Kiên Cao:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Seyedfarzad Sarfarazi reports financial support was provided by the German Federal Ministry for Economy and Energy.

Data availability

The authors do not have permission to share data.

Table A.1
List of abbreviations and acronyms.

Shortened form	Description
ABM	Agent-based model
AP	Aggregated prosumers
BAU	Business-as-usual
CAPEX	Capital expenditure
EEG	Renewable energy act (Erneuerbare-Energien-Gesetz)
EMS	Energy management system
ESOM	Energy system optimization model
EUMA	Europe and Maghreb
dEEG	Dynamic EEG levy
GER	Germany
GHG	Greenhouse gas
O&M	Operation and maintenance
OPC	Other power consumers
OPEX	Operational expenditure
PV	Photovoltaic
REF	Reference energy system
RTP	Real-time pricing
VAT	Value-added tax
vFiT	Variable feed-in tariff

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Appendix A. Abbreviations

Table A.1 presents a list of the acronyms and abbreviations used in this paper.

Appendix B. Structure of AMIRIS

The structure of the ABM AMIRIS and the financial, information, and power flows among the enabled agents in this study are illustrated in Fig. B.1. A more detailed description of AMIRIS can be found in Deissenroth et al. (2017). AMIRIS has already been used in several electricity market studies (Torralba-Diaz et al., 2020; Frey et al., 2020; Nitsch et al., 2021; Safarazi et al., 2020).

For the assessment of PV-prosumer stakeholder behavior, we have further developed the model and added two new agents, i.e., prosumer and aggregator agents. The aggregator agent provides electricity tariffs for the prosumers and trades according to their electricity excess or deficit in the wholesale market. The prosumer agent reacts to the electricity prices and optimizes the operation of the storage system to minimize their costs. Note that, at the time of publishing this paper, the developed aggregator and prosumer models for this analysis are not part of the open-source model.

Appendix C. Data exchange details

As shown in Fig. 2, the data from REMix are processed within iog2x before being sent to AMIRIS. Table C.1 lists the data types and units that REMix and AMIRIS require and how they are translated by iog2x.

Appendix D. Calculation of market constants

The instruments under investigation are determined in such a way that their implementation disadvantages a benchmark user. In the case of RTP and dEEG, the benchmark user is assumed to be a household with no storage and generation potential. For the calibration of the vFiT instrument, we consider a stand-alone PV

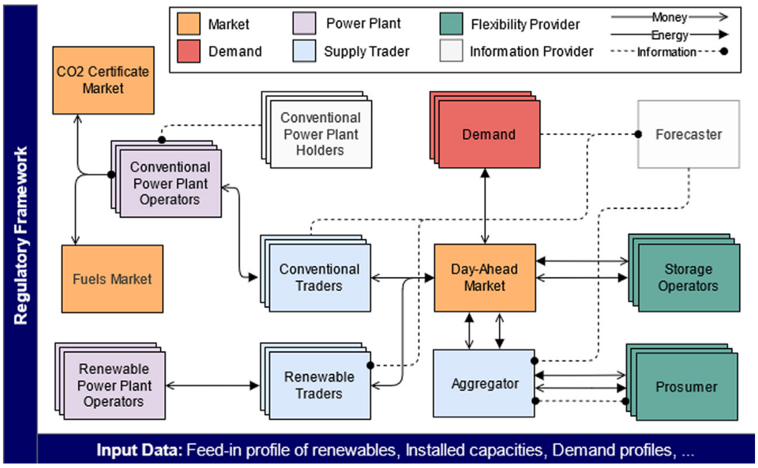

Fig. B.1. Schematic structure of AMIRIS in this study.

Table C.1
Data exchange from REMix to AMIRIS within iog2x.

	Parameter	REMix	Transformation	AMIRIS
Global	CO_2 price	Scalar [k€/t]	Scalar to time series	Time series [k€/t]
	Fuel price	Scalar [k€/MWh_{th}]	Scalar to time series	Time series [k€/MWh_{th}]
	Specific CO_2 emissions per fuel	Scalar [t/MWh_{th}]	–	Scalar [t/MWh_{th}]
Demand	Demand Germany (D_t^{total})	Time series [GWh]	$(D_t^{conv} + D_t^{hp} + D_t^{eBoiler} + D_t^{eCars} + E_t^{export} - E_t^{import} + Z_t^{C,stor} - Z_t^{D,stor} + L_t^{trans}) * 10^3$	Time series [MWh]
	Demand Prosumer (D_t^{AP})	Time series [GWh]	$^*\ 10^3$	Time series [MWh]
	Demand OPC (D_t^{OPC})	–	$D_t^{total} - D_t^{AP}$	Time series [MWh]
Storages	Storage converter capacity	Scalar [GW]	($^*\ 10^3$) to time series	Time series [MW]
	Energy-to-power-ratio	Scalar [TWh]	$^*\ 10^6$/storage converter capacity [MW]	Scalar [h]
	Charge efficiency	Scalar [–]	–	Scalar [–]
	Discharge efficiency	Scalar [–]	–	Scalar [–]
Power plants	Installed power	Scalar [GW]	($^*\ 10^3$) to time series	Time series [MW]
	RE yield profile	Time series [GWh]	(power generation + curtailment) * 10^3/installed power [MW]	Time series [–]
	Variable O&M cost	Scalar [k€/MWh]	$^*\ 10^3$	Scalar [€/MWh]
	Availability factor	Scalar [–]	Scalar to time series	Time series [–]
	Minimum efficiency	Scalar [–]	Scalar to time series	Time series [–]
	Maximum efficiency	Scalar [–]	Scalar to time series	Time series [–]

system as the benchmark user. We derive the scaling factor χ of the instruments in its general form as follows:

$$p_t^x = \chi p_t^{mc}, \tag{D.1a}$$

$$\chi = \frac{p_{avg}^{mc} \sum_{t=1}^{Z} m_t^{AP}}{\sum_{t=1}^{Z} p_t^{mc} m_t^{AP}}. \tag{D.1b}$$

The scaling factor χ and the price p_t^x respectively represent κ, ι, θ, and p_t^{elec}, p_t^{eeg}, p_t^p for the RTP, dEEG, and vFiT instruments. p_{avg}^{mc} is the average market price and p_t^{mc} is the capped market price with lower and upper bounds (zero and $\overline{p^m}$). m_t^{AP} is the normalized electricity demand of the prosumers (d_t^{AP}) in the RTP and dEEG calculations and the normalized generation profile (g_t^{AP}) in the vFit calibration. We carry out the calculation with an hourly resolution and for a simulation time of one year ($Z = 8760$ h).

Appendix E. Prosumer optimization model

Eqs. (E.1a)–(E.1f) describe the EMS logic, i.e., the cost function and the optimization constraints of the prosumer.

$$\underset{\xi}{\text{Minimize}}\ C = \sum_{t=1}^{T} (p_t^s e_t^s - p_t^p e_t^p) \tag{E.1a}$$

$$\text{subject to: } a_t = a_{t-1} + E^C z_t^C - \frac{z_t^D}{E^D}, \forall t \neq 0, \tag{E.1b}$$

$$0 \leq a_t \leq \varphi\varsigma, \forall t \neq 0, \tag{E.1c}$$

$$a_t = A_0, t = 0, \tag{E.1d}$$

$$G_t^{AP} - D_t^{AP} = e_t^s - e_t^p - z_t^C + z_t^D, \forall t \neq 0, \tag{E.1e}$$

$$G_t^{AP} = \gamma^{AP} g_t^{AP}, \forall t \neq 0, \tag{E.1f}$$

$$0 \leq z_t^C \leq \frac{\varphi}{E^C}, \forall t \neq 0, \tag{E.1g}$$

$$0 \leq z_t^D \leq \varphi E^D, \forall t \neq 0. \tag{E.1h}$$

ξ in Eq. (E.1a) is the set of prosumer decision variables $\xi = \{e_t^s, e_t^p, a_t, z_t^C, z_t^D\}$. C is the cost of the prosumer agent during one optimization period (T), calculated based on the grid usage (e_t^s) and grid feed-in (e_t^p) of the prosumer. Note that the investment, operation, and maintenance costs of PV-storage systems are not considered in the cost function. In Eq. (E.1b), which represents the storage state of the charge constraint to the prosumer's optimization problem, a_t is the energy content of the battery in time step t. The storage technical parameters E^C and E^D are the battery's charging and discharging efficiency, respectively. Constraint (E.1c) ensures that the energy content of the battery remains between the minimum (zero) and maximum allowed

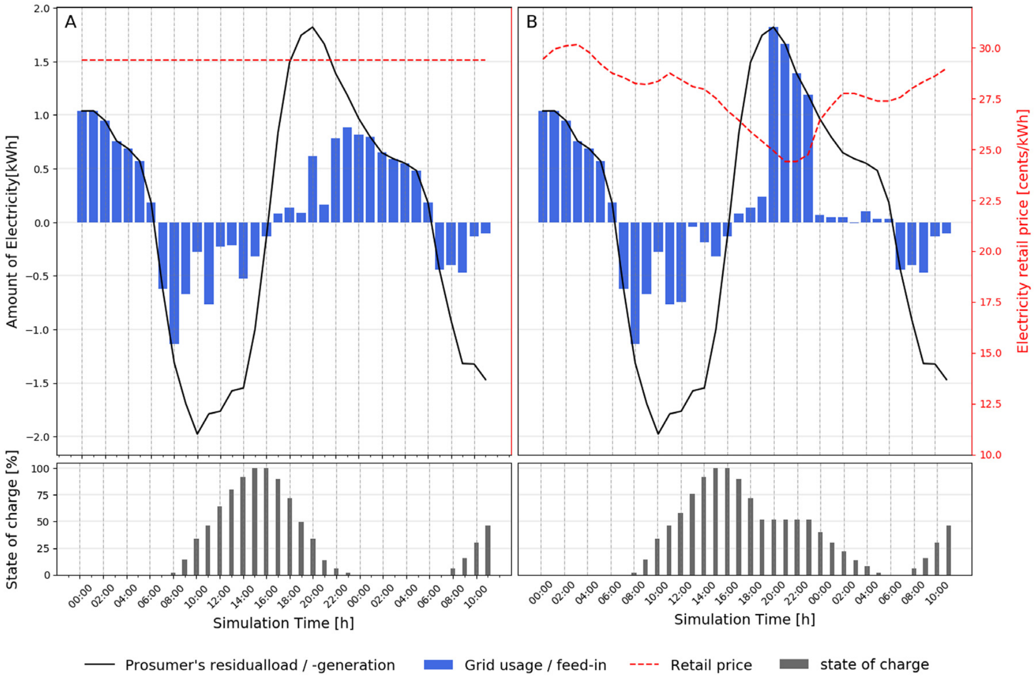

Fig. E.1. Prosumer dispatch for an exemplary 36 h simulation time for the BAU (A) and RTP (B) use-cases. Positive electricity amounts correspond to residual load and grid usage, negative amounts are residual generation and grid feed-in.

limits, i.e., maximum battery capacity, which is represented by the battery's installed power (φ) multiplied by its energy to power ratio (ς). Moreover, Eq. (E.1d) updates the initial battery energy content (A_0) in every optimization period. Note that the value of A_0 depends on the previous optimization result and therefore, needs to be updated before every optimization. The constraint formulated as Eq. (E.1e) balances the hourly power flows managed by the EMS. Based on this equation, we assume that the prosumer primarily utilize the electricity generation to cover the electricity demand. We make this assumption due to the near-zero marginal costs of produced solar energy and the exemption of the self-consumed electricity from the regulatory-induced charges. Electricity generated by prosumer is calculated according to Eq. (E.1f) from the average PV generation profile (g_t^{AP}) and installed PV rooftop capacity (γ^{AP}). Finally, the electricity charged (z_t^C) or discharged (z_t^D) from the battery in each time step is limited in Eqs. (E.1g) and (E.1h). Note that in our modeling, we neglect the grid restrictions and losses.

Fig. E.1 shows the dispatch of PV-storage systems in the BAU (A) and RTP (B) use-cases in AMIRIS. As can be seen, the introduction of a dynamic electricity tariff scheme influences the self-consumption pattern of prosumers. The most prominent change in the usage of battery storage happens from 20:00 to 22:00. In the case of an RTP tariff, the prosumer takes advantage of low retail prices in these hours and covers the electricity demand from the grid. The battery discharges later, from 00:00 to 04:00, to cover the electricity demand. In BAU, in contrast, the battery discharges as soon as the electricity demand exceeds the generation.

Appendix F. Reference energy system in Germany

Table F.1 presents the installed capacities in Germany in REF as a reference for the capacity differences shown in Fig. 6.

Table F.1
Installed capacities in GER in REF.

Technology	Capacity [GW]
Gas	11.14
Coal	8.36
Lignite	9.71
Oil	0.37
Hydro run-of-river	4.38
PV central	23.23
PV decentral	34.94
Wind onshore	49.64
Wind offshore	6.42
Grid	118.69
Lithium-ion battery	8.74
Pumped hydro-storage	6.49

Table F.2
Annual power generation in GER in REF.

Technology	Power generation [TWh]
Gas	22.64
Coal	19.78
Lignite	39.00
Oil	0.05
Hydro run-of-river	21.80
PV central	27.54
PV decentral	25.39
Wind onshore	97.50
Wind offshore	18.96
Import	306.82

Table F.2 presents the power generation and imports in Germany in REF as reference for the deviations in the use-cases in Fig. 7.

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4.2 Paper 4: Integration of energy communities in the electricity market: A hybrid agent-based modeling and bilevel optimization approach

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Research Paper

Integration of energy communities in the electricity market: A hybrid agent-based modeling and bilevel optimization approach ☆

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ABSTRACT

In recent years, many energy markets have seen the rise of battery storage systems (BSSs). This study focuses on home energy storage (HES) and community energy storage (CES) as two known applications of distributed BSSs in energy communities (ECs). We explore the challenge of efficient market integration of these systems by proposing a hybrid methodology combining agent-based electricity market modeling with bilevel EC optimization. This approach allows for deriving an optimal real-time pricing (ORTP) mechanism for the EC users. We apply our methodology to a case study of Germany in 2030, where a BSS capacity of 1.5 GW is installed within the ECs. Subsequently, we evaluate the impact of static energy-based charges included in the end-consumer's electricity price on BSS operations. Our results reveal that future market price fluctuations, when passed through to end-consumers, increase the incentive for market-aligned BSS operations. The ORTP strategy significantly aligns HES with market dynamics, reducing system costs and facilitating renewable energy integration. The profit-driven CES operation emerges as the most efficient use-case, increasing community welfare by 88 k€/MW-year and concurrently reducing the annual operational system costs by 0.6 %. However, static energy-based charges on power consumption hinder cost-effective BSS operations from both community and system perspectives. Our research contributes to understanding the intertwined dynamics between decentralized and central markets, thus advancing the modeling of complex energy markets.

1. Introduction

1.1. Background and motivation

The prospects for distributed solar photovoltaics (PV) applications in residential and commercial sectors are promising, mainly due to decline in PV system costs and the rise in consumer electricity prices. This trend indicates a future increase in the number of so-called prosumers (International Energy Agency (IEA), 2022). Furthermore, the decreasing feed-in remuneration and battery storage system (BSS) costs has led to the growing adoption of BSSs to moderate the intermittent nature of solar energy generation and promote self-consumption in the residential energy sector (Schmidt and Staffell, 2024). This shift towards distributed solar PV and BSS is a fundamental component of establishing a sustainable energy supply and represents a paradigm shift from the conventional centralized energy system (Agnew and Dargusch, 2015; Jayaraj et al., 2024).

Home energy storage (HES) and community energy storage (CES) are two promising applications of BSSs for residential users, each offering unique advantages (Dong et al., 2020b). HES allows prosumagers, i.e., prosumers with energy storage systems, to enhance their behind-the-meter self-consumption rate. This business model is proven to be economically viable under specific market and regulatory conditions and local generation potential (Bertsch et al., 2017; Aniello and Bertsch, 2023). HES encourages private investment in storage technologies, providing additional flexibility to the energy system and catalyzing sector coupling, for example, by allowing for the flexible utilization of self-generated solar electricity for electric vehicles or power-to-heat appliances (Schill et al., 2017; Zakeri et al., 2021). Despite these benefits, the partially independent operation of prosumagers presents new technical and economic challenges for the broader energy systems (Klein, 2020). It may pose risks to the stability of the electricity grid, lead to distributional impacts associated with grid charge savings, and operate in a manner that is misaligned with market signals of scarcity and surplus (Li et al., 2023; Aniello et al., 2024).

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Nomenclature

Parameters

F_i^{pr}, F^{ag}	HES/CES energy to power ratio
K_i^{pr}, K^{ag}	HES/CES capacity
$\Lambda_i^{pr}, \Lambda^{ag}$	HES/CES self-discharge rate
U_{it}^{pr}, U_t^{ag}	HES/CES availability
$\epsilon_i^{pr}, \epsilon^{ag}$	HES/CES charge efficiency
$\varepsilon_i^{pr}, \varepsilon^{ag}$	HES/CES discharge efficiency
P_i^{ch}	Marginal operational cost of charging/discharging the BSS
M^-, M^+	Sufficiently large constants in the MILP formulation
Γ	Aggregator's margin in benchmark pricing strategies
P^{rc}	Regulatory induced charges on electricity consumption from the grid
P^+, P^-	Aggregator's discrete sale and purchase prices
P_t^{ag+}, P_t^{ag-}	Aggregator sale and purchase prices in t in SP scheme
ω	Forecast period of the BSS operator
π	Schedule duration for the BSS optimization
D_{it}	User's power demand
G_{it}	User's power generation
H_{it}	User's residual load
E	Market exchange during the simulation
E_t^{ag-}, E_t^{ag+}	Grid feed-in and usage limits for the aggregator in t
$E_{it}^{pr-}, E_{it}^{pr+}$	Grid feed-in and usage limits for prosumager i in t
P_t^M	Wholesale electricity market price in t
P_{min}^M, P_{max}^M	Minimum and maximum market prices in one ω
Φ	Community welfare
C_i^{pr}	Cost of prosumager i
C'	Total cost of all users
C^{sy}	Operational system costs of the simulation period
C_{ps}^{ca}	Carbon emission allowance costs of power plant p in t
ϵ_p	Efficiency of power plant p
C_{ps}^{fu}	Fuel costs of power plant p in t
Q_{ps}	Awarded generation of power plant p in t
C_{ps}^{ma}	Marginal cost of power plant p in t
$C_{ps}^{O\&M}$	Operation and maintenance costs of power plant p in t
B	Total number of power plants

Sets

Ψ	Set of decision variables in (1)
$\mathbf{B}$	Set of power plants outside the EC
$\mathcal{B}$	Set of all users within the EC
ξ	Set of decision variables in (13)
ζ	Set of decision variables in (3) and (4)

Indices

ag	Aggregator
k	Discretization step
$*$	Trade direction: Sale or purchase
t	Optimization time
p	Power plant index
pr	Prosumager
s	Simulation time
i	User's index

Variables

w^{ag}	Aggregator's objective in the self-sufficiency driven CES strategy
r	Aggregator's profit
$\alpha, \beta, \lambda, \gamma, \tau, \upsilon, \mu$	Dual variables
b_{tk}^+, b_{tk}^-	Binary variables in the MILP formulation
$z_{it}^{pr+}, z_{it}^{pr-}$	HES charged and discharged amount
z_t^{ag+}, z_t^{ag-}	CES charged and discharged amount
h_{itk}^+, h_{itk}^-	Continuous variables in the MILP formulation
d_t^-, d_t^+	Spanning variables
π_{it}^+, π_{it}^-	Bilinear term intermediate values
e_t^{ag-}, e_t^{ag+}	Aggregator's sold and purchased power in the market
$e_{it}^{pr+}, e_{it}^{pr-}$	Prosumager's grid usage and feed-in
p_t^{ag+}, p_t^{ag-}	Aggregator's sale and purchase prices
a_{it}^{pr}, a_t^{ag}	HES/CES energy content

Community energy storage (CES) has emerged as a viable alternative to both grid-scale and single-home BSS solutions, offering a range of benefits for both distribution grid operators and energy users within an energy community (EC). CES facilitates self-consumption and energy sharing within the EC, provides auxiliary grid services, and generates economic revenues by participating in various markets, thereby internalizing system-wide benefits (Gjorgievski et al., 2021). While successful pilot projects have demonstrated promising results, the commercial rollout of CES has faced challenges due to high BSS costs and inadequate regulatory frameworks (Parra et al., 2017). Specifically, regulatory fees imposed on the charged electricity have been identified as a major economic burden for CES business models (Gährs and Knoefel, 2020).

Given the challenges and opportunities highlighted above, this study aims to investigate the system integration of distributed BSSs in a post-feed-in incentive era. Specifically, we aim to address the following central research question: "Under what circumstances does the operation of CES and HES for self-consumption within ECs contribute to a more effective integration of renewable energies in the energy market?" To answer this question, we first propose a novel methodology that integrates a bottom-up EC model in an agent-based electricity market model. We then use the developed models to analyze the systemic impacts of various EC use-cases under different market and regulatory environments.

