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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	✓	✓	✓	✓	✓