In the remainder of this section, we provide an overview of related research in Section 1.2, and we highlight the research gap and the contributions of this paper in Section 1.3.

1.2. Related works

This paper contributes to the intersection of two strands of literature. The first strand of research concentrates on the operation of distributed BSS and the effective aggregation of energy storage assets within ECs, a review of which is presented in Section 1.2.1. The second branch investigates the broader system integration of ECs, exploring this subject from a holistic perspective. We provide an overview of this research in Section 1.2.2.

1.2.1. Community-level analysis of BSSs

The technical and economic performance of HES and CES is significantly affected by various factors, including pricing structures, country-specific regulatory frameworks, and weather conditions. In the existing literature, we can identify two sub-categories of research. The first sub-category focuses on modeling the operations of BSS and conducting techno-economic analyses under specific regulatory environments and pricing mechanisms. Several studies have explored the profitability of investing in PV-storage systems for residential prosumagers in different countries. For instance, the profitability of PV-storage systems for prosumagers in Germany and Ireland was examined by the authors of Bertsch et al. (2017). Similarly, the economic viability of PV self-consumption combined with lithium-ion batteries in the French residential sector was assessed in Yu (2018). Another study conducted in Spain investigated the impact of fixed charges added to electricity tariffs on prosumager self-consumption (Solano et al., 2018). The authors of Green and Staffell (2017) analyzed the self-sufficiency operation of HES in Germany, Spain, and the UK, highlighting that such operations, even in Spain with ample solar resources, resulted in oversized storage capacities and inefficient investments. To explore the potential advantages of CES over HES, the studies presented in Van Der Stelt et al. (2018), Dong et al. (2020a), Barbour et al. (2018) have conducted a comparison of the profitability and efficiency of these two technologies for residential users. The simulation results presented in Barbour et al. (2018) demonstrate that the optimal capacity of CES is 65% of the capacity at the individual household level. This finding suggests that in scenarios with high adoption of PV systems, the installed storage capacity can be utilized more efficiently with CES compared to HES.

The reviewed studies have assumed predetermined pricing rules such as real-time pricing and time-of-use tariffs. However, in the context of smart ECs, a narrow focus on the BSS operation overlooks the role and interests of the EC managing entity. To overcome this limitation, the second category of studies considers both the pricing design and the BSS operation in a simultaneous modeling approach. This modeling typically employs game-theoretic techniques and bilevel optimization methods to simulate the interaction between an aggregator[1] and the EC users. For instance, in Mediwaththe and Blackhall (2020), a competitive operator of CES trades with the grid and establishes time-varying prices for the users while considering the distribution grid voltage constraints. Similarly, in Liu et al. (2021), an aggregator manages the reserve capacity provided by electric vehicles using dynamic price incentives to effectively participate in the day-ahead reserve market. Similarly, the aggregator in Sarfarazi et al. (2020) operates a CES and develops an optimal real-time pricing (ORTP) scheme for an EC with heterogeneous actors. The study demonstrates that the ORTP strategy leads to higher community welfare compared to a simpler real-time pricing strategy. The simulation results in Sarfarazi et al. (2023a) further support the superiority of the ORTP. In this study, the aggregator creates price incentives to facilitate energy trading with prosumagers and electric vehicles in the EC, taking into account various sources of uncertainty.

1.2.2. Overall system integration of distributed BSSs

Researchers have used various methodologies to examine the widespread adoption of HES from a systemic perspective. In an idealized, frictionless power system, wholesale market prices serve as effective indicators of scarcity or surplus in the energy system. To evaluate the potential systemic impact of prosumager self-consumption, the authors of the study presented in Klein et al. (2019) propose a "market-alignment indicator". This indicator measures the ratio of the welfare generated by HES to that of an arbitrage battery. Similarly, the authors in Sarfarazi et al. (2020) propose a comparable indicator for an EC. Both studies identify potential inefficiencies in static pricing (SP) and suggest real-time pricing strategies for improved market alignment.

The research presented in Yu (2018, 2021) investigates the role of HES in the French energy system by 2030. In Yu (2021), the author highlights significant systemic challenges within the seasonal backup power system in relation to integrating variable PV sources. They propose a load management model that relies on the secondary utilization of HES to address these challenges. Similarly, in Yu (2018), the author argues that incorporating HES for solar PV self-consumption can effectively alleviate the systemic challenges associated with PV integration, such as daily balancing and annual backup issues, as opposed to relying solely on full PV grid injection.

The authors in Günther et al. (2021) examine the investment choices made by prosumagers and the systemic consequences of their operation within the German power sector in 2030. Their findings indicate that when higher fixed annual expenses and lower volumetric grid usage charges are introduced, households bear a greater portion of the non-energy power sector costs. The authors also suggest that the implementation of an hourly feed-in limit for households could help mitigate stress on the distribution grid without necessarily having adverse effects on the prosumage model. These results are aligned with the findings in Fett et al. (2021), where the long-term impact of HES diffusion on German electricity market is investigated. In Schick et al. (2020), the research explores the suitability of high self-consumption rates among prosumagers within an energy system with a substantial share of renewable energy sources (RES). The investigation suggests that inflexible HES operations driven solely by individual economic interests might worsen the integration of RES, leading to higher carbon emissions and increased system expenses. Moreover, the authors of Sarfarazi et al. (2023b) use a model-coupling approach to investigate the impact of prosumagers' behavior under different tariff mechanisms on optimal system operation and design. This study highlights that increasing the dynamic parts of the electricity usage and variable feed-in remuneration can reduce the economic granularity gap between the actual and the optimized energy systems.

1.3. Literature gap and contributions

In light of the above, we identify a research gap that exists at the intersection of the two literature reviews. The studies focusing on the EC perspective make significant assumptions about future market dynamics and price developments. They also tend to overlook the aggregated feedback effect of a large number of ECs on the larger power system. Conversely, power sector studies often lack detailed models of EC business models. Table 1 compares the focus of this paper with the reviewed literature and highlights this gap. Focusing on energy system operation, this paper contributes to this research gap from both a methodological and substantive perspective:

- We propose a bottom-up methodology using an agent-based electricity market model to facilitate assessing the market integration of HES and CES. In particular, we develop a novel hybrid approach that combines bilevel optimization with agent-based energy market modeling. This approach allows for simulating the decision-making interdependencies of the EC actors as well as the self-interested behavior of other wholesale market participants. While the bilevel optimization of EC allows for the derivation of internal EC prices, referred to as ORTP, the agent-based market simulation calculates the hourly wholesale market prices. Therefore, unlike the main body of literature, our model architecture, as shown in Fig. 1, accounts for the role of the aggregator and its hierarchical interactions with EC users.

[1] defined as an entity responsible for organizing distributed energy resources (Botelho et al., 2022).

Table 1
Comparative overview of the relevant literature on the system integration of distributed BSS.

Articles	EC level analysis	CES and HES applications	EC pricing	Overall system implications	Energy system model
Bertsch et al. (2017), Solano et al. (2018), Green and Staffell (2017)	✓	✗	✗	✗	✗
Van Der Stelt et al. (2018), Dong et al. (2020a), Barbour et al. (2018)	✓	✓	✗	✗	✗
Mediwaththe and Blackhall (2020), Liu et al. (2021), Sarfarazi et al. (2023a)	✓	✓	✓	✓	✗
Sarfarazi et al. (2020)	✓	✓	✓	✓	✗
Klein et al. (2019)	✓	✗	✗	✓	✗
Sarfarazi et al. (2023b), Schick et al. (2020)	✗	✗	✗	✓	✓
Yu (2018, 2021), Günther et al. (2021), Fett et al. (2021)	✓	✗	✗	✓	✓
This article	✓	✓	✓	✓	✓

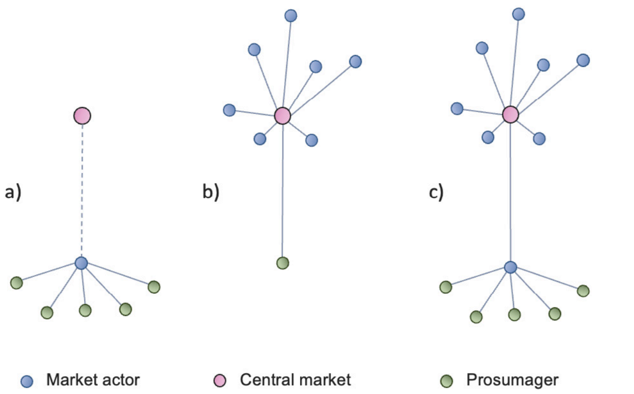

Fig. 1. Model architecture in (a) the first body of literature focusing on EC (b) the second strand of literature on system integration of prosumagers and (c) this paper.

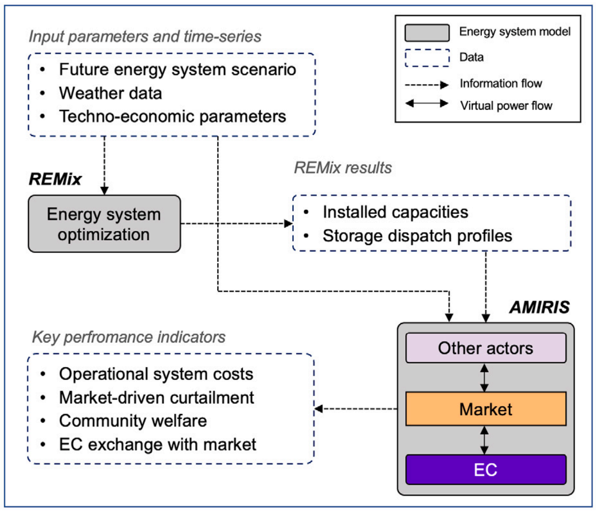

Fig. 2. Schematic overview of the overall workflow to analyze the integration of ECs in the future energy system.

- We apply our methodology to a case-study of German energy system and conduct a comprehensive analysis on the short-term systemic effects of different EC use-cases in two energy system scenarios: one that represents the current status quo system in Germany and another that projects the German power system in 2030. The EC use-cases under investigation can be distinguish by three central factors: the choice of BSS application (CES or HES), the operational strategy for CES (autarky-driven or profit-maximizing), and the users' pricing design, which can be either SP or ORTP. The analysis concludes with an exploration of the influence of regulatory induced charges on grid usage and a benchmarking of the performance of distributed BSSs against a system-cost minimizing storage operation.

The remainder of this paper is structured as follows. In Section 2, we briefly describe the overall workflow of our methodology and provide a description of the models used. Furthermore, this section details the model parameterization for the analysis and introduces key performance indicators to assess the results. We present the findings of our analysis in Section 3, followed by a discussion of the limitations of our methodology in Section 4. Finally, Section 5 concludes the paper and outlines potential directions for future research.

2. Methodology

2.1. Overview

The core of our methodology revolves around the modeling of representative EC use-cases and their integration into the electricity market simulation model AMIRIS. The design of ECs is influenced by various factors such as their organization structure, stakeholders involved, and available technologies (Gjorgievski et al., 2021). In this paper, we consider an EC with a hierarchical structure that is not isolated from the wholesale market. In this setup, the aggregator is the intermediary entity between the EC users and the market. Besides trading activities, the aggregator is responsible for creating sale and purchase prices for bilateral trading with EC users. The available storage and generation resources in the EC are BSSs, which are either operated by the prosumagers as HES or by the aggregator as a CES, and households' rooftop PV systems.

We assess the performance of HES and CES in various EC use-cases and within current and future German energy systems (respectively referred to as current and future scenarios). In order to simulate the current scenario, we parameterize AMIRIS using historical data. To represent the energy system in the future scenario, we derive the necessary parameters and time-series by utilizing the energy system optimization model REMix. Finally, we introduce four key performance indicators (KPIs) to evaluate the outcomes obtained from AMIRIS. Fig. 2 demonstrates a schematic overview of the overall workflow employed in our methodology for the future scenario. This section provides a comprehensive explanation of all building blocks comprising this workflow. Section 2.2 gives a concise introduction to the energy system models, AMIRIS and REMix, outlining their key characteristics and functionalities. In Section 2.3, we explain our approach towards integrating the EC models into AMIRIS and detail the mathematical formulation of the optimization models. Section 2.4 describes the energy system scenarios, the constructed EC use-cases, and the data used for parameterizing the models. Finally, Section 2.5 introduces the selected KPIs to measure the performance of the simulated ECs and their feedback impact on the overall energy system.

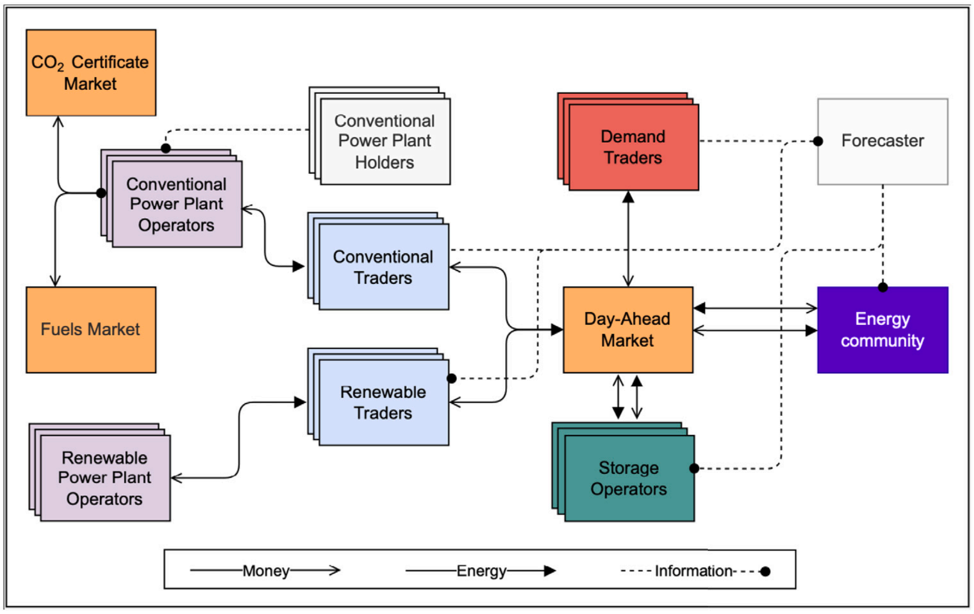

Fig. 3. Schematic structure of the basic agents in AMIRIS.

2.2. Energy system models

2.2.1. AMIRIS

Agent-based models provide robust tools to simulate the effects of actor behavior on energy systems (Yao et al., 2023). AMIRIS is an open-source agent-based model for electricity markets[2] that is designed to facilitate such analyses (Schimeczek et al., 2023a; Deissenroth et al., 2017). Fig. 3 delineates the structure of AMIRIS and the key agents relevant to this analysis.

AMIRIS enables model endogenous simulation of the Energy-Only-Market with an hourly resolution. After all participants have submitted their bids, these are sorted according to the merit order model. The market is cleared hourly with the wholesale market price determined at the intersection of the supply and demand curves. In AMIRIS, power plants offer their generated electricity based on their marginal costs. These costs are calculated considering plant-specific techno-economic parameters (including efficiency and variable costs), fuel prices, and CO_2 prices.[3] Policy regimes may entitle renewable power plants to receive a market premium, consequently influencing their bidding strategy. AMIRIS is used in this paper exclusively to simulate the German electricity market. Power exchanges with neighboring countries are treated as exogenous input data for the model. Consequently, if electricity generation exceeds demand at any point during the simulation, power from variable renewable energies will be curtailed.

In AMIRIS, a "forecaster" agent generates forecasts of electricity prices and supply/demand bids of other market actors for future periods (e.g., 24 h). Flexibility operators can use these forecasts, which may be perfect or erroneous, to optimize their bidding strategies and maximize their objective functions. One of these flexibility options is a storage module that minimizes the operational system costs (Cao et al., 2019). However, AMIRIS does not endogenously model strategic competition among actors, thereby allowing for the implementation of a single storage entity.[4] Hence, our analysis confines the available flexibility options in the system to distributed BSS within the EC.

2.2.2. REMix

The current application of AMIRIS is accompanied by certain restrictions. Firstly, it does not endogenously simulate investment decisions, instead relying on external inputs regarding the historical or future design of the energy system. Secondly, it can only implement one flexibility option. To circumvent these limitations, we utilize the REMix model in this paper.

REMix is a modeling framework utilized to build energy system optimization models that aim to optimize the capacity and hourly dispatch of various technologies in a target year by minimizing the total incurred costs. These optimizations are based on the assumption that decisions are made by a benevolent system planner, aiming to find the most cost-effective solutions for the entire system (Gils et al., 2017). The total system costs include investment expenses, covering the costs for the expansion of power plants, grid infrastructure, and storage technologies, as well as operational expenditures, such as fuel costs. Hence, power plants are constructed and operated only if they contribute to the most cost-effective solution within a one-year operational timeframe.

The modeled power sector includes a variety of power plant technologies, energy storage facilities, and power transmission capacities. It also considers the electricity demand from conventional consumers, heat pumps, heat boilers, and electric vehicles. To feed data into the model, techno-economic parameters for each technology, feed-in time series, and potential data for renewable power generation (such as wind and solar radiation) are necessary. Additionally, the input data comprises prescribed and maximum capacities for power generation, storage, and transmission, along with costs associated with CO_2 certificates, forming a comprehensive scenario dataset. To realistically estimate operating power plants in 2030, we restrict capacity expansions in REMix according to available energy system scenarios. The assumptions utilized in this regard are detailed in Section 2.4.

[2] AMIRIS has been published as open-source software in Schimeczek et al. (2023a), with the code accessible under (Schimeczek et al., 2023b). However, the model developments related to the bilevel optimization are not included in the open-source version at the time of publication.

[3] To align the bid behavior of the simulated power generators with the price patterns observed in actual markets, offsets termed as mark-ups and mark-downs can be incorporated into the marginal values. However, to reduce the complexity of the analysis, this study does not take into account mark-ups and mark-downs.

[4] Simultaneous operation of storage systems using the same forecast results in extreme price peaks due to the so-called avalanche effect (Ensslen et al., 2018), which is a model artifact.

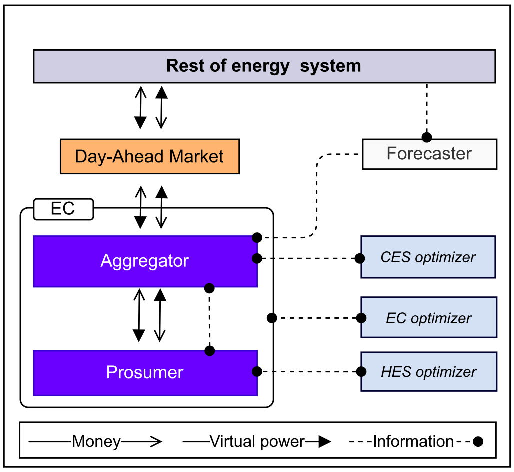

Fig. 4. Implementation of the EC models in AMIRIS.

As illustrated previously in Fig. 2, two REMix results are primarily used in AMIRIS: installed capacities and dispatch profiles representing the operation of flexibility options within the system. Note that the REMix results do not differentiate between load, generation, and storage in the EC and other market actors. Therefore, to parameterize the EC in AMIRIS, we divide the data related to PV and BSS capacities, as well as electricity demand and storage dispatch profiles, between the EC and other market actors. The assumptions related to this division are explained in Section 2.4.

2.3. EC models

We use two different approaches to model the ECs in AMIRIS. The first approach involves modeling two separate entities, the "aggregator" and the "prosumager", with each optimizing their BSS independently in order to maximize their individual utilities. The aggregator obtains forecasts of upcoming prices and demand/supply bids from the forecaster agent and creates two sets of electricity prices for bidirectional trading with the prosumager. Given these prices, the prosumager determines its trading strategy by optimizing the HES. Upon receiving the prosumager's strategy, the aggregator generates bids for market trading. In this approach, the aggregator may use a CES to optimize its market trading strategy.

The second modeling approach involves the concurrent optimization of both the aggregator and prosumager, where the aggregator anticipates the prosumagers' response to price signals and develops a pricing strategy that maximizes its overall profits. Unlike the first approach, where the electricity prices are calculated based on predetermined rules, in the second approach, the bidirectional energy trading prices with the prosumagers (what we refer to as ORTP) are derived by solving a bilevel optimization problem. As the strategies of the aggregator and prosumager are inherently interconnected, they are treated as a single "Energy community" entity. Fig. 4 illustrates the implementation of the EC models and their corresponding optimization models in AMIRIS.

To optimize the operation of ECs during the simulation process, a rolling horizon optimization methodology is implemented. The agents undertake their respective optimizations over the "forecast period" (ω), and store the results of this optimization for the "schedule duration" (π, $\pi \leq \omega$). Fig. 5 A depicts the ω and π during the simulation time, s. The optimization results compiled during the π are subsequently employed in the ensuing simulation steps. π time steps after this optimization, an optimization for the new planning horizon (Fig. 5 B) is executed.

We develop and incorporate three optimization models into AMIRIS to represent different EC use-cases effectively. The "HES optimizer" is responsible for the optimization of behind-the-meter BSS systems, which are operated by prosumagers. The "CES optimizer" enables the aggregator to determine the operation strategy of the CES. Finally, the "EC optimizer" comprises a bilevel optimization model where both the aggregator's pricing strategy and HES dispatch are determined simultaneously. Detailed step-by-step information exchange among the actors in both EC implementation approaches is describe in Appendix A.1. The remainder of this section explains these three models in details.

2.3.1. HES optimization model

A prosumager is defined as a household equipped with a PV system that owns and operates a HES. The prosumager can be parameterized to represent either a single household or an aggregate of households. The schematic representation of the prosumager model is illustrated in Fig. 6.

We assume that the prosumagers have a flawless forecast of their solar PV generation (G_{it}) and power demand (D_{it}). Additionally, we presume that the power generated is predominantly used to meet the household's electricity demand. The energy management system then manages any residual load or generation ($H_{it} = D_{it} - G_{it}$) from the household to minimize the prosumager's electricity bill (C_i^{pr}). To accomplish this, the energy management system acquires the sale and purchase prices, then decides the hourly grid usage and feed-in (e_{it}^{pr+} and e_{it}^{pr-}), and the HES charge/discharge schedule (z_{it}^{pr+}, z_{it}^{pr-}). Note that if the EC users are not parameterized with a HES, the optimization is bypassed and the H_{it} is announced to the aggregator. The optimization problem for prosumager i is mathematically modeled as follows:

$$\underset{\psi}{\text{Minimize}}\ C_i^{pr} = \sum\nolimits_t ((P_t^{ag+} + P^{rc}) e_{it}^{pr+} - P_t^{ag-} e_{it}^{pr-} + P_i^{ch}(z_{it}^{pr+} + z_{it}^{pr-})) \tag{1a}$$

$$\text{subject to: } a_{it}^{pr} = (1 - \Lambda_i^{pr}) a_{i(t-1)}^{pr} + \epsilon_i^{pr} z_{it}^{pr+} - \frac{z_{it}^{pr-}}{\varepsilon_i^{pr}} \ : (\lambda_{it}^{a}), \tag{1b}$$

$$z_{it}^{pr+} = e_{it}^{pr+} - e_{it}^{pr-} - H_{it} + z_{it}^{pr-} \ : (\lambda_{it}^{z}) \tag{1c}$$

$$0 \leq a_{it}^{pr} \leq K_i^{pr} F_i^{pr} \ : \left(\underline{\tau}_{it}, \overline{\tau}_{it}\right), \tag{1d}$$

$$a_{i(t-1)}^{pr} = A_{i0}^{pr} \ : \left(\lambda_{i0}^{a0}\right), t = 1, \tag{1e}$$

$$0 \leq e_{it}^{pr+} \leq E_{it}^{pr+} \ : \left(\underline{\upsilon}_{it}, \overline{\upsilon}_{it}\right), \tag{1f}$$

$$0 \leq e_{it}^{pr-} \leq E_{it}^{pr-} \ : (\underline{\mu}_{it}, \overline{\mu}_{it}), \tag{1g}$$

$$0 \leq z_{it}^{pr+} \leq \frac{U_{it}^{pr} K_i^{pr}}{\epsilon_i^{pr}} \ : (\underline{\beta}_{it}, \overline{\beta}_{it}), \tag{1h}$$

$$0 \leq z_{it}^{pr-} \leq U_{it}^{pr} K_i^{pr} \varepsilon_i^{pr} \ : (\underline{\gamma}_{it}, \overline{\gamma}_{it}), \tag{1i}$$

Eq. (1a) portrays the cost-minimizing objective function of the prosumager. The term ψ symbolizes the set of optimization variables, i.e., $\psi = \{e_{it}^{pr+}, e_{it}^{pr-}, z_{it}^{pr+}, z_{it}^{pr-}, a_{it}^{pr}\}$. In our model, t and i respectively denote the optimization time step and the user index. The terms in parentheses (i.e., λ_{it}^{a}, λ_{it}^{z}, $\underline{\tau}_{it}$, $\overline{\tau}_{it}$, λ_{i0}^{a0}, $\underline{\upsilon}_{it}$, $\overline{\upsilon}_{it}$, $\underline{\mu}_{it}$, $\overline{\mu}_{it}$, $\underline{\beta}_{it}$, $\overline{\beta}_{it}$, $\underline{\gamma}_{it}$, $\overline{\gamma}_{it}$) are the Lagrangian dual variables of the constraints in the prosumager HES optimization model and are defined for later use in the EC optimization model. P_t^{ag+} and P_t^{ag-} in (1a) represent the electricity sale and purchase prices offered to the prosumager. The aggregator, when selling electricity to the users, is obliged to incorporate regulatory-induced charges (P^{rc}) into the end-user price. P_i^{ch} is the marginal cost of charging or discharging the HES.

Eq. (1b) describes on the state of charge (SOC) of the HES, which depends on the SOC from the preceding time step, the self-discharge rate (Λ_i^{pr}), the charged and discharged power (z_{it}^{pr+} and z_{it}^{pr-}), and the HES's charging and discharging efficiencies (ϵ_i^{pr} and ε_i^{pr}). The balance of incoming and outgoing power flows for each prosumager and time step is maintained as per the constraint in (1c). Eq. (1d) ensures that the stored energy is neither negative nor exceeds the energy capacity

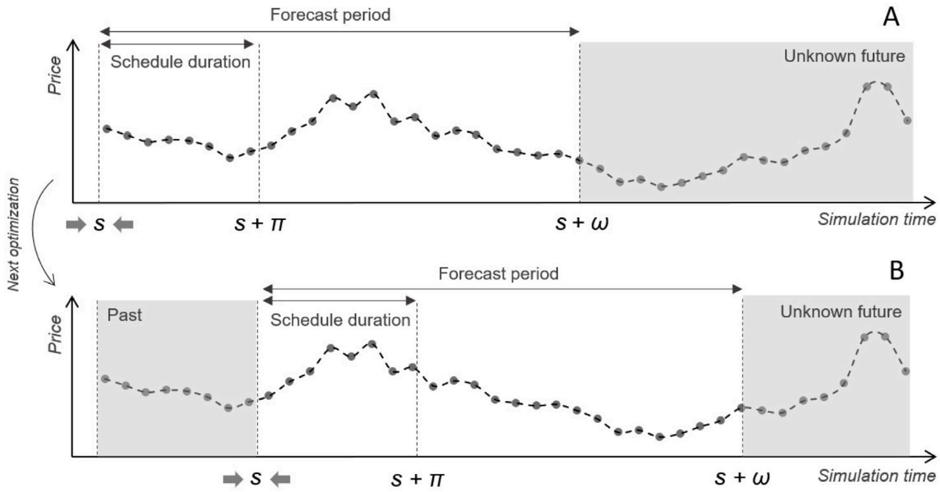

Fig. 5. Forecast period (ω) and schedule duration (π) in two consequent optimization runs A and B.

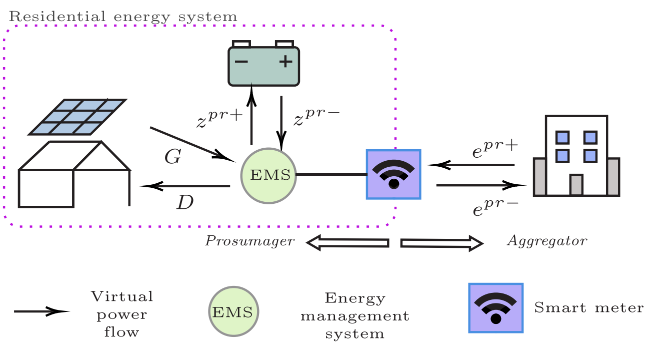

Fig. 6. Schematic overview of the prosumager's model.

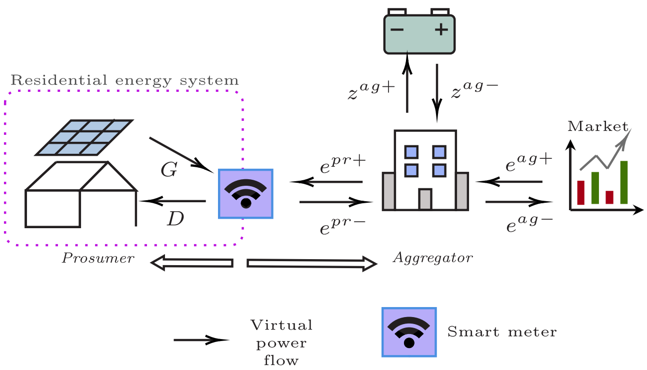

Fig. 7. Schematic overview of the CES model.

of the HES (represented as BSS power K_i^{pr} multiplied by its energy-to-power ratio F_i^{pr}). The initial SOC of the HES (A_{i0}^{pr}) is established in (1e), with the rolling horizon parameter A_{i0}^{pr} updated according to the SOC stored from the prior simulation step $(s-1)$. The maximum permissible grid usage (E_{it}^{pr+}) and feed-in (E_{it}^{pr-}) by the prosumager are outlined in constraints (1f) and (1g) respectively. The upper bounds of the grid interactions are computed as shown in (2).

$$E_{it}^{pr+} = \max\{0, K_i^{pr} + H_{it}\} \tag{2a}$$

$$E_{it}^{pr-} = \max\{0, K_i^{pr} - H_{it}\} \tag{2b}$$

Eqs. (1h) and (1i) limit the charging and discharging power in each time step. The term U_{it}^{pr} delineates the availability of the HES in a time step and can assume a value between 0 and 1. We solve the optimization problem in (1) by discretizing the SOC and applying a dynamic programming model (DPM) similar to the approach used in Sarfarazi et al. (2020).

2.3.2. CES optimization model

Once the users' grid interaction is planned (that is, e_{it}^{pr+} and e_{it}^{pr-} are determined), the aggregator can leverage the CES to optimize its bidding strategy, denoted as e_t^{ag*}. As depicted in Fig. 7, if the aggregator does not possess a CES, e_t^{ag*} equals to the grid interaction of all EC users ($\sum_i^{\mathcal{B}} e_{it}^{pr*}$, $*$ stands for both $+$ and $-$ indices and $\mathcal{B}$ is set of all users in the EC).

The aggregator can adopt either a self-sufficiency driven or a profit-maximizing strategy for CES optimization. Given that these strategies share similar constraints with the HES optimization model detailed in 2.3.1, the relevant equations are described in Appendix A.2. In the following, we describe the objective functions for these two CES strategies.

Self-sufficiency driven: With this strategy, the CES is employed to minimize interactions with the wholesale market. Consequently, the objective function can be expressed as follows:

$$\underset{\zeta}{\text{Minimize}}\, w^{ag} = \sum_t (e_t^{ag-} + e_t^{ag+})^2 \tag{3}$$

In (3), ζ represents the set of optimization variables: $\zeta = \{e_t^{ag+}, e_t^{ag-}, z_t^{ag+}, z_t^{ag-}, a_t^{ag}\}$. The implemented quadratic function aims to minimize the power exchange with the market while preventing sudden peaks in charge and discharge.

Profit maximization: The aggregator employs the CES to capitalize on market price fluctuations and maximize its revenue. Given the forecast of upcoming power supply and demand bids over ω, the aggregator has knowledge of its market power when optimizing the CES. The objective function in this strategy is given in Eq. (4):

$$\underset{\eta}{\text{Maximize}}\, r = \sum_t (p_t^M (e_t^{ag-} - e_t^{ag+}) + P_t^{ag+} \sum_i e_{it}^{pr+} - P_t^{ag-} \sum_i e_{it}^{pr-} - P^{rc} z_t^{ag+}) \tag{4}$$

In this equation, p_t^M refers to the anticipated market price, considering the aggregator's bids. The set of decision variables, η, includes p_t^M, e_t^{ag+}, e_t^{ag-}, z_t^{ag+}, z_t^{ag-}, and a_t^{ag}. The term $P^{rc} z_t^{ag+}$ accounts for potential regulatory charges that may be levied when the CES charges.

As illustrated in Fig. 8, during a full charge–discharge cycle of the CES, the market clearing price may adopt higher (P_t^{Mc}) or lower (P_t^{Md})

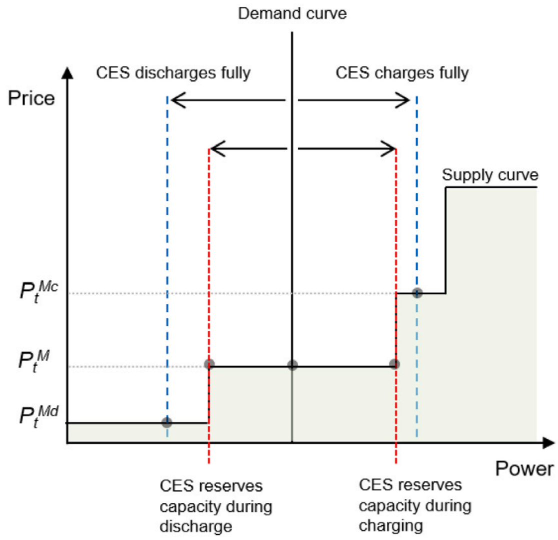

Fig. 8. Illustrative example of CES exercising market power.

values than the forecasted price (P_t^M). In such a scenario, the CES might reserve some of its capacity to avoid inflated purchase prices during charging or revenue lower than expected while discharging. Similar to the HES model, the CES optimization model also employs a DPM.

2.3.3. EC optimization model

The second approach involves the simultaneous optimization of the aggregator and the prosumager objective functions. While the prosumagers aim to minimize their electricity bills (similar to the first approach), the aggregator seeks to maximize its profit by setting the ORTP for bidirectional energy trading with prosumagers. In order to isolate the effect of ORTP, it is assumed that the aggregator is not equipped with CES in the EC optimization model. Therefore, the aggregator's bids in terms of quantity are identical to the prosumagers' grid interaction ($e_t^{ag*} = \sum_i e_{it}^{pr*}$). The interplay between the users of the EC and the aggregator is modeled as a bilevel optimization problem:

$$\underset{p_t^{ag+},\, p_t^{ag-}}{\text{Maximize}}\ r = \sum_{i,t}\left(P_t^M\left(e_{it}^{pr-} - e_{it}^{pr+}\right) + p_t^{ag+}e_{it}^{pr+} - p_t^{ag-}e_{it}^{pr-}\right) \tag{5a}$$

$$\text{subject to: } P_{min}^M + \Gamma \leq p_t^{ag+} \leq P_{max}^M + \Gamma, \tag{5b}$$

$$P_{min}^M - \Gamma \leq p_t^{ag-} \leq P_{max}^M - \Gamma, \tag{5c}$$

$$\text{where } e_{it}^{pr+}, e_{it}^{pr-} \in \underset{\Psi}{\text{argmin}}\ C_i^{pr} = \sum_t\left(\left(p_t^{ag+} + P^{rc}\right)e_{it}^{pr+} - p_t^{ag-}e_{it}^{pr-} + P_i^{ch}\left(z_{it}^{pr+} + z_{it}^{pr-}\right)\right), \tag{5d}$$

$$\text{(1b)–(1i).} \tag{5e}$$

Eq. (5a) represents the objective function for profit maximization with decision variables p_t^{ag+} and p_t^{ag-}. Here, P_t^M refers to the forecast of the electricity market price, which is obtained from the forecaster agent. In this model, the aggregator assumes that prices after the market clearing will not deviate from the forecast, and thus, it does not factor in its market power during the optimization process.

The lower and upper bounds for the aggregator's sale and purchase prices are constrained by Eqs. (5b) and (5c), respectively. These constraints are put in place to ensure that the prices remain attractive for prosumagers, especially in the absence of competition among multiple aggregators. We set the upper and lower price bounds based on the forecast prices, as exemplified in Fig. 9. Here, P_{min}^M and P_{max}^M represent the minimum and maximum market prices for each optimization period (from simulation time s to $s+\omega$), and these values can change during the simulation. Eqs. (5d) and (5e) represent the objective function and constraints for the lower-level problem. These are identical to the prosumager's model that was described in Section 2.3.1.

In order to solve the problem formulated in (5), a single-level reduction approach is applied. This approach uses the Karush-Kuhn–Tucker (KKT) optimality conditions, which are both necessary and sufficient, to transform the problem into an equivalent mathematical program with equilibrium constraints. The dual feasibility conditions are described in Eq. (6).

$$\underline{\beta}_{it}, \overline{\beta}_{it}, \underline{\gamma}_{it}, \overline{\gamma}_{it}, \underline{\mu}_{it}, \overline{\mu}_{it}, \underline{\tau}_{it}, \overline{\tau}_{it}, \underline{\upsilon}_{it}, \overline{\upsilon}_{it} \geq 0, \tag{6}$$

where $\underline{\beta}_{it}$, $\overline{\beta}_{it}$, $\underline{\gamma}_{it}$, $\overline{\gamma}_{it}$, $\underline{\mu}_{it}$, $\overline{\mu}_{it}$, $\underline{\tau}_{it}$, $\overline{\tau}_{it}$, $\underline{\upsilon}_{it}$, $\overline{\upsilon}_{it}$ are the Lagrangian dual variables of the lower-level problem constraints, as defined in (1). The stationary conditions are given in (7).

$$p_t^{ag+} + P^{rc} + \lambda_{it}^z + \overline{\upsilon}_{it} - \underline{\upsilon}_{it} = 0 : e_{it}^{pr+}, \tag{7a}$$

$$-p_t^{ag-} - \lambda_{it}^z + \overline{\mu}_{it} - \underline{\mu}_{it} = 0 : e_{it}^{pr-}, \tag{7b}$$

$$-\lambda_{it}^a + (1 - \Lambda_i^{pr})\lambda_{i(t+1)}^a - \underline{\tau}_{it} + \overline{\tau}_{it} = 0 : a_{it}^{pr}, \tag{7c}$$

$$(1 - \Lambda_i^{pr})\lambda_{i1}^a - \lambda_{i0}^{a0} = 0 : a_{it}^{pr}, t = 1, \tag{7d}$$

$$P_i^{ch} - \frac{1}{\varepsilon_i^{pr}}\lambda_{it}^a + \lambda_{it}^z - \underline{\gamma}_{it} + \overline{\gamma}_{it} = 0 : z_{it}^{pr-}, \tag{7e}$$

$$P_i^{ch} + \varepsilon_i^{pr}\lambda_{it}^a - \lambda_{it}^z - \underline{\beta}_{it} + \overline{\beta}_{it} = 0 : z_{it}^{pr+}. \tag{7f}$$

Complementary slackness conditions for the lower-level problem result in several nonlinear terms, but, since the prosumager's problem is a linear program, these can be replaced with the strong duality condition (Bard, 2013). The strong duality condition for the lower-level problem can be formulated as:

$$\begin{aligned}-\sum_t\left(p_t^{ag+}e_{it}^{pr+} + P^{rc}e_{it}^{pr+} - p_t^{ag-}e_{it}^{pr-} + P_i^{ch}\left(z_{it}^{pr+} + z_{it}^{pr-}\right)\right) = \\ \sum -\lambda_{i0}^{a0}A_{i0}^{pr} + \sum_t\Big(\overline{\tau}_{it}K_i^{pr}F_i^{pr} + \overline{\mu}_{it}E_t^{ag-} + \overline{\upsilon}_{it}E_t^{ag+} + \lambda_{it}^z H_{it} \\ + \overline{\beta}_{it}\frac{U_{it}^{pr}K_i^{pr}}{\varepsilon_i^{pr}} + \overline{\gamma}_{it}U_{it}^{pr}K_i^{pr}\varepsilon_i^{pr}\Big)\end{aligned} \tag{8}$$

In the single-level reduction process, two bilinear terms emerge in the objective function (5a) and the strong duality condition (8): $p_t^{ag+}e_{it}^{pr+}$ and $p_t^{ag-}e_{it}^{pr-}$. To handle the resulting non-linearity, as proposed in Sarfarazi et al. (2023a), we assume that p_t^{ag+} and p_t^{ag-} can only take discrete values. Hence, a disjunctive formulation for the bilinear terms is proposed as follows:

$$p_t^* e_{it}^{pr*} = \bigvee_{k=1}^n P_{kt}^* e_{it}^{pr*} \tag{9}$$

In this case, k is the disjunction index and $\bigvee$ is the disjunction operator. The binary expansion technique is then used to introduce binary variables b_{tk}^* and reformulate the disjunctive program $\bigvee_{k=1}^n P_{kt}^* e_{it}^{pr*}$.

$$-M^* b_{tk}^* \leq h_{itk}^* \leq M^* b_{tk}^*, \forall itk \tag{10a}$$

$$-M^*(1 - b_{tk}^*) \leq h_{itk}^* - P_{kt}^* e_{it}^{pr*} \leq M^*(1 - b_{tk}^*), \forall itk \tag{10b}$$

$$\sum_{k=1}^n b_{tk}^* = 1 \tag{10c}$$

M^* in (10) is a sufficiently large number and h_{itk}^* is a continuous variable which is enforced to adopt corresponding discrete value. Hence, we can substitute the bilinear terms and the aggregator prices as:

$$\bigvee_{k=1}^n P_{kt}^* e_{it}^{pr*} = \sum_{k=1}^n h_{itk}^*, \tag{11a}$$

$$p_t^* = \sum_{k=1}^n P_{kt}^* b_{tk}^*. \tag{11b}$$

Consequently, the original bilevel optimization problem in (5) can be reformulated with additional constraints derived in (10) and (11) as:

$$\underset{\xi}{\text{Maximize}}\ r = \sum_{t,i}\left(P_t^M\left(e_{it}^{pr-} - e_{it}^{pr+}\right) + \sum_{k=1}^n h_{itk}^+ - \sum_{k=1}^n h_{itk}^-\right)$$

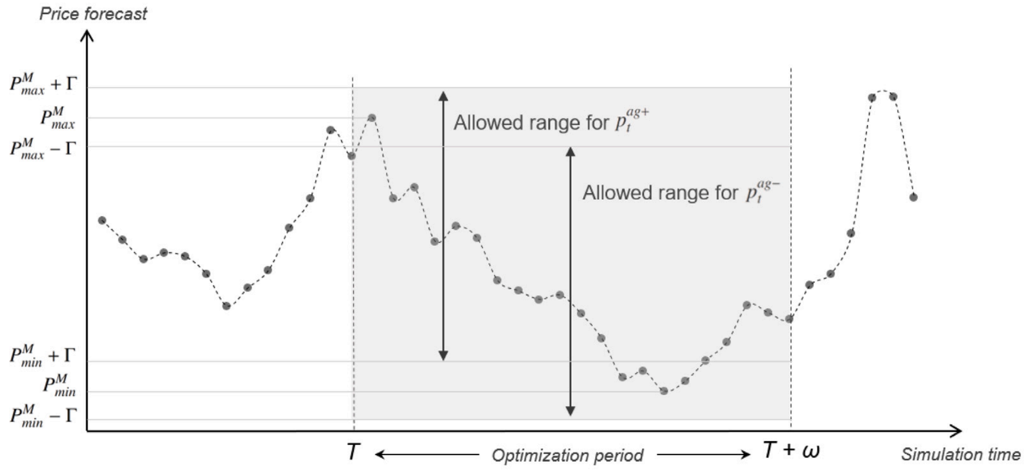

Fig. 9. Sale and purchase price limits for one exemplary optimization period.

Subject to: (5b) and (5c),
(8) rewritten with (9) and (11a),
(1b) – (1i), (6) and (7),
(10) and (11a). (13)

In this formulation, ξ includes $\{p_t^{ag+}, p_t^{ag-}, e_{it}^{pr+}, e_{it}^{pr-}, z_{it}^{pr+}, z_{it}^{pr-}, a^{pr}, \lambda_{it}^{a}, \lambda_{it}^{z}, \underline{\tau}_{it}, \overline{\tau}_{it}, \lambda_{i0}^{a0}, \underline{\upsilon}_{it}, \overline{\upsilon}_{it}, \underline{\mu}_{it}, \overline{\mu}_{it}, \underline{\beta}_{it}, \overline{\beta}_{it}, \underline{\gamma}_{it}, \overline{\gamma}_{it}, b_{tk}^{+}, b_{tk}^{-}, h_{itk}^{+}, h_{itk}^{-}\}$. The problem in (13) is a mixed integer linear problem (MILP) and can be solved using standard commercial MILP solvers and branch-and-bound algorithms.

2.4. Model parameterization and data

This section introduces the energy system scenarios and EC use-cases, explaining the data used and the underlying parameterization.

We investigate the systemic impacts of distributed BSS within two energy systems. The current scenario resembles the German electricity market and the installed capacities for the year 2019. The parameterization and back-testing of AMIRIS for this scenario, founded on historical data, is illustrated in Nitsch et al. (2021). The future scenario represents a projection of the German energy system for the year 2030. As detailed in Section 2.2, we utilize the energy system optimization model REMix to derive the optimal capacity expansions and storage operations for the future scenario.

The REMix model configuration used in this research is grounded on Cao et al. (2018), treating Germany as a singular model node with imports/exports to neighboring countries considered as exogenous. The primary emphasis is on the power sector, integrating renewable and conventional power converters, the electricity grid, and electricity storage technologies into the analysis. By 2030, we assume that Germany will cease the use of coal or lignite power plants,[5] adhering to the projections set out in the energy scenario of Agora Energiewende and Prognos (2022). As such, only gas power plants can be expanded and dispatched. A carbon emission price serves as a stimulus for the investment and operation of renewable power plants. As shown in Table 2, Agora Energiewende and Prognos (2022) proposes a CO_2 price of 100 € per ton for the year 2030. The same source also anticipates that the price of natural gas, after the price shocks in 2022, will stabilize at 38 €/MWh. Furthermore, an average energy-to-power ratio of 3 h, based on the analysis in Hesse et al. (2017), is included as a constraint on the expansion of lithium-ion batteries.

To adapt AMIRIS for the future scenario, we use input data and results derived from REMix. We assume that renewable power plants do not receive feed-in incentives and the operations of pump storage and lithium-ion BSS in AMIRIS, excluding those located within the EC, mirror those of their REMix counterparts. REMix does not differentiate between centralized and decentralized generation or storage resources. As such, we assume an existing EC that possesses a total installed capacity of 3 GW for PV generation and 1.5 GW for BSS, along with an annual power demand of 2.25 TWh in both scenarios. These values are subsequently subtracted from the total capacities and profiles derived from REMix.[6]

Our model supports the integration of multiple ECs, with each EC comprising various users (as denoted by the index i). However, due to data scarcity and for simplicity, our analysis is constrained to a single representative EC composed of an aggregator and a representative prosumager ($|i|$=1). We use household power demand profile data from (Tjaden et al., 2015), which offers high-resolution load profiles for 74 households. The aggregate of these profiles yields a single demand profile with an hourly resolution, closely approximating the standard load profile due to smoothing effects.

We assume that both the aggregator and the prosumager possess precise foresight of the upcoming prices for the next 24 h ($\omega = 24$), adjusting their strategies bi-daily ($\pi = 12$). Furthermore, we assume that all BSSs are available at all times ($U_t^{ag} = 1, \forall t$). In all cases, with the exception of the profit-maximizing CES where the aggregator might reserve a portion of its capacity to exert market power, we assume that it opts for exceedingly high prices for demand bids and extremely low prices for supply bids, ensuring that the bids are always awarded. The aggregator is also mandated to include volumetric charges, denoted as P^{rc}, comprising taxes, levies, and grid charges in the prosumager electricity tariff. These charges may also apply when the CES is drawing power from the grid. The elimination of the EEG-levy in Germany in 2022 resulted in a reduction in the total value of added charges from 22.7 cents/kWh to 18.5 cents/kWh (Anon, 2022). Therefore, we conduct our simulations for two cases: one incorporating regulatory charges ($P^{rc} = 18.5$), and a hypothetical case devoid of regulatory charges ($P^{rc} = 0$).

In this paper, we study five EC use-cases, depicted in Table 3, by considering three fundamental components of EC business models:

[5] According to various studies, including (Hauenstein et al., 2022), achieving a coal phase-out by 2030 remains a feasible scenario, considering the ambitious goals of the German federal government and the substantial expansion of renewable energy sources.

[6] To prevent disproportionate systemic effects provoked by the EC, the proposed storage capacity is significantly below future energy scenario predictions. The installed HES is projected to reach capacities of 26 GW by 2030 (Agora Energiewende and Prognos, 2022) and 64 GW by 2037 (Bundesnetzagentur, 2022).

Table 2
Fuel and CO_2 costs in the energy system scenarios.

Item	Current scenario (Nitsch et al., 2021)	Future scenario (Agora Energiewende and Prognos, 2022)
CO_2 [€/ton]	24.7	100
Gas [€/MWh]	27.3	38
Coal [€/MWh]	7.8	–
Lignite [€/MWh]	5	–
Oil [€/MWh]	30.7	–
Nuclear [€/MWh]	3.0	–

Table 3
Studied EC use-cases.

Use-case	Model	Storage	Pricing scheme	Goal
No_stor	No optimization	–	SP	–
CES_A	Single-level optimization in (3)	CES	SP	Autarky
CES_P	Single-level optimization in (4)	CES	SP	Profit
SP	Single-level optimization in (1)	HES	SP	Profit
ORTP	Bilevel optimization in (5)	HES	ORTP	Profit

Pricing scheme, BSS application, and the aggregator's optimization objective. Among these, the *No_stor* acts as the reference point, enabling the evaluation of the performance of other use-cases that deploy a BSS within the EC.

In addition to the aforementioned EC use-cases, we introduce a *Sys_min* case, wherein the built-in storage module in AMIRIS is used to minimize system operational costs (Cao et al., 2019). Thus, while the EC model in this case mirrors the *No_stor*, an optimization for a BSS with a capacity of 1.5 GW, hypothetically located outside the EC, is undertaken. We consider this case to benchmark the most desirable system-wide outcome for a BSS operation, against which we assess the system-friendly operation of our EC use-cases.

2.5. Key performance indicators

In this paper, we study the performance of the EC use-cases by observing and assessing indicators at both the community and overall energy system levels:

- **Community welfare** (Φ): This refers to the total revenue generated by all participants in the EC, including the aggregator and users. It is calculated using the equation presented in (14).[7] Efficient trading practices can enhance Φ, while paid regulatory charges may negatively influence it. It is worth noting that the internal transactions within the EC do not impact the Φ value. This analysis, therefore, does not cover the actual redistribution of welfare among EC stakeholders.

$$\Phi = \sum_s (r_s - \sum_i C_{is}^{pr}) = \sum_s P_s^M (e_s^{ag+} - e_s^{ag-}) - P^{rc}(z_s^{ag+} + \sum_i e_{is}^{pr+}) \tag{14}$$

- **Market exchange** (E): This indicator pertains to the total power exchanged with the higher-level grid or market. Although self-consumption and self-sufficiency ratios are prevalent measures of prosumager autonomy from the larger energy system, they fail to accurately depict the scenario in ECs due to continuous interactions of a grid-connected CES with the broader energy system. Therefore, the necessity arises for alternative methods to evaluate the level of independency of ECs. We define the market exchange indicator as a suitable measure to assess the self-sufficient operation of the EC:

$$E = \sum_s (e_s^{ag+} + e_s^{ag-}) \tag{15}$$

- **Market-driven curtailment**: This event takes place when a renewable energy power plant fails to secure contract awards despite submitting bids to the wholesale market. Consequently, the potential generation of solar or wind power plants cannot be sold on the market and has to be curtailed. Considering the near-zero marginal costs of renewable power generation and the national geographical scope of this analysis, such curtailment becomes necessary if the potential RES generation exceeds the electricity demand in Germany. Note that in our model, the solar PV generated in the EC is never curtailed.
- **Operational system costs** (C^{sy}): This refers to the sum of short-term running costs of all power plants, i.e., the summation of the marginal costs of all awarded power plants:

$$C^{sy} = \sum_s \sum_p^B Q_{ps} C_{ps}^{ma}, \tag{16}$$

where the marginal cost of power plant p (C_{ps}^{ma}) is determined as follows:

$$C_{ps}^{ma} = \frac{C_{ps}^{fu} + C_{ps}^{ca}}{\epsilon_p} + C_{ps}^{O\&M}. \tag{17}$$

Here, C_{ps}^{fu}, C_{ps}^{ca}, and $C_{ps}^{O\&M}$ respectively denote the fuel, CO_2, and variable costs of the power plant p at time t, while ϵ_p signifies the efficiency of each power plant.

3. Results

The forthcoming section provides a comprehensive presentation of our analytical findings for different readerships. Sections 3.1 to 3.3 accommodate those readers who seek a detailed understanding of the results. Section 3.1 describes the results from simulating the two energy system scenarios as introduced in Section 2.4. Subsequently, Section 3.2 presents the operation of BSS, showcasing the local consumption and energy arbitrage across various EC use-cases. In Section 3.3, we evaluate the introduced EC and overall system level KPIs. Moreover, Section 3.4 summarizes our main findings and serves readers more inclined towards high-level insights, who may prioritize a concise overview and are less focused on methodological complexities and specific details.

3.1. Energy system scenarios

Fig. 10 depicts the installed capacities for the simulated energy systems. Capacities in the current scenario are derived from historical data, while the capacities for the future scenario are direct outcomes of REMix, under the assumptions explicated in Section 2.4.

Before incorporating the EC into AMIRIS, we simulate the electricity markets for the two energy system scenarios to provide an overview of the key market indicators. The simulation outcomes are shown in Table 4. In the current scenario, renewable sources contribute to 42% of the power generation, while this figure rises to 82% in the future scenario. These results are in line with the objectives set forth in the federal government's climate emergency program (Easter Package), published in early 2022, which aimed for a minimum of 80% of gross electricity consumption to come from renewable sources (Abuzayed and Hartmann, 2022). The future scenario sees higher operational system costs due to the increased cost of conventional power generation. With a larger proportion of renewable energy sources and a phase-out

[7] Given that the value of P_i^{ch} is negligible in comparison to P_t^M and P^{rc}, we have omitted the term $P_i^{ch}(z_{it}^{pr+} + z_{it}^{pr-})$ in the definition of Φ.

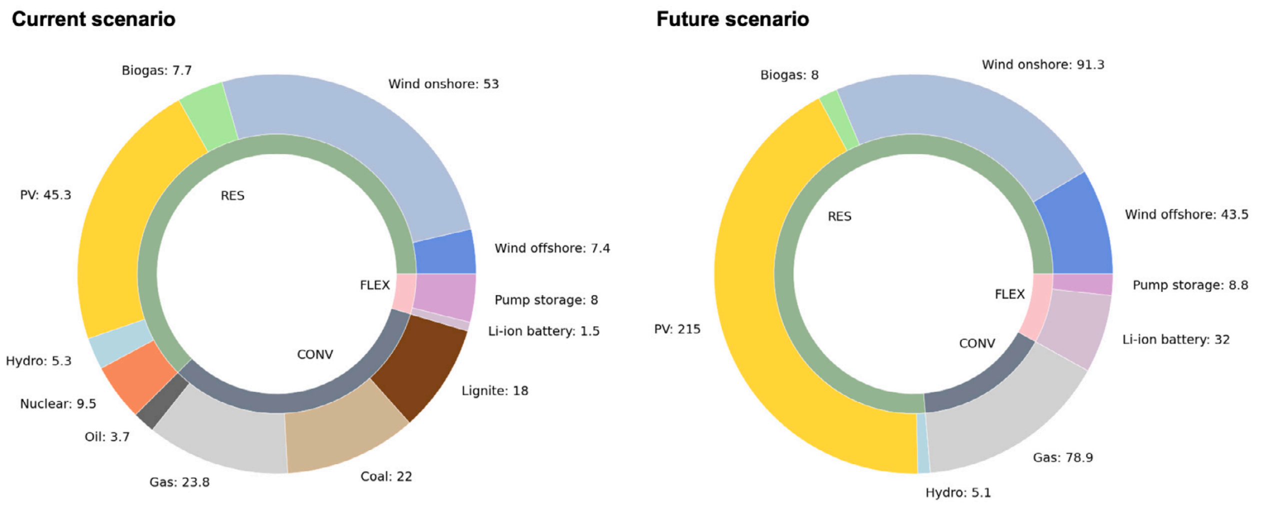

Fig. 10. Installed power plant capacities in the current and future scenarios.

Table 4
Descriptive energy system indicators resulted from AMIRIS simulations.

Indicator	Current scenario	Future scenario
Renewable power generation [TWh]	224.0	578.5
Conventional power generation [TWh]	303.19	125.1
Operational system costs [M€]	9227.8	14 004.4
CO_2 emissions [Mt]	155.1	47.9
Curtailed power generation [GWh]	0.9	92 609.3

Table 5
Descriptive statistics of the market prices before EC integration.

Indicator	Current scenario	Future scenario
mean [€/MWh]	43.0	57.4
std [€/MWh]	4.7	62.7
min [€/MWh]	0	0
max [€/MWh]	63.8	173.7
median [€/MWh]	42.5	6.6

of coal, the future scenario results in a 69% reduction in CO_2 emissions compared to the current scenario. The curtailment of power generation from renewable energy sources is 0.9 GWh in the current scenario. This figure escalates to 93.5 TWh in the future scenario.

Table 5 provides an overview of the market price statistics. In the future energy scenario, the average market price escalates by 14.4 €/MWh due to the higher marginal costs of gas power plants, an outcome primarily arising from the projected increase in gas and CO_2 prices. The peak electricity price rises from 63.8 €/MWh to 173.7 €/MWh in the future scenario, also attributable to the projected hikes in fuel and CO_2 prices. Notably, the lowest market price remains constant at 0 €/MWh in both scenarios because of the absence of regulatory incentives for renewable feed-in, coupled with the presumption that the marginal cost of power generation from RES is zero. In the future scenario, the duration of RES price-setting extends drastically from a single hour[8] in the current scenario to 4350 hours, thus decreasing the median price from 42.5 €/MWh to 6.6 €/MWh. The increased standard deviation distinctly showcases the intensified market volatility in the future scenario. This volatility becomes more evident in the Bollinger bands chart depicted in Fig. 11. The price fluctuations in the future scenario during the spring and summer seasons become particularly striking due to the surge in solar PV power generation.

3.2. EC operation

The operation of the EC varies across the case studies due to differences in the BSS operating entity, optimization goals, and pricing mechanisms for the prosumagers. Fig. 12 displays the simulated EC dispatch over three exemplary days in the current scenario with regulatory-induced charges assumed to be zero ($P^{rc} = 0$). Fig. 12(A) shows the predicted market prices to which the aggregator is exposed. Fig. 12(B) displays the direct electricity consumption and residual demand of the prosumer in the *No_stor*. The BSS dispatch and the residual load of the EC in different use-cases are presented in Figs. 12(C) to 12(F).

The storage optimization approach employed in the *CES_A* actively disregards market dynamics, while the users in the *SP* do not receive any time-varying price signals. Consequently, the charging schedule of the BSS in these two cases remains unaffected by the fluctuations in market prices. In the *CES_A*, the CES aims to minimize the power traded in the market, and on a sunny day, it accumulates excess generation to meet the evening electricity demand. Similarly, the HES in the *SP* follows this pattern on the first day, as selling electricity to the grid is not cost-effective due to lower market prices. However, on the following two days, the charging profiles of the BSS in these cases diverge. While the CES in the *CES_A* utilizes the stored energy to sustain a stable grid usage, the cost-optimizing HES in the *SP* use-case finds no incentive to charge the battery.

In contrast to the previous use-cases, the BSS operation in the *ORTP* and the *CES_P* is subject to market fluctuations. In both cases, the aggregator endeavors to align the BSS operation with market signals. In the *CES_P*, this is achieved by direct optimization of the CES, while in the *ORTP*, dynamic incentives in the form of time-varying electricity prices are created. The simulation results clearly demonstrate that the BSS charging and discharging strategy in the *CES_P* closely follows market price developments, with charging occurring during periods of high prices and discharging when prices are low. In the *ORTP*, however, the behind-the-meter self-consumption still remains more attractive than selling self-generated electricity to the grid. Nonetheless, the HES shifts the electricity load to hours of low market prices (e.g., in timesteps 385, 387, and 412). Our observations reveal that due to significant price fluctuations in the future scenario (as shown in Fig. 11), selling self-generated solar energy is occasionally more attractive than self-consumption. Additional insights regarding the BSS dispatch can be obtained from the annual duration curves, as depicted in Appendix A.3.

[8] The deviation of this value from historical data can be explained by the electricity demand and generation of the EC, which are not considered in this simulation.

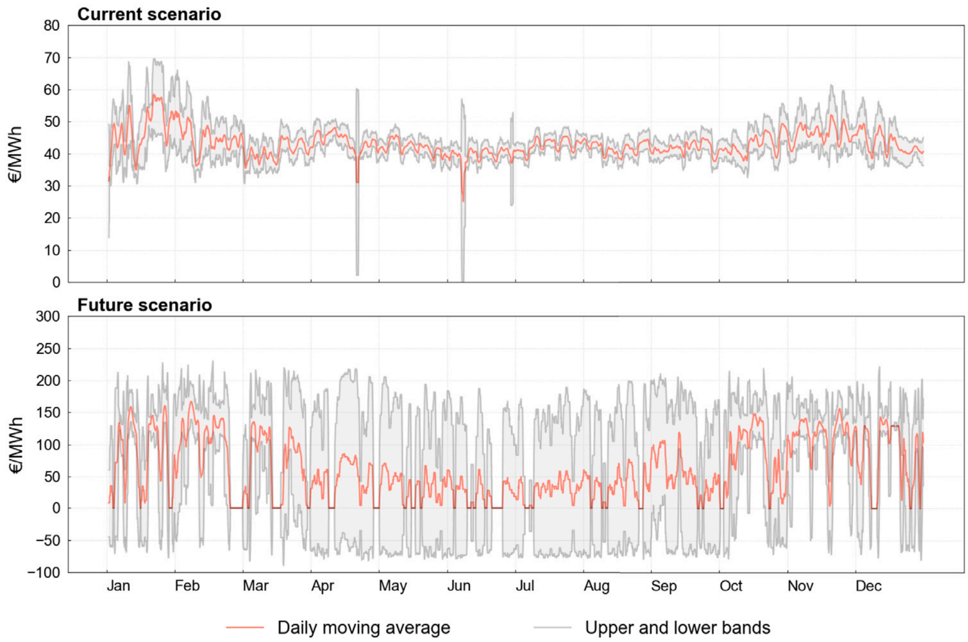

Fig. 11. Bollinger bands chart for the market prices in current and future scenarios. The chart illustrates two standard deviations, both above and below, from the 24-hour moving average trend.

3.3. KPI results

In this section, we examine the KPIs introduced in Section 2.5. To isolate the effects of the BSS operation on the KPIs, we present relative values compared to the *No_stor*.

Fig. 13 presents the community-level KPIs. As shown in Fig. 13(A), the EC in the *CES_A* and *SP* simulations significantly reduces its interaction with the wholesale market (50.7% and 48.4% respectively). Conversely, the EC in *CES_P* shows the highest trading volume. The incentive for trading activities is notably higher in the future scenario due to increased short-term volatility (54.7% compared to 15.5% in the current scenario). In both scenarios, the incentive for market arbitrage diminishes significantly if the CES is required to pay an additional 18.5 cents/kWh for charging the battery. Prosumagers' behavior in *ORTP* contrasts somewhat across scenarios: Although electricity self-consumption remains a priority in the current scenario (with nearly 45% less grid usage and feed-in), the HES shows up to a 23% higher market trading volume in the future scenario. Even when $P^{rc} = 18.5$ cents/kWh, where the market signals of scarcity and excess do not "directly" reach the EC users, prosumagers interact 15% more with the grid.

Fig. 13(B) illustrates how the use of BSS in each case impacts community welfare. The changes in community welfare are, by definition (as expressed in Eq. (14)), driven by the overall profit gained in the market and the regulatory fees paid. The aggregated impact of these two drivers differs in the current and future scenarios: In the current market with comparably lower arbitrage potential, higher end-user electricity prices incentivize a higher level of behind-the-meter self-consumption and encourage the users to invest more in self-sufficiency. In such environment, the operation of front-of-the-meter CES does not generate a positive welfare effect. Due to higher power prices in the future market, the welfare gain using a BSS is significantly higher, where the least favorable case, *CES_A* with $P^{rc} = 18.5$ cents/kWh, generates over 34 M€ (i.e., ≈ 22.6 k€/MW-year) additional welfare for the community. Moreover, the profit potential from volatile market dynamics in the simulated future scenario generally outweighs the cost savings through self-consumption, leading to viable use-cases in market driven CES (*CES_P*) and HES (*ORTP*) solutions. The most profitable use-case, *CES_P* with $P^{rc} = 0$, generates an additional 132 M€, (i.e., ≈ 88 k€/MW-year).

The BSS operation in the *CES_P* effectively aligns the EC's operation with market price signals, resulting in the highest Φ. Nevertheless, due to limited foresight, the operator may still experience misalignment as the forecast for the entire simulation period is not available. The sensitivity analysis presented in Fig. 14 illustrates that extending the forecast period from 2 to 256 h significantly improves the community welfare, but the improvements are diminished when the forecast period exceeds 64 h. This is mainly due to the short charging cycle of the BSS that is taken into account. In addition, the analysis indicates that a shorter schedule duration leads to superior performance of the BSS operation, and the most favorable outcomes are attained with a $\pi = 1$. However, the considerable computational effort demanded by the bilevel optimization in the *ORTP* justifies the choice of the schedule duration ($\pi = 0.5\omega$) in our analysis.

Fig. 15 shows the impact of the EC on overall system KPIs, i.e., the operational system costs and the market-driven curtailment of RES, and compares them against a benchmark case where the BSS is used to minimize the system costs (*Sys_min*). The benchmark case assumes that the BSS operator has the same foresight as the aggregator in the EC, enabling a comparison of the system-friendly behavior of the different use-cases.

The results show that the BSS operation can have a more significant impact on system costs in the future scenario, owing to the higher marginal costs of gas power plants in this scenario. While the BSS in the *Sys_min* reduces the system costs by as much as 2.7 M€ (0.03% of total operational costs) in the current scenario, cost savings increases to 132.16 M€ (0.94%) in the future scenario. Among the EC use-cases, the most substantial reduction in system costs is achieved in the *CES_P*, where market-oriented BSS optimization leads to a reduction of up to 2.4 M€ (0.026%) and 83.5 M€ (0.6%) in the current scenario and the future scenario, respectively. In the current scenario, the high level of local self-consumption in the *SP*, *ORTP*, and *CES_A* increases the operational system costs. The negative impact of local self-consumption on system costs is reduced in the future scenario, with the EC operation in the *SP* resulting in an increase of 12.7 M€ (0.09%) in this scenario,

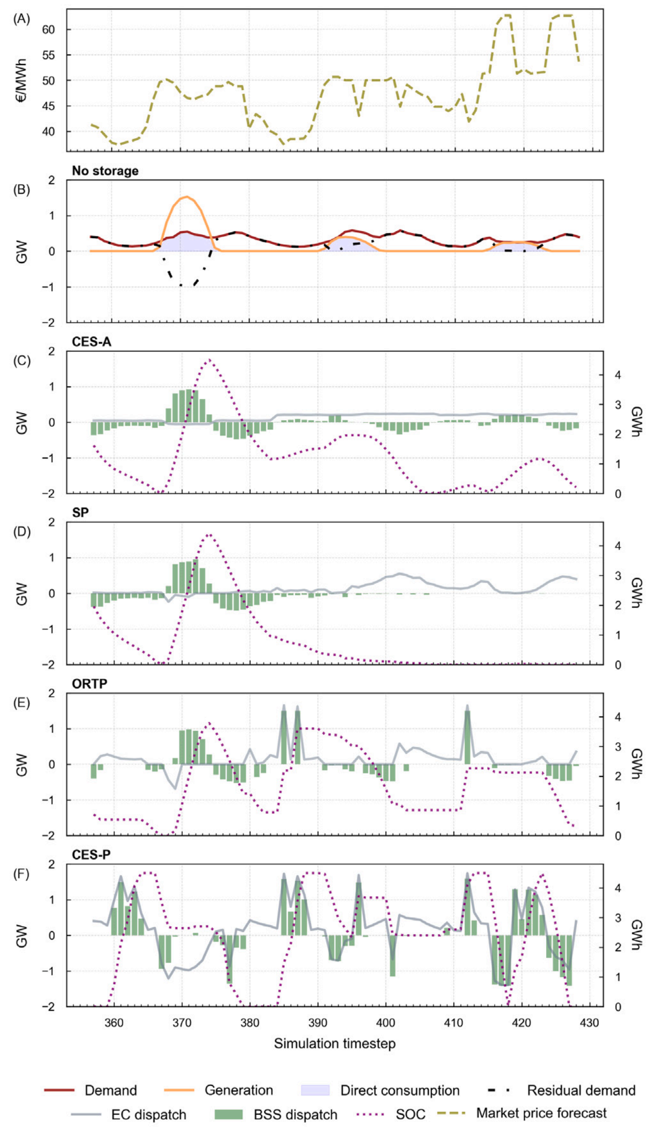

Fig. 12. EC dispatch in different use-cases over three exemplary days. Market price forecast is shown in A. User's direct consumption and residual demand are presented in B. subplots C, D, E, F respectively show the EC dispatch in the *CES_A*, *SP*, *ORTP* and *CES_P* use-case (as described in Table 3).

while system costs in the *ORTP* and *CES_A* decrease by 59.9 M€ (0.42%) and 8.2 M€ (0.05%), respectively. The negative impact of volumetric regulatory-induced charges on BSS performance is most visible for the *CES_P* and *ORTP*. The system costs for the *CES_P* increase by 1.87 M€ and 4.47 M€, while for the *ORTP* they increase by 0.36 M€ and 1.14 M€ in the current scenario and the future scenario, respectively, compared to the simulations with $P^{rc} = 0$. The impact of these charges in other cases is comparatively insignificant.

As presented earlier in Table 4, there is a significant increase in market-driven curtailment in the future energy system scenario, notably characterized by a high level of RES generation. It is important to note, as will be discussed in the following section, that the high level of market-driven curtailment in our findings is primarily a model artifact resulting from the omission of endogenous modeling of sector coupling and cross-border power exchange. Specifically, the untapped potential of RES generation that could not be marketed even at the price of 0 €/MWh escalate from a mere 0.9 GWh in the current scenario to over 92 TWh in the future scenario. In our benchmark scenario (*Sys_min*), the BSS operator absorbs 100% (0.9 GWh) and 1.25% (1156.45 GWh) of the unused RES generation in the current scenario and the future scenario, respectively, with the aim of minimizing the operational system costs. Our analysis indicates that the BSS operation had a minor effect on the curtailment in the *CES_A* and *SP*, with the exception of the *SP* in the future scenario, where the curtailment increased by 206 GWh more. In contrast, in the *CES_P* and *ORTP*, the BSS effectively absorbed all the surplus generation in the current scenario. Similarly, the battery operation in the *CES_P* and *ORTP* reduces the amount of market-driven curtailment by up to 290 GWh and 205 GWh, respectively. Furthermore, our results show that the regulatory induced charges do not have a fundamental effect on the curtailment.

3.4. Key takeaways

The key findings in the context of the central research question of our study can be summarized as follows:

In the current energy system, distributed BSSs are used to reduce reliance on the grid by promoting self-consumption. Within the existing regulatory framework, where energy consumers face substantial static energy-based charges for taxes, levies, and fees aimed at covering grid investment and operational expenses, the most financially viable BSS use-case remains behind-the-meter self-consumption using HES systems. This observation aligns with current realities, with over 83% of stationary battery installations in Germany being HES.[9] While such self-consumption approach improves the integration of local PV generation, the full potential of energy storage systems remains largely untapped. Our findings indicate that focusing solely on self-sufficiency-oriented operation yields only marginal improvements in system-level KPIs compared to approaches oriented towards the wholesale market. As we move towards a future energy system, in which the abundant RES need to be curtailed during certain hours and RES scarcity leads to expensive power generation from conventional, high-CO_2 footprint fuels, efficient utilization of available flexibility becomes crucial. The simulated scenario in 2030 with an 82% share of RES exhibits a potential for significant price volatility in the future energy system, which may lead to growing incentive for BSSs to engage in energy arbitrage. It is important to note that our study did not address grid constraints related to electricity transportation. Given that a significant amount of RES is already curtailed due to transmission grid limitations, relying solely on local consumption and generation through BSS operation could exacerbate efficiency losses from the system perspective (Monforti-Ferrario and Blanco, 2021). Moreover, as for example shown in van Westering and Hellendoorn (2020) CES can provide services to distribution grid operators to reduce the congestion caused by decentralized RES generation in the low voltage grid.

The proposed ORTP scheme, which results from the simultaneous optimization of the aggregator and prosumagers' profit-maximizing utility functions, improves the alignment of the HES systems' operation with the real-time conditions of the overall energy system. In contrast to the straightforward real-time pricing strategies examined in the existing literature (such as those discussed in Klein et al. (2019), Sarfarazi et al. (2023b), and Günther et al. (2021)), which simply pass wholesale prices through to end-users, ORTP ensures an equilibrium in the EC. As mathematically proved in Sarfarazi et al. (2023a), this equilibrium guarantees the highest welfare for the EC. While this approach effectively communicates market signals to the EC users, the preference

[9] As of March 1st, 2024, the total installed battery storage capacity in Germany amounts to 12.4 GWh. Among these installations, 10.4 GWh are attributed to HES systems, typically with a size of up to 30 kWh. Additionally, 488 MWh are associated with commercial and industrial batteries, ranging from 30 kWh to 1 MWh in size, while 1.5 GWh are accounted for by large-scale batteries exceeding 1 MWh in capacity (Figgener et al., 2022, 2024).

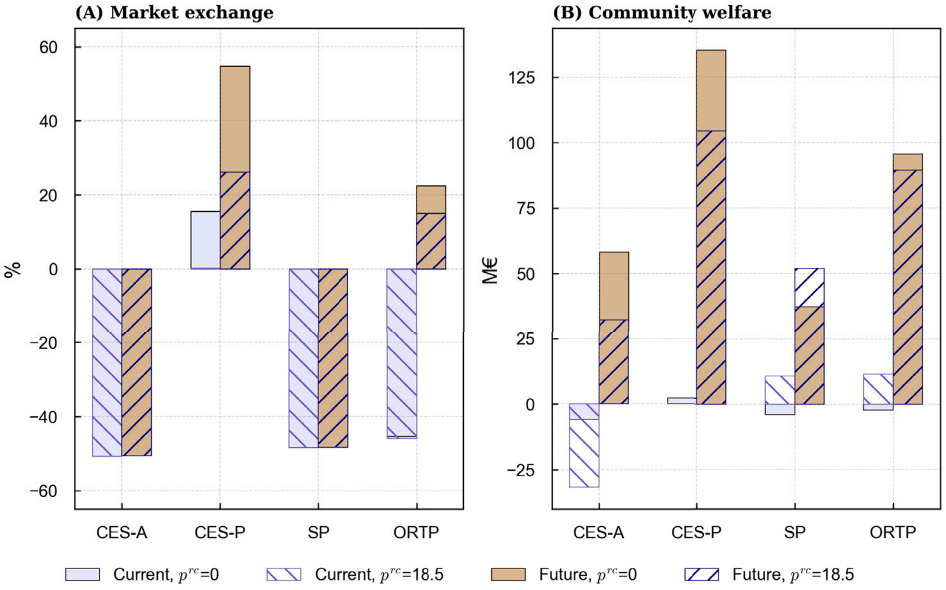

Fig. 13. Community level KPIs: market exchange (A) and community welfare (B) in the *CES_A*, *SP*, *ORTP* and *CES_P* relative to the *No_stor*(as described in Table 3). Note that subplots are scaled differently.

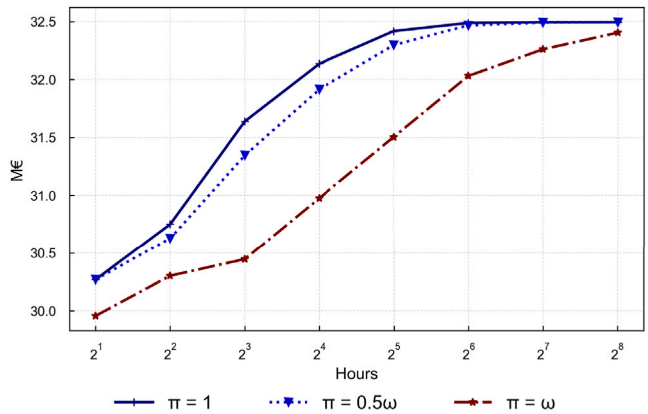

Fig. 14. Sensitivity analysis regarding the impact of the schedule duration (π) and forecast period (ω) on the community welfare (Φ).

for behind-the-meter self-consumption of PV electricity remains strong among prosumagers in the current market. However, the simulated future energy system scenario reveals increased short-term price volatility in the market, amplifying the incentive for grid interactions during specific hours. This contributes to the cost-effective operation of the HES and improves the nationwide integration of RES. Nevertheless, the effectiveness of such a mechanism is compromised if the tariff structure incorporates static energy-based charges that distort real-time signals.

The profit-oriented operation of CES emerges as the most system-friendly approach, yielding the highest EC welfare among the studied use-cases. It is important to note that the profit derived from CES cannot be directly compared with that of HES, as we evaluated the generated welfare across the entire EC. The profitability of CES operation through arbitrage is heavily dependent on prevailing market conditions. Our findings indicate a per-unit arbitrage opportunity ranging from 1.7 k€/MW in the current system to 88 k€/MW in the future energy system. These figures fall on the lower and upper bounds of the spectrum of data compiled from 176 individual valuation studies and market transactions, which range from 5 to 85 k€/MW-year in Schmidt and Staffell (2024).[10] The operation of CES becomes even more sensitive to regulatory charges in the absence of behind-the-meter potential. The recent decision by the German government to exempt BSS projects commissioned until 2029 from grid fees for 20 years (German Energy Storage Systems Association (BVES), 2024), enhances the attractiveness of investment in this sector. Additionally, under current market conditions revenue stacking by providing multiple services within a specified time frame, though not explored in this study, has the potential to significantly improve the profitability of BSSs (Schmidt and Staffell, 2024). For instance, the study in Sorourifar et al. (2018) demonstrates that under specific market conditions, simultaneous participation in energy and ancillary services markets can yield a 4- to 5-fold increase in net present value compared to solely engaging in energy transactions in the day-ahead market.

Furthermore, our results underscore the systemic advantages of energy arbitrage in the market using BSSs. The considered 1.5 GW battery in our study results in a reduction of operational system costs by 2.4 M€ and 83.5 M€ in current and future scenarios, respectively. Despite these positive effects on the system, the operation of BSSs often diverges from the optimization of system costs, as the business economic benefits of BSS operation do not always align perfectly with the system's requirements. One such scenario arises when a price-setting BSS deliberately withholds its full capacity to respond to energy scarcity and excess, aiming to prevent price cannibalization. The assumption of system-cost minimizing BSS operation is commonly employed when assessing the potential of batteries in future energy systems using energy system optimization models.

4. Discussion of limitations

We conducted a comprehensive analysis to assess the efficiency of BSS operations across different EC use-cases, taking into account the perspectives of the EC and the overall energy system. Our evaluation, encompassing assessments at both the EC and wholesale market levels,

[10] To provide context, the current investment cost for Lithium Ion Phosphate batteries is estimated approximately 300 k€/MW.

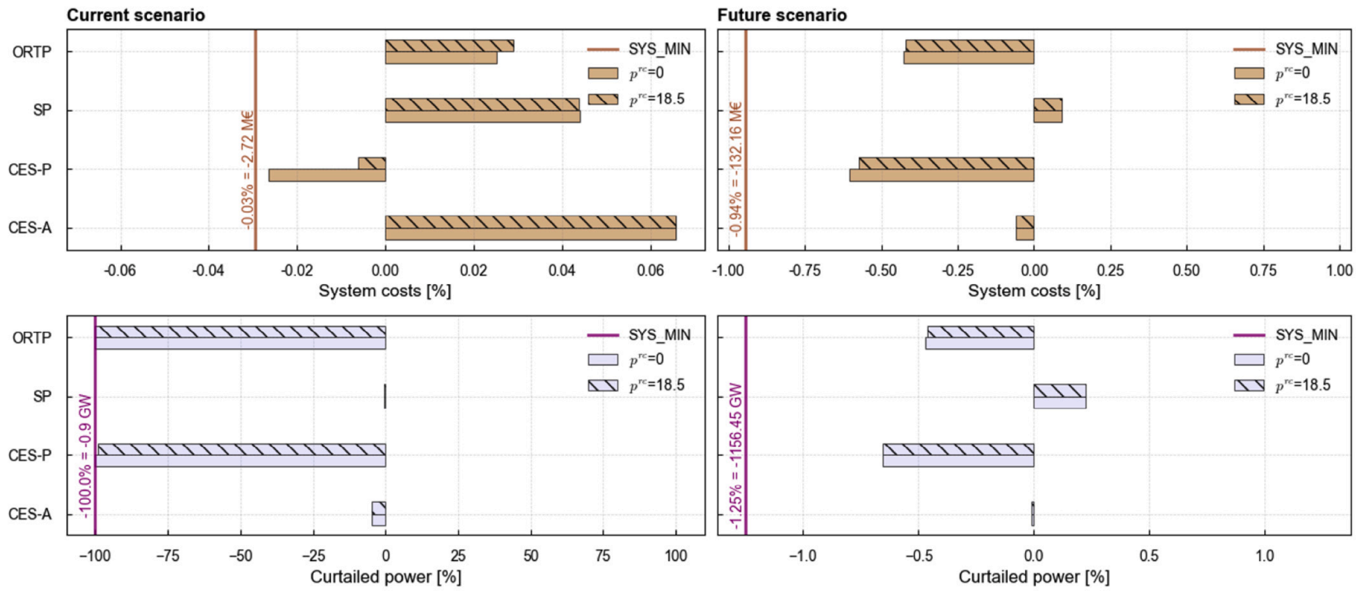

Fig. 15. Changes in system costs and RES generation curtailment in both energy system scenarios and in the *CES_A*, *SP*, *ORTP* and *CES_P* (as described in Table 3). Note that subplots are scaled differently.

was subject to various constraints. Firstly, in terms of the market, we did not account for the potential externalities of BSS operation on non-energy power sector costs, such as those associated with the electricity network. To ascertain whether BSS operation has any adverse effects on the distribution grid, it would be necessary to explicitly model the underlying power flows, a task that exceeded the scope of our study. In this context, one vital avenue for future research involves establishing appropriate incentives and coordination mechanisms that align BSS operations with both market and grid signals.

Secondly, our market simulation was subject to several simplifying assumptions. By solely focusing on Germany, our results are prone to overestimating price fluctuations and required curtailment due to market reasons. Furthermore, neglecting uncertainties and forecast errors has a tendency to exaggerate the efficiency of storage operations. Additionally, our model did not take into account the competition among flexibility operators. We anticipate that strategic bidding by various storage operators and aggregators of sector coupling technologies will mitigate the intense price fluctuations observed in future energy system scenarios. Correspondingly, if we parameterize our model to represent a large array of ECs, each encompassing diverse actors, we anticipate a similar effect. The effective modeling and data supply for the large-scale integration of small actors in the energy market is a topic of another research path.

Thirdly, our study imposed restrictions on the available technologies within the EC, limiting it to PV and lithium-ion battery systems, which were parameterized exogenously. However, if capacity expansions are optimized endogenously, prosumagers invest extensively in self-sufficiency when regulatory-induced charges are in place (Bertsch et al., 2017). Moreover, we did not consider the heterogeneity of households and instead parameterized a single prosumager with a standard load profile and national generation profile. In Sarfarazi et al. (2023a), we demonstrated that incorporating actor heterogeneity within the EC leads to greater welfare, as there are more opportunities for local trading and balancing within the EC.

Last, we analyzed the impact of regulatory charges as static energy-based charges added to the electricity price and demonstrated that such charges distort market signals, leading to sub-optimal utilization of demand-side flexibility options. Furthermore, while prosumagers benefit from reduced costs through self-consumption, they contribute less to taxes, levies, and grid expenses. In the case of grid costs, these expenses must be borne by non-privileged consumers, raising distributional concerns (Mehigan et al., 2018). Future research should delve into alternative tariff options, such as time-varying levies (Sarfarazi et al., 2023b) or capacity-based grid charges (Khalilpour and Lusis, 2020; Klein et al., 2019), and also consider feed-in remunerations as well as CO_2-oriented reforms of retail tariffs abolishing the regulatory-induced energy taxes and surcharges altogether (Aniello and Bertsch, 2023). Although the aggregator in our model participates in a single electricity market, multi-use business models can enhance the profitability of BSS operation (Gährs and Knoefel, 2020), particularly as the storage remains idle for numerous hours in the year. Collective self-consumption within the EC and providing grid services can create additional revenue streams for BSS, making the investment more attractive. We demonstrated that the community welfare in the EC can be increased, but the question of how the resulting welfare is distributed among stakeholders remains unanswered; specifically, what financial incentives encourage users to participate in this business model, rather than switch to another aggregator.

5. Conclusion

Decreasing battery storage system (BSS) costs and growing interest in self-consumption of solar electricity have driven significant private investments in home energy storage (HES). On the other hand, multi-use business models using community energy storage (CES) are proposed as alternatives to behind-the-meter HES operation. The rise of distributed BSSs for local consumption poses a challenge to efficient energy system operation and design. This study employed the agent-based market model AMIRIS to evaluate the distributed BSS operation from the EC and overall energy system perspectives. For CES, we analyzed profit and autarky-oriented operations. We investigated HES operation under static pricing and an optimal Real-Time Pricing (ORTP) scheme. Additionally, we benchmarked these cases against a system-cost minimizing battery.

Our study explored the ECs in current and future energy systems. Simulations of the future energy market, with an 82% share of fluctuating renewable energies, revealed an increase in price volatility. In this market environment, BSSs exhibit significant arbitrage potential, thereby aiding the integration of renewable energies. In the current system, a 1.5 GW BSS minimizes the operational system costs by mere 2.72 M€ in one year. However, in the future scenario, this value rises impressively to 132.16 M€. Despite this, the favorable impact of BSS on studied EC use-cases is lower than system-cost minimizing operation. Consequently, our conclusion emphasizes that policy decisions relying solely on system-cost minimizing storage assumptions, commonly employed in large-scale energy system models, without considering the micro-economic interests of BSS operators, may lead to an underestimation of future storage system needs.

Our findings highlighted inefficiencies in autarky-oriented CES operation. Despite trading 50% less power in the market compared to profit-seeking CES, the self-sufficiency-driven CES has limited effectiveness in reducing system operational costs and consuming surplus energy during high RES generation. The reduced EC interaction with the larger energy system may result from the prevailing regulatory framework, such as free of charge behind-the-meter self-consumption, and lack of dynamic price incentives rather than being intentional. Our proposed ORTP design creates time-varying incentives, enhancing community welfare and aligning BSS operation with market signals. Implementing such real-time pricing schemes, currently hindered by smart grid infrastructure, will be increasingly crucial in the future energy system.

Incorporating high static energy-based regulatory charges into consumer tariffs promotes prosumager self-consumption, but our study underscored potential trade-offs. During periods of high market fluctuations, the efficiency gain through market participation may outweigh savings from regulatory-induced charges, increasing overall community welfare. Without incentives for local self-consumption, regulatory charges decrease the efficiency of front-of-the-meter BSS operation. Our investigation showed that profit-maximizing CES remains idle for over half of the year, emphasizing the potential benefits of multi-use business models for both ECs and the energy system.

This study provides a valuable foundation for further exploration, fostering comprehensive understanding of EC dynamics in sustainable energy system transitions. The methodology allows for extended analysis of distributed energy systems, considering technological diversity and regulatory frameworks. Future research may enhance the ORTP scheme to incorporate physical energy system signals for a more system-friendly operation of distributed BSS. Additionally, endogenous modeling of investment decisions, both within the EC and at the macro energy system level, offers significant prospects for a comprehensive understanding of energy system design aspects.

CRediT authorship contribution statement

Seyedfarzad Sarfarazi: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Shima Sasanpour:** Methodology. **Valentin Bertsch:** Writing – review & editing, Supervision.

Data availability

The authors do not have permission to share data.

Declaration of competing interest

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

Appendix

A.1. Information exchange in EC models

In Section 2.3.3, we introduced the integration of two EC models in AMIRIS and introduced two modeling approaches to represent EC use-cases in AMIRIS. The main difference between these approaches lies in the definition of EC prices. In the first method, the aggregator uses a "Tariff strategist" module to calculate the prices using predetermined rules, such as SP or simple real-time pricing. In the second method the aggregator passes the forecasted market prices to the "Energy community" and the internal EC prices (ORTP) are derived by solving the bilevel optimization. The interplay between the actors during simulation in both approaches is described in Fig. 16.

A.2. Constraints for the CES optimization model

The CES optimization model can adopt the self-sufficiency driven or profit maximizing objective functions as respectively formulated in (3) or (4). The constraints to the CES optimization problem are formulated as:

$$a_t^{ag} = (1 - \Lambda^{ag})a_{(t-1)}^{ag} + \epsilon^{ag} z_t^{ag+} - \frac{z_t^{ag-}}{\varepsilon^{ag}}, \tag{18a}$$

$$z_t^{ag+} = e_t^{ag+} - e_t^{ag-} - \sum_i (e_{it}^{pr+} - e_{it}^{pr-}) + z_t^{ag-} \tag{18b}$$

$$0 \le a_t^{ag} \le K^{ag} F^{ag}, \tag{18c}$$

$$a_{t-1}^{ag} = A_0^{ag}, t = 1, \tag{18d}$$

$$0 \le e_t^{ag-} \le E_t^{ag+}, \tag{18e}$$

$$0 \le e_t^{ag+} \le E_t^{ag-}, \tag{18f}$$

$$0 \le z_t^{ag+} \le \frac{U_t^{ag} K^{ag}}{\epsilon^{ag}}, \tag{18g}$$

$$0 \le z_t^{ag-} \le U_t^{ag} K^{ag} \varepsilon^{ag} \tag{18h}$$

where the storage parameters ϵ^{ag}, ε^{ag}, Λ^{ag}, K^{ag}, U_t^{ag}, and F^{ag} are similar to those of prosumagers. In Eq. (18a), the SOC of the CES is determined by various factors including the self-discharge rate (Λ^{ag}), the charged and discharged power (z_t^{ag+} and z_t^{ag-}), as well as the CES charge and discharge efficiencies (ϵ^{ag} and ε^{ag}), in addition to the SOC in the previous time step. To ensure that power flows are balanced in each time step, constraint (18b) is in place. Eq. (18c) sets a limit to the amount of stored energy to prevent negative storage levels or exceeding the HES energy capacity, which is determined by the power capacity (K^{ag}) multiplied by the energy to power ratio (F^{ag}). Furthermore, the initial SOC of the CES is established in Eq. (18d), with the rolling horizon parameter A_0^{ag} being updated based on the previous simulation step's ($s - 1$) stored SOC. Aggregator market bids are capped in (18e) and (18f). Specifically, the upper bounds for power purchase and sale from the market are defined as followed:

$$E_t^{ag+} = \max\{0, K^{ag} + \sum_i (e_{it}^{pr+} - e_{it}^{pr-})\} \tag{19a}$$

$$E_t^{ag-} = \max\{0, K^{ag} - \sum_i (e_{it}^{pr+} - e_{it}^{pr-})\} \tag{19b}$$

We restrict the charging and discharging power of the CES through (18g) and (18h). To complete the formulation, we add U_t^{ag} to denote the availability of the CES in each time step, which takes a value between 0 and 1.

A.3. Storage dispatch duration curves

Fig. 17 shows the charging duration curves of the BSS for different use-cases and scenarios, with and without regulatory charges. The charging duration curves for the *CES_A* and the *SP* can be seen to remain constant, as they function independently of the broader energy

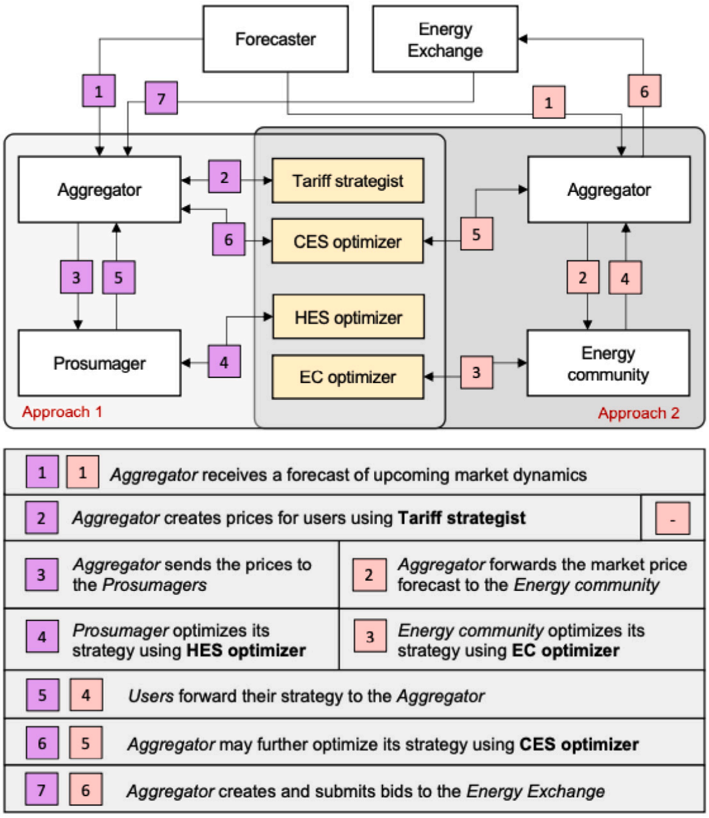

Fig. 16. Interaction among AMIRIS agents in one simulation step: Purple and pink boxes respectively correspond to information flows in the first and second approaches.

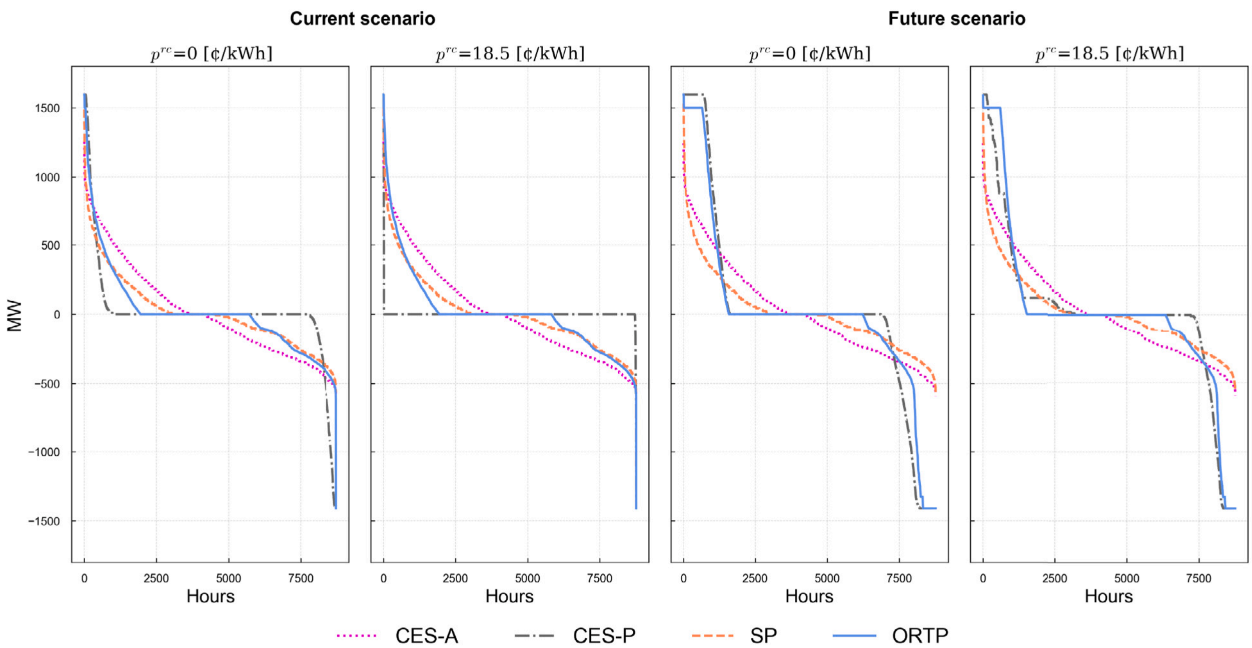

Fig. 17. BSS usage duration curves for different use-cases and scenarios. Positive and negative values respectively indicate charging and discharging of the BSS.

system and are unaffected by scenario modifications. Conversely, the operation of the BSS in the *CES_P* is substantially impacted by regulatory charges, particularly in the current scenario, where the CES is charged or discharged for a mere 63 h annually (compared to 1975 h in the absence of regulatory charges). However, the existence of intense short-term price fluctuations in the future scenario suggest potentially profitable CES market trading activities. Thus, a significant increase in CES charging cycles compared to those in the current scenario can be noticed in this scenario, a trend that persists even with regulatory charges in place. In the current scenario, the HES in the *ORTP* primarily serves the purpose of self-consumption. However, in the future scenario, there is an increase in the charging and discharging hours of the HES, suggesting expanded opportunities for trading in the market. Notably, the BSS in the *CES_P* and *ORTP* deviates from the behavior of the *CES_A* and *SP*, exhibiting less frequent charging or discharging in terms of the number of hours.

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Chapter 5

Discussion and conclusion

This doctoral thesis was motivated by the ongoing decentralization of the German energy system and the challenges encountered by policy makers, regulators, and emerging market actors to ensure a cost-efficient operation of the energy system. Alongside this, an investigation into innovative mechanisms for the effective operationalisation of decentralized energy systems (DESs) has emerged as an important area of focus within energy research. However, as discussed in section 1.2, a significant research gap exists between studies that focus on the techno-economic analysis of energy communitys (ECs) and those that examine the overall system integration of DESs. The former fails to consider the feedback effects of ECs on the larger energy system, while the latter often lacks the necessary level of detail to comprehensively capture the diverse and complex nature of EC business models. As a response, this thesis aimed to contribute to this gap by proposing novel methodological developments (as reviewed in Chapter 2) to bridge these two body of literature for the first time. The developed methods, for the first time, enable holistic analysis of EC integration and is capable of supporting important political decision-making processes.

Following a bottom-up approach, this thesis studied the research questions concerning the operation of distributed energy resources (DERs) in ECs (related to guiding question A) before investigating their overall systemic integration (related to guiding question B). The most significant findings related to the research questions are presented in section 5.1. In section 5.2 of this chapter, the author undertakes a critical evaluation of the thesis's methodologies and findings. Finally, section 5.3 provides a concise summary of the thesis's accomplishments and findings, along with a prospective outlook on future research.

5.1 Summary of key findings and achievements

The contributions of the thesis at hand are related to the guiding questions A and B, introduced in Section 1.2:

A: What operation strategies can intermediary entities employ to effectively organize DERs in ECs?

A.1: What modeling and optimization methods can be employed to represent the local aggregation of DERs in ECs?

This research question is primarily examined in Paper 1 and 2. Both research works introduce innovative EC models that encapsulate the microeconomic behavior of the participating actors. Although these models each have unique characteristics, their primary contribution lies in representing the bilateral energy trading game within ECs that feature hierarchical aggregator–user structures.

Internal energy trading within an EC is commonly depicted as a 1-leader, n-followers Stackelberg game. In this game, an aggregator (the Stackelberg leader) first establishes a strategy, and then the users (the Stackelberg followers) respond by selecting their individual strategies. As explained in Section 2.1.1, the internal EC prices render the strategies of the aggregator and users interdependent. This Stackelberg game can be expressed as a bilevel optimization problem (BIOP), with the followers' decision-making optimization problem nested within the leader's outer optimization problem. BIOPs are NP-hard and pose considerable challenges to solve. Therefore, discovering the Stackelberg equilibrium of the energy trading game and determining the optimal real-time pricing (ORTP) strategy requires a balance between the exact techno-economic modeling of the actors' objective functions and constraints and the complexity of the required solution methodologies and algorithms. Both papers addressed this trade-off by increasing the model's granularity compared to existing literature, and suggesting advanced methodologies to effectively manage the increased complexity.

Paper 1 introduced an innovative bottom-up approach to model the self-interested behavior of the stakeholders in an EC and developed a genetic algorithm (GA) that iterates between the leader's and followers' problems and searches the non-convex solution space for the Stackelberg equilibrium of the energy trading game. Employing such a heuristic approach to optimization allows for an increase in the problem's complexity: households are portrayed as heterogeneous agents; these include consumers, prosumers, prosumagers, and flexible consumers with heat pumps (HPs). Consequently, the followers' problem is a sum of separable sub-problems. Moreover, the aggregator in the proposed model operates a community energy storage (CES). Thus, both problem levels involve storage optimization, indicating a significant overall problem complexity. While finding the global optimum using heuristic approaches like GA is not guaranteed, the ORTP solution obtained through the proposed algorithm significantly outperformed the studied benchmark pricing strategies.

Paper 2 frames the bilateral energy trading game as a BIOP and adopts a single-level reduction method to solve the problem to its global optimum. The users are represented by a prototype agent, which can be parameterised to portray a consumer, a prosumer, a prosumager, or an electric vehicle (EV) owner. Furthermore, the model takes into account the uncertainties regarding wholesale market prices as well as the power demand and generation of the users, making the problem a stochastic BIOP. Paper 2 also propose a cluster-based scenario generation algorithm to prepare the required scenarios for the stochastic optimization. Another unique feature of the EC model is the incorporation of the maximum available line capacity behind the point of common coupling as a constraint. This indicates that the price incentives in the EC can promote an operation favorable to the physical power system.

In this research, several mathematical theories and techniques (outlined in Section 2.1.2) are applied to transform the stochastic non-linear BIOP into a problem solvable using commercial solvers. The study first applies a single-level reduction technique using Karush–Kuhn–Tucker (KKT) optimality conditions to derive a single-level optimization problem. To manage the non-linearity inherent in the resultant mathematical problem, the big-M technique is utilized, enforcing a discrete value state for two optimization variables, namely, the aggregator's purchase and sale prices. Accordingly, a mixed-integer linear program (MILP) is derived.

This paper enhances the body of literature on bilevel optimization by introducing an alternative solution technique to the classic big-M approach. It proposes a novel linear quasi-relaxation technique combined with a modified branch-and-bound algorithm for efficient problem-solving. A noteworthy feature of the developed algorithm is its dynamic partitioning. After finding the optimal solution to the discrete problem, the algorithm considers a reduced solution space close to the found solution and initiates a new round of optimization. By doing this, the found solution gradually moves closer to the global optimal solution within a continuous solution space. The performance of the algorithm is assessed through various case studies. The largest case study demonstrated a 91% reduction in overall CPU time compared to the MILP benchmark formulation.

Additionally, Paper 4 extends the model proposed in Paper 2, incorporating the charges induced by grid usage regulations. This development facilitates the analysis of the impact of existing regulatory frameworks on the operation of ECs, thereby enhancing the policy implications of the proposed methodology.

A.2: What are the advantages of EC business models for the stakeholders involved?

The stakeholder benefits of aggregating DERs within an EC are evaluated in research papers 1, 2, and 4. These assessments focus on two essential, interrelated elements of EC business models. The first element concerns the operation of distributed photovoltaic (PV) generation and various flexibility options, which serve as key energy resources within the EC. From the end-user perspective, this thesis explores the use of HPs and EVs, as well as the combined PV-storage operation as a home energy storage (HES) to decrease users' electricity costs. From the aggregator's viewpoint, the grid-connected CES is analyzed for its potential to augment the aggregator's profits or reduce the EC's reliance on broader system exchanges.

The second business model element pertains to the pricing design for the EC members. Three pricing schemes are studied: the static pricing (SP), incorporating a fixed fee for electricity procurement and sale, which represents the prevalent pricing structure for the majority of power consumers in Germany. Second, the real-time pricing (RTP) strategy is considered, in which time-varying wholesale market price signals are directly integrated into end-user prices. Finally, this thesis derived an optimized internal pricing scheme for the EC, termed ORTP, where prices are affected by market prices and local generation and consumption patterns.

From the users' viewpoint, operating flexibility options under both dynamic pricing schemes can yield cost-saving benefits. For flexible consumers, electricity demand can be met when prices are lower. Furthermore, users with battery storage system (BSS) can engage in energy arbitrage, strategically charging and discharging their batteries based on fluctuating electricity prices. For instance, EVs can either purchase or sell power to the grid[1] during their charging station connection. However, volumetric charges on grid usage can challenge this business model as they often push the purchase price from the grid above the selling price. In such a regulatory environment, prosumagers gain a significant advantage as they can use the HES for behind-the-meter self-consumption of their generated electricity. However, real-time scarcity signals could make grid feed-in more profitable in certain hours than self-consumption. While the fairness of dynamic pricing is part of a broader debate [118, 119] and beyond the scope of this thesis, the findings show that market-based pricing can raise traditional consumers' electricity bills. This drawback can be strategically mitigated in tailored community pricing schemes, such as the studied ORTP.

From policymakers' perspective, the profitability of prosumage under current regulations may trigger distributional concerns. Since grid infrastructure maintenance costs are levied on a per unit basis, an increase in the number of prosumagers, who draw a small portion of their power demand from the grid, increases the per unit charges for other households [28]. This can create a further incentive to disconnect from the grid, a trend known as the "death spiral" [120]. To counter this, introducing fixed network charges, which are not proportional to household energy consumption but instead related to their peak usage or fixed per connection [121], is often discussed as a fairer cost allocation method that ensures network cost recovery [122].

Similar to the users, the operation of flexibility options available in the EC can offer significant financial advantages for the aggregator. These benefits might become more noticeable if the market price volatility increases due to the high penetration of renewable energy sources (RES) and the rising cost of conventional power generation in future energy systems (as demonstrated in the simulated scenario in Paper 4). To leverage the price oscillations in the market, the aggregator can operate its own storage system, such as a CES, while managing the power usage and grid feed-in of its

[1]A concept known as vehicle-to-grid [117].

customers. Unlike behind-the-meter HES, a CES needs to access the public grid during each charging cycle. Thus, the regulatory-imposed charges on the consumed electricity can significantly reduce its financial viability. This challenge is a predominant obstacle to their incorporation in several pilot projects in Germany, as evidenced in [123] and [124].

In addition, the aggregator has the ability to employ time-varying price incentives to optimize the coordination of users' energy storage in line with its financial objectives. In this context, RTP strategies, which are developed concurrently or proportionally to wholesale market prices, are broadly acknowledged as effective instruments. They expose users to an almost accurate representation of electricity price at each time interval[1] [125]. Nevertheless, this thesis interrogates the optimality of RTP in the context of EC, revealing that the obtained welfare[2] via internal EC pricing mechanisms, such as ORTP, surpasses that of RTP when the count of EC members increases. The effectiveness of ORTP originates from its ability to incorporate power demand and supply patterns in the EC, as well as those in the overall energy system, in the price building process. Additionally, ORTP can accommodate the constraints of the physical power network, consequently contributing valuable grid services. While such applications in this thesis (Paper 2) were not monetized, they hold the potential to generate additional revenue streams for the aggregator.

If self-sufficiency is perceived as the primary objective of the EC business model, the aggregator can manage the flexibility options to considerably curtail the dependence on energy exchange with the market. In this setting, local consumption is prioritized and CES serves as a means to store the EC's generation surplus for subsequent utilization. Likewise, internal EC pricing via ORTP can be employed to stimulate electricity usage when local generation is abundant, and conversely, encourage conservation when it is low. The assessments presented in this thesis (papers 1 and 4) indicated that such operational strategy results in a welfare loss compared to a profit-driven approach. However, regulatory incentives aimed at promoting power consumption within the EC can enhance the profitability of such business models. One such regulation in Germany is the tenant law (*Mieterstromgesetz* in German), which provides a financial incentive[3] for the direct supply of rooftop solar PV electricity to tenants, encouraging landlords to install new PV systems [126].

B: What are the broader energy system implications of emerging ECs?

B.1: How can the potential system-wide impacts of large-scale integration of self-optimizing ECs be measured and quantified?

[1] Simultaneously, real-time prices introduce a certain risk to the users due to higher variance compared to SP.

[2] The cost and revenue streams of the EC actors are interconnected. Therefore, this thesis proposed community welfare, defined as the summation of costs and revenues of the aggregator and all users, as a suitable indicator to assess the financial merits of various EC use-cases.

[3] In form of a surcharge, termed *Mieterstromzuschlage* in German

Extending upon existing approaches, this thesis expands two existing methodologies as well as introduces a new methodology aiming to assess the systemic impacts of ECs, thus addressing the research question at hand. These methods are presented in papers 1, 3, and 4.

Paper 1 introduced a method for evaluating the alignment between the operation of an EC and wholesale market signals. The foundation of this methodology originates from [47] and [79], where the authors establish a market alignment indicator (MAI) to compare the performance of a HES with a benchmark system operating in complete harmony with market signals, defined as an arbitrage BSS in their work. A significant advantage of this approach is its capability to assess the system-friendly operation of DESs without necessitating explicit modeling of the broader energy system.

While effective for evaluating prosumager behavior, this concept proves challenging to adopt for more complex system structures involving various stakeholders and flexibility options. For example, comparing the operation of HPs to arbitrage batteries is not meaningful. This comparison becomes even more intricate when multiple different sector-coupling technologies are involved. The innovation in the methodology presented in paper 1 addresses this challenge by offering a more robust approach to defining the most market-aligned behavior of ECs.

The proposed MAI compares the welfare generated by the EC to that of a benchmark EC of identical size. This benchmark EC is characterized by the aggregator's complete control not only over its own storage assets (e.g., CES) but also over other available flexibility options, such as HES and HPs, within the EC. To simulate such a benchmark scenario, this thesis adapted the genetic-algorithm-based bilevel optimization methodology, originally developed for deriving the ORTP. This approach enables the search for the aggregated optimal solution for an EC with a heterogeneous stakeholder and technology structure while maintaining the distributed implementation of the optimization problems. Therefore, unlike the centralized optimization approach (where the EC is considered as one operating entity, as seen, for example, in [78]), the distributed optimization proposed in this dissertation can be integrated into the agent-based environment.

Paper 3 and 4 employed the agent-based model (ABM) AMIRIS to explore the systemic impacts of DESs. For this purpose, I expanded the functionality of AMIRIS by integrating new agents and modules to emulate the operational behavior of ECs.

Paper 3 introduced the aggregator and prosumager agents into AMIRIS, empowering the model to evaluate the impact of electricity prosumage under a variety of pricing mechanisms. Furthermore, Paper 3 established an automated and reproducible modeling workflow by bidirectionally coupling the ABM AMIRIS with the energy system optimization model (ESOM) REMix, thereby enabling an assessment of the economic granularity gap. This gap represents the divergence in optimal investment and operational costs of the energy system when stakeholders' behavior is taken into account. The proposed workflow commences with an optimization of the energy system using the REMix model. Subsequently, AMIRIS is calibrated using the results obtained from REMix. The simulated behavior of selected actors within AMIRIS is then integrated back into REMix, prompting a re-optimization of the energy system. This methodology is specifically applied to the case of prosumager self-consumption in Germany. In this context, the storage operation in the second REMix optimization is constrained in line with the simulated dispatch of HES within AMIRIS. Finally, the economic granularity gap is quantified for two distinct spatial scopes, namely Germany and a broader scope including Europe and Maghreb.

The proposed model-coupling approach allows for the integration of the features, scopes, and perspectives of two (or potentially more) energy system models, thereby offering two substantial benefits: Firstly, the features of different models can complement each other, thereby reducing the necessity for extensive model development. For instance, in the case of AMIRIS, one significant limitation was the absence of investment modeling, which was addressed by the incorporation of REMix. Secondly, merging different model perspectives offers valuable insights that could not be obtained from individual models without significant modeling efforts and fundamental changes to the underlying modeling logic of each model. In this thesis, the coupling of the benevolent energy system planner perspective of the ESOM with the actor perspective of the ABM facilitated the analysis of deviations in the optimal operation and design of the energy system (embodied in the economic granularity gap) in the context of prosumager self-consumption.

This methodology builds upon the prior works by Torralba-Díaz et al. presented in [84, 85], where the authors measure the "efficiency gap" resulting from storage system operation strategies in the electricity market. In this study, the authors proposed a workflow for harmonizing both models, which serves as a critical preparatory step for further analysis. This workflow is also utilized in Paper 3. However, the novelty in Paper 3 lies in the feedback loop of AMIRIS results into the ESOM for a secondary optimization of energy system operation and design. Thus, while the study in [84] compares operational system costs resulting from both models, Paper 3 additionally evaluates changes in total investment costs, as well as alterations in energy system design and operation. Furthermore, the model-coupling process in Paper 3 is significantly more automated: Integration of the iog2x tool facilitates quick translation of gdx data (a typical format of ESOM results) into readable inputs for AMIRIS. Additionally, incorporating all steps into the Remote Control Environment (RCE) enables decentralized implementation of the involved models.

The studies introduced in [127, 128, 129] propose an automated iterative coupling approach to diminish the efficiency gap and explore the convergence behavior for two coupling parameters: peak capacity usage and storage dispatch. In each iteration, the power plant fleet optimization is adjusted to meet the demands of AMIRIS until convergence is achieved. In contrast to the RCE setup in Paper 3, the models in this ongoing study are centrally implemented, requiring both models to be configured within a single system. Figure 5.1 provides a schematic comparison of the coupling

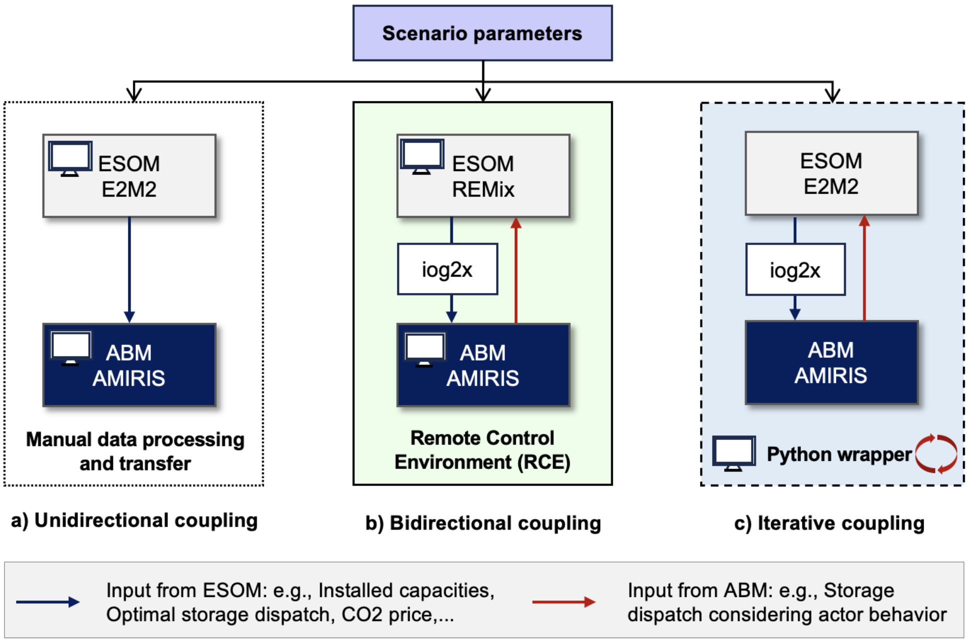

Figure 5.1: Comparison of the model-coupling approaches in a) previous studies [85, 84], b) this dissertation, and c) ongoing research as introduced in [127, 128, 129]

approach in this dissertation with previous works conducted both before and after the publication of Paper 3.

Paper 4 considerably contributes to this research question by extending the model enhancements of Paper 3 and proposing a novel combination of agent-based modeling and bilevel optimization. This innovative approach is employed to assess the system integration of more complex DESs, such as ECs. The methodology implements a rolling-horizon of the bilevel EC model from Paper 2 into AMIRIS, thereby creating the necessary interfaces for seamless communication between the "external" EC model and AMIRIS. This model development enables AMIRIS, for the first time, to capture hierarchical decision-making interdependencies among various actors. As depicted in Figure 5.2, this approach introduces a new coordination mechanism among the actors, superseding the fixed predefined protocols. This mechanism is particularly critical for representing the equilibrium dynamics between aggregators and contracted DER operators. The introduced methodology addresses a substantial gap in the existing literature (as discussed in Section 1.2) by connecting a detailed EC model to an agent-based market model. Consequently, this approach permits an exploration of the interconnected dynamics between community markets and wholesale markets.

Additionally, Paper 4 further enhanced the aggregator agent by incorporating a storage module and enabling the assessment of EC use-cases with profit-maximizing and self-sufficiency-driven CES strategies. This paper focused on analyzing system-level indicators derived directly from AMIRIS. Specifically, it evaluated the market integra-

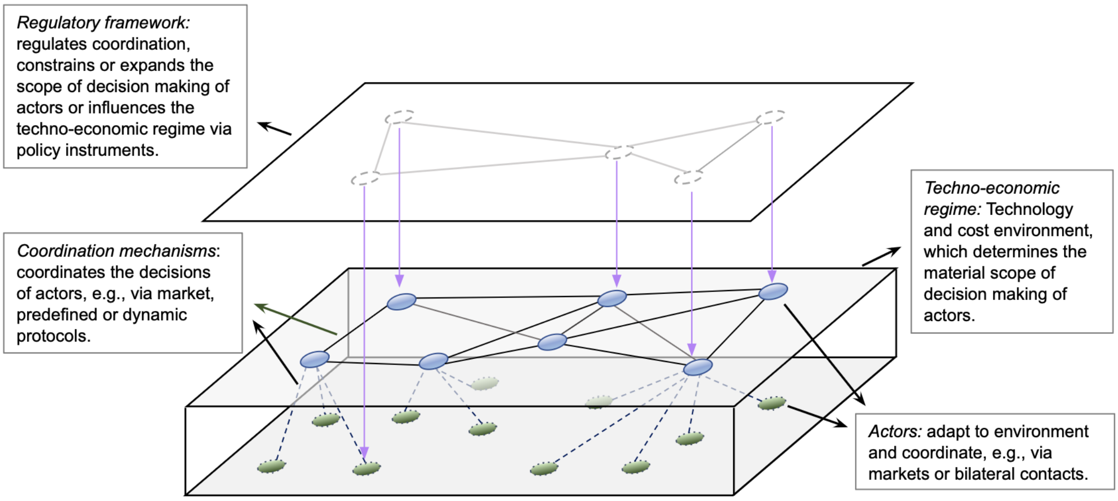

Figure 5.2: Abstract model architecture of AMIRIS model. Adjusted representation based on [83].

tion of HES and CES by measuring the operational costs of the system, defined as the aggregate short-term running costs of all power plants, as well as the market-driven curtailment resulting from the non-awarded market bids of a RES power plant.

In conclusion, this thesis developed and employed three distinct methodologies to quantify the systemic impacts of DES operations: The first method compared the operation of DES with a benchmark system using the MAI. The second approach involved bidirectional model-coupling of AMIRIS and REMix, measuring the emerging economic granularity gap in the case of prosumager self-consumption. The third approach integrated the bilevel EC model into AMIRIS and assessed system indicators for more complex EC use-cases.

B.2: Under what circumstances do ECs operate aligned with the needs of the broader energy system?

The exploration of this research question is detailed in papers 1, 3, and 4, utilizing the methodology developed in research question B.1, and applying it to various simulated case studies. The subsequent analyses, which draw parallels to those of research question A.2, focus on two interconnected strategies. The first involves the operation of existing distributed BSSs within the EC, and the second pertains to the formulation of pricing mechanisms for users of the EC.

The prospective energy system, characterized by a substantial proportion of energy from RES, is heavily dependent on the contribution of flexibility options. Projected simulations of Germany's electricity market in 2030 with a RES share surpassing 80%, suggesting that events of energy excess and scarcity could occur frequently. This could subsequently lead to increased price volatility in the market. In such a landscape, the efficient deployment of available DERs within the ECs to stabilize electricity demand

and supply across the broader system becomes pivotal from the perspective of the energy system.

Among the case studies investigated in this thesis, those featuring a CES with a self-sufficiency driven strategy and HES under the SP scheme were found to be the most inefficient in terms of all measured system indicators. For instance, Paper 3's analysis revealed that in 2030, given prosumage by half of Germany's prosumers under the SP scheme, the required capacities for lithium-ion BSS and PV in an idealized energy system would increase by 6.3 GWh and 4.2 GW, respectively. In both cases, the energy exchange between the EC and the wholesale market is significantly reduced. While this reduction in the first use-case is a result of an overarching autarky-driven strategy, there are strong economic incentives for prioritizing self-sufficiency for households exposed to SP. Specifically, if an investment in storage is already made, the higher invariant grid usage costs compared to feed-in remuneration always justify prioritizing self-consumption and using the grid according to the residual load. Even though storage in these cases can still provide some benefits by improving the local integration of distributed RES generation, its contribution to the overall efficient integration of RES into the energy system remains limited.

The investigation carried out in Paper 4 reveals that the market-oriented operation of EC positively impacts key system indicators, i.e., operational system costs and market-driven curtailment. Within these ECs, the use-case with the profit-maximizing CES, whose operation remains uninterrupted by regulatory-induced charges, demonstrates the most considerable reduction in these two indicators. However, due to a limited forecast horizon and strategic bidding behavior, such as reserving a portion of capacity to exercise market power, discrepancies arise when compared to the system-optimal operation of storage. Moreover, imposing volumetric regulatory charges on storage grid usage constitutes another factor that diminishes the systemic benefits of CES. Nonetheless, the impact of these charges may become less significant in the future system with high short-term price volatility. Under such market dynamics, energy arbitrage could still be feasible during numerous hours, even when factoring in the regulatory charges incurred.

Dynamic pricing schemes can incentivize a system-friendly behavior of EC users by reflecting the real-time cost of electricity production. The findings of this thesis reveal that by exposing prosumagers to uninterrupted (predicted) market prices under a RTP scheme, a better alignment of DES operation with market signals can be achieved. This results in reduced system costs and a smaller economic granularity gap. However, similar to the observed effect for CES, the incorporation of static volumetric charges into grid consumption hampers the effectiveness of the price signals reaching households. The analysis in Paper 3 demonstrates that the dynamization of the EEG levy[1] [131] as a regulated component of the consumer tariff, combined with variable feed-in tariff (FiT) [32], significantly aligns the system closer to one that would result

[1] Recently, the German government has decided to eliminate the EEG levy in order to reduce the cost burden on power consumers [130].

from optimal storage dispatch.

The internal EC pricing design, as examined under the ORTP scheme, can yield benefits similar to those provided by the RTP scheme. However, the alignment of the operation of DERs with the larger system's signals may be skewed due to the consideration of local generation and consumption patterns within the EC. This becomes particularly relevant when there are incentives for local consumption, such as reduced taxes and levies. For instance, in the case study featured in Paper 1, the EC operation under the ORTP scheme adopted a lower MAI value compared to the RTP scheme. Nevertheless, the signals of scarcity and excess, translated into very high and low market prices, encouraged the EC to provide support during critical periods. This resulted in significantly improved system indicators compared to the SP scheme.

In conclusion, this thesis showed that ECs can enhance the integration of RES and reduce the system costs within the larger system, if they do not prioritize local electricity consumption. This prioritization could either be an explicit goal of ECs or could arise from regulatory frameworks that incentivize local consumption. Therefore, policy makers face a challenge in devising the regulatory framework for ECs: they should provide financial incentives to encourage investment in DERs, while simultaneously avoiding the promotion of operations driven solely by self-sufficiency.

This thesis highlighted the efficiency gains achievable by subjecting EC users to the real-time cost of electricity production, thus incentivizing a system-aligned deployment of flexibility options. Nevertheless, the desired impact can be distorted by a constant offset added due to static per unit regulatory charges, even when dynamic prices are in place. To facilitate more direct exposure to system signals, the author suggests that regulators consider revising the tariff structure for power consumers. While the implementation of dynamic levying, as studied in this thesis, may present challenges [132], the distortion to real-time system signals could be mitigated by replacing volumetric network charges with capacity-based tariffs, thereby reducing the static offset. Such tariff reform could be complemented by replacing energy taxes and surcharges with a uniform CO_2 pricing mechanism, effectively abolishing static volumetric charges altogether [133]. Such a measure could concurrently address concerns around the contribution of prosumagers to power network maintenance costs (a topic discussed while addressing research question A.2). It's important, however, to acknowledge that this approach may diminish the cost-saving potential of HES investments, and could possibly jeopardize the refinancing of already installed units.

Lastly, this thesis revealed a significant deviation between the operation of storage systems in all examined ECs and the operation that minimizes system costs. This deviation is particularly critical for policymakers to consider when interpreting future energy system scenarios developed with ESOMs, as these scenarios could potentially underestimate the required generation and storage capacities in the future energy system.

5.2 Discussion of limitations

Simplifying assumptions and limited system boundaries are inherent aspects of energy system modeling. This section discusses some of the key limitations of the models and methods introduced in this thesis. I will first address these limitations at the EC level (Section 5.2.1), followed by a discussion at the overall system level (Section 5.2.2). Finally, in Section 5.2.3, I will provide a critical reflection on the proposed game-theoretic framework.

5.2.1 Energy community modeling

The models developed in this thesis offered significant insights into the economics of ECs. However, a number of important limitations narrowed the technical and economic breadth of the analyses. In this regard, a critical constraint stemmed from the model assumption that there was no competition between the aggregator under study and other aggregators. As a result, the question of "why would users prefer to participate in the EC model instead of alternative business models?" remains only partially addressed.

From a methodological standpoint, the single aggregator assumption was made to reduce the complexity of the energy trading game within the EC. This allowed for a manageable mathematical problem formulation and solution given the available computational resources. Competition among aggregators is often modeled as a multi-leader multi-follower Stackelberg game. However, these types of games are comparatively understudied [134], and current literature often resorts to simplifying assumptions regarding the EC structure, price building, and available technologies to manage the resulting problem complexity [135]. Despite these constraints, the monopoly assumption in this thesis can be somewhat justified due to the often unique relationship among EC stakeholders. For instance, in the case of energy cooperative business models (known as *Energiegenossenschaft* in German), the aggregator is owned by the community and users' commitment to the business models is typically higher [136].

In the absence of competition among different aggregators, this thesis ensured the "fairness" of the aggregator's trading with users, for instance, by constraining the ORTP to ensure that it left users better off compared to a benchmark business model. However, the related assumptions influenced the revenue and cost flows of the EC stakeholders. For example, the study by [137] shows that in the case of competing retailers, each providing real-time prices for users, their profit can even fall below that of the SP tariff; a result that contradicts the findings of the study in Paper 1. Consequently, this thesis primarily measured community welfare to evaluate the economic performance of different use-cases, without extensively investigating the question of welfare redistribution among various stakeholders within the EC.

This dissertation focused on the operation of an EC within an existing community energy system, thereby neglecting a crucial aspect of EC business models concerning the investment decisions in DER. Consequently, it largely leaves unanswered the question of whether the financial benefits derived from establishing an EC justify the investment in DER and the requisite measurement and control equipment for efficient and secure data transmission, or if they potentially jeopardize the refinancing of already made investments. Furthermore, the parameterization of available technologies in the community energy system was based on a literature review and may not necessarily reflect the optimal sizing of each technology. In this context, understanding investment decisions into DERs is critical for policy-makers when crafting regulatory frameworks for ECs, as such investments may justify their potential operational inefficiencies from the overall system perspectives. Furthermore, this thesis fell short in considering current EC-specific incentives, such as those under the German tenant electricity law [138], which are important in supporting such decision-making processes.

Furthermore, the analysis in this thesis primarily focused on virtual energy trades among actors and the market, thereby overlooking the physical power system. Although Paper 2 somewhat addresses this issue, quantifying the technical and economic value of the delivered flexibility requires a more comprehensive study, preferably using a distribution grid model. This evaluation becomes particularly crucial in view of the high level of sector-coupling, as local self-consumption may decrease the expansion, operation, and maintenance costs of the distribution network or mitigate necessary RES curtailment due to grid constraints. Without considering the physical power system, the "system-friendly" operation of DESs is only partially evaluated. If the physical power network is taken into account, the model could provide further insights into the critical issue of cost allocation in the power network. Alongside a more detailed study of alternative network tariffs like the discussed capacity-based charges, the proposed EC model could be expanded to examine distribution locational marginal pricing and the location-specific costs associated with delivering electricity across different parts of the EC's distribution grid [139].

This thesis endeavored to model EC business models with sufficient granularity to answer the research questions. However, several aspects were modeled in a simplified manner. For instance, energy exchanges with the broader energy system were limited to a single wholesale market. In reality, aggregators and storage operators participate in multiple markets (e.g., intraday and control reserve markets) to further optimize their revenue [140]. Another example is the potential for multi-use applications of CES [141], instead of the binary choice of either profit-driven or self-sufficiency-driven operations, which could provide additional revenues for the aggregator while simultaneously increasing the self-sufficiency degree of the EC. Particularly, the findings showed that an arbitrage CES, depending on the market and regulatory environment, may remain significantly underutilized. Therefore, a dynamic prioritization [142] of BSS operation could facilitate energy sharing within the EC without markedly interrupting market trading activities.

Lastly, the techno-economic modeling of energy systems in this thesis was rather coarse. For instance, when modeling the BSS, factors such as charge-dependent efficiencies, battery aging, and inverter interactions were not considered. Additionally, the households' electricity demand was presumed to be inelastic to prices, and an average household demand profile, based on measured values from [143] that resembled a standard load profile, was used. In terms of the PV system, an external solar generation profile was simply scaled up based on the peak performance of the installed system, thereby ignoring other factors such as efficiency, tilt angle, or orientation of the rooftop system. In reality, generation profiles and especially their demand curves may significantly differ from each other, providing a more substantial potential for local balancing of demand and supply within the EC.

5.2.2 Overall energy system analysis

The models and methods used to assess the overall system integration of ECs on a broader level in this thesis faced a number of limitations, many of which could be attributed to the current state of AMIRIS:

The first limitation pertains to the national scope of the utilized model and the use of exogenous input time-series to consider cross-border energy exchanges. The import/export to and from neighboring countries was exogenous input parameter to the model. In this regard, the market-coupling approach proposed in [144] to connect the day-ahead market in Germany with those of neighboring countries can significantly address this limitation in the future. The second limitation is related to strategic bidding. AMIRIS did not consider the behavior of competitors when actors make their bids. This is especially crucial for sector coupling technologies and storage technologies, which highly rely on the market predictions of a simple forecasting agent. To address this issue in the future, [145] proposes the use of smarter forecasting methods based on machine learning algorithms. However, to avoid the resulting model artifacts caused by the overreaction of flexibility options to the same price prediction [113] with this approach, the operation of a single flexibility option could be simulated in AMIRIS in a feasible manner. Lastly, AMIRIS did not endogenously calculate investments into generation and storage technologies.

To address these limitations, the REMix model is used to provide a starting point for the simulation of future energy markets. However, the missing features in AMIRIS resulted in inelastic demand and supply curves during the simulation. For instance, periods of high scarcity prices could theoretically create incentives for new investments in energy generation units to increase supply, an aspect that AMIRIS was unable to capture due to its missing investment feature. Moreover, in AMIRIS, when RES generation exceedede the national power demand, the excess had to be curtailed instead of being stored or exported to neighboring countries. As a result, AMIRIS might overestimate the amount of energy scarcity and excess, as well as price volatility, and consequently overestimate the potential welfare for flexibility options in future energy markets.

This thesis demonstrates that the back-coupling of an ABM with an ESOM offers a suitable method for evaluating the impact of DES operation on optimal system operation and design. However, it's plausible to argue that such an analysis could be conducted using a single model. On one side, the operation of the DES could be modeled in an ESOM as a self-optimizing cell, an approach widely adopted in most research works exploring the system integration of prosumagers, such as [31]. However, in this case, the operation of the DES would be disconnected from market dynamics in disequilibrium. For instance, a RES support regime can induce negative market prices [146], subsequently affecting the operation of DESs. In this context, one overarching limitation of the overall system analyses presented in this dissertation is that it did not to systematically take into account the stakeholder behavior outside the energy system, causing the operation of the technologies beyond the EC to resemble those of the ESOM.

Conversely, one could evaluate alterations in the optimal system design employing an ABM. This could be achieved, for instance, by introducing system cost minimizing strategies for various storage operators and investment agents. Despite the complexity involved in implementing such an approach due to the plurality and bounded rationality of agents, this application runs counter to the primary aim of ABMs in simulating self-interested actor behavior. In this regard, a potentially superior approach for investigating the optimal system design via ABM might be a multi-scenario analysis, which would explore the range of possibilities for future energy systems as suggested in [79].

Therefore, while both models could be further developed to somewhat measure the economic granularity gap, coupling models emerges as a plausible choice. This approach is relatively easier to implement and doesn't necessitate a fundamental shift in the underlying modeling logic. Yet, the full potential of the proposed model-coupling methodology can be realized if the behavior of more than one actor in the ABM deviates from that of the ESOM.

A significant challenge in assessing the large-scale integration of DES in the ABM lies in the up-scaling of DES models. Providing the necessary data and computational resources to simulate millions of DES is practically unfeasible. Consequently, this thesis focused on an aggregated DES, which tends to exaggerate the impact of DES operation on the overall energy system. This overestimation occurs as the model neglects the smoothing effects arising from the aggregation of a large number of DESs, each exhibiting unique demand and generation patterns.

Additionally, the aggregated representation of EC gives the aggregator substantial market power. However, strategic bidding of the aggregator, considering its market power, is only modeled for the case of profit-maximizing CES. In other examined use-cases, the aggregator operates as a price-taker (with regard to the wholesale market) and opts for a simplified strategy, ensuring its bids are consistently awarded in the market. This approach results in sub-optimal outcomes for the aggregator, as it does not account for shifts in market clearing prices when submitting its bids. Including the price-maker behavior of the aggregator, significantly increases the already complex bilevel EC energy trading problem, but, in the author's opinion, is essential to address.

5.2.3 Game-theoretic framework

In this dissertation, considerable effort was dedicated to investigating the partial-equilibrium in decentralized energy system decentralization: A Stackelberg equilibrium within the EC, viewed as a small subset of the larger energy market in disequilibrium. Two critical aspects of the studied framework warrant further discussion: the information structure and the cooperation of the players.

Firstly, in terms of the information structure of the energy trading game, the Stackelberg competition presumed perfect information among the involved players. This assumption implies that all players possess complete and accurate knowledge of the game's structure, the strategies available to each player, and the payoffs associated with each combination of strategies. Consequently, the leader knows the followers' potential strategies and their corresponding payoffs, while the followers observe the strategy chosen by the leader before making their own decisions. It is important to highlight that the incorporation of stochastic elements into the game formulation, as suggested in Paper 2, did not change the game's information structure, as the information accessible to all players remained comprehensive. The assumption of perfect information in the studied Stackelberg game somewhat oversimplifies the decision-making process and neglects the challenges and uncertainties present in real-world markets. Nevertheless, in the author's opinion, the assumption of perfect information within the context of smart grids and ECs can be justified. In such markets, informational asymmetries are minimized due to the availability of advanced communication infrastructure for real-time data collection and transmission. Moreover, the actors within the EC are typically willing to share information and collaborate to achieve the EC objectives.

Secondly, the studied Stackelberg equilibrium arises from a non-cooperative game structure, where the players act according to their individual self-interest and do not explicitly coordinate their strategies. In this scenario, the aggregator exercises market power within the EC and leverages its first-mover advantage to shape the game's outcome in its favor, while the users react strategically based on the aggregator's actions. This assumption might not entirely capture the dynamics of ECs, which frequently involve actors with shared objectives and cooperative behaviors. Paper 2 mathematically proved that the outcome of the proposed non-cooperative energy trading game maximizes community welfare. However, as the aggregator does not explicitly consider collective welfare, its choices might lead to a sub-optimal overall outcome if the objectives or strategies of the involved players were to change. For certain EC business models, alternative game-theoretic frameworks that explicitly incorporate cooperation among players, such as cooperative game theory [147] or coalition formation [148], may be more suitable.

This dissertation proposed two methodologies for finding the optimal solution to the bilevel optimization problem, serving as a proxy to identify the equilibrium in the Stackelberg game within the EC. Each of these methodologies presents its own set of advantages and limitations:

The proposed heuristic method using a genetic algorithm offers a mathematically simpler approach to search for the Stackelberg equilibrium, as the optimization problems of the players can be solved independently. Consequently, the user-side problem could be a summation of several distinct sub-problems, and the complexity of each problem can be increased. Additionally, the distributed nature of this approach aligns better with real-world implications, as it does not require the users to disclose their information to the aggregator. However, this approach comes with a notable limitation, in that the attainment of the globally optimal solution is not guaranteed.

Solving the energy trading game using the single-level reduction technique also raises several notable concerns: In this approach, the users' information is fully exposed to the aggregator, which could give rise to privacy concerns from an engineering perspective. Additionally, the mathematical complexity of this method poses challenges to its application in real-world problems with a large number of users and lengthy optimization periods. While the proposed stochastic BIOP model demonstrated relatively good scalability with respect to increasing uncertainties, increasing the number of users and specially extending the optimization time steps markedly increased the computational effort required to solve the problem. Moreover, the applied discretization technique to address the non-linearities arising in the single-level transformation process conditions the finding of the global optimal solution on a very high granularity of the discretization intervals, in order to replicate the continuous solution space. Practically, increasing the number of discrete steps is computationally very demanding. To address this issue, one significant contribution of this thesis was the proposal of the modified branch-and-bound algorithm with a dynamic partitioning technique. After finding the optimal solution to the discrete problem, this approach considers a smaller solution space close to the found solution and initiates a new round of optimization. However, achieving the global optimal solution to the original bilevel problem was not mathematically confirmed.

The proposed hybrid approach of agent-based modeling and bilevel optimization was an innovative effort to identify the Stackelberg equilibrium among a subset of market actors. While this innovative methodology yielded invaluable insights into the interrelated dynamics of the community and wholesale markets, there are two interlinked constraints I would like to briefly discuss:

Firstly, the computational cost of solving the BIOP problem is high. This challenge becomes particularly apparent when studying large-scale energy systems, where simulations are typically conducted over a period of at least one year. In this thesis, during the energy market simulation for one year, the BIOP for an EC with relatively straightforward parameterization was solved 720 times, taking an average of 26 hours[1][2]. This computation time may still be justifiable for studying a specific research question. However, as ABMs increasingly aim to capture the strategic behaviors of numerous energy market actors and their competitions across multiple dimensions, the application of such complex methodologies may become impractical.

Secondly, the assumption of perfect information in the EC energy trading game is somewhat plausible when the system boundaries are confined to the community. However, this assumption can be substantially challenged when the system boundaries extend to broader energy systems and the EC Stackelberg game emerges as a subgame within the larger energy trading game in the wholesale market, marked by imperfect information. Within such a game, identifying the Nash equilibrium may become unfeasible: On one hand, the aggregator may have incomplete or uncertain knowledge of the precise strategies or payoffs of other market players. On the other hand, in games with imperfect information, the number of possible strategies for each player can increase substantially, as they need to consider a wide array of possible actions to make their decisions. This complexity increases as the number of players and the size of the strategy space grow, making it challenging to enumerate and analyze all possible strategy combinations [149]. Therefore, games with imperfect information become computationally complex due to the increased dimensionality and uncertainty. Consequently, solving for Nash equilibrium in such games requires the use of sophisticated mathematical techniques, numerical methods, or approximations, which can be computationally demanding or unfeasible for larger games.

Within this context, "learning" becomes an essential feature in navigating the complexities posed by lack of complete information, limitations of solution concepts, and high computational demands [150]. The requirement for adaptive multi-agent systems and the complexity of managing interacting learners have encouraged the development of the field of multi-agent reinforcement learning [151, 152]. Additionally, alternative game-theoretic frameworks are deployed to model learning agents within an environment marked by imperfect information. For instance, Bayesian games, as exemplified in [153], capture uncertainty and enable players to refine their strategy based on observed actions. Similarly, Repeated games, as in [154], facilitate strategic learning over multiple iterations by adapting strategies in light of previous outcomes. Furthermore, evolutionary game theory, although not explicitly integrating learning, leverages mechanisms like imitation and selection to aid agents in adapting to the market and responding to incomplete information [155].

[1] On a laptop with an Intel Core i7-8650U CPU running at 1.90 GHz with eight nodes and 16 threads.

[2] In contrast, the AMIRIS simulation incorporating linear storage optimization was completed within an approximate duration of 7 minutes.

5.3 Conclusion and outlook

This dissertation was motivated by the ongoing trends of decentralization and digitalization in the German energy system. The aim of this thesis was to deliver an holistic analysis of ECs, and to investigate potential strategies for their efficient coordination within the broader energy landscape.

To achieve this aim, this thesis developed innovative methodologies that encompassed both the perspective of the community and the overall energy system. At the community level, the operation of various DERs, including PV, HES, CES, HP, and EV, were modeled to represent the microeconomic behavior of the EC stakeholders. This methodology was extended by proposing a game-theoretic framework that modeled the hierarchical decision-making interdependencies between the aggregator and users. This led to the derivation of an ORTP design, serving as an internal pricing mechanism for EC. Moreover, significant effort was dedicated to the development of efficient mathematical techniques and algorithms, necessary for solving the emerging complex bilevel optimization problem.

To evaluate the systemic effects of ECs, three methodologies were proposed: firstly, a market alignment indicator, which served as a proxy for assessing the system-friendly operation of ECs without the need for a large-scale energy system model. Secondly, the agent-based electricity market model, AMIRIS, was expanded by implementing new agents and modules to represent the EC stakeholders. This development enabled further comprehensive analysis of DESs at the overall system level. Perhaps the most interesting methodological contribution of this thesis lies in the integration of the game-theoretic EC model into AMIRIS, enabling the exploration of the interconnected dynamics between community and wholesale markets. Lastly, an automated model-coupling framework was introduced to couple AMIRIS with an energy system optimization model. This methodology enabled the evaluation of the impact of EC actor behavior on optimal energy system operation and design, thus defining and quantifying the economic granularity gap.

In addition to methodological contributions, the analyses presented in this thesis provided valuable policy-relevant insights regarding the conditions under which the aggregation of DERs in ECs can be efficiently integrated into the German energy system. These assessments revealed that the aggregation of DERs in ECs is not inherently desirable or detrimental. The extent to which these decentralized systems are coordinated with the broader energy system is significantly influenced by the market mechanisms and regulatory frameworks in place.

In this context, this thesis highlighted the inefficiencies of current business models and regulations in the residential power sector. Specifically, time-invariant consumer prices fail to incentivize system-friendly operation of flexibility options, as they do not reflect the actual costs of electricity generation and, consequently, the real-time availability of RES in the system. This inefficiency is further exacerbated when power consumption is charged with static volumetric grid fees, taxes, and levies. Such tariff structures significantly incentivize prosumagers to prioritize self-consumption, irrespective of energy market dynamics. The findings of this thesis demonstrated that such prioritization, whether on a household or community scale, could potentially unfold disruptive effects on the power system, resulting in a significant deviation from the optimal energy system operation and design.

To improve the coordination of DES operations, the tariff design should be revised to favor business models that incentivize a more conscious interaction with the broader energy system. Such reforms should permit a certain level of local consumption, securing economic benefits for EC stakeholders and thereby providing incentives for new investments in DERs. Simultaneously, they must provide adequate system signals for DESs to respond to market conditions, especially during periods of energy scarcity or excess. If appropriately designed, RTP mechanisms can serve as effective tools to achieve this objective. However, constructing RTPs solely based on the wholesale market price overlooks the power demand and generation patterns of heterogeneous EC actors. Taking these factors into account, as proposed in the ORTP scheme, offers a compromise between slightly distorted alignment with the wholesale market and increased community welfare. Nonetheless, to expose the DES more "directly" to dynamic price signals, it is necessary to reduce static regulatory induced elements. This could be accomplished by either dynamizing the volumetric regulated tariff elements or replacing the per unit charges with mechanisms such as capacity network charges.

The methodologies and analyses presented in this thesis, while comprehensive, are subject to several limitations, as discussed in section 5.2. These limitations help identify potential avenues for future research:

Concerning the efficient operation of ECs, a critical aspect that warrants further exploration is the development of more complex or complementary pricing mechanisms to coordinate the operation of DES with the conditions of the physical system, particularly in distribution grids with a high degree of sector-coupling. In this context, alternative mechanisms related to network charges should be investigated for a more equitable cost allocation of the operation and expansion of grid costs. Additionally, modeling the investment decisions in DER represents a crucial step in determining whether potential efficiency losses from local self-consumption can be justified by additional investments in clean energy technologies.

Simulating the systemic effects of DES using AMIRIS, particularly in power systems that are more or less carbon neutral, demands several methodological advancements. Firstly, the strategic behavior of various market actors should be modeled with enhanced precision. This includes enabling actors to anticipate the strategies of their competitors and evolve within the dynamic market environment. Secondly, solutions must be devised to sensibly incorporate institutional investments in power plants and storage technologies into the model. Furthermore, the current lack of transnational scope should be addressed by including market-coupling. Finally, future research should concentrate on developing methodologies capable of modeling the representative behavior of numerous DESs, each with its unique set of parameters.

In a nutshell, this dissertation has made several significant methodological and substantive contributions regarding the modeling of DES operations in ECs, as well as measuring their systemic impacts. Nevertheless, there is an evident need for continued research. The author hopes that this thesis, whether directly or indirectly, can provide valuable support to the multitude of important decision-making processes required by the transition of the European energy system toward a more sustainable future.

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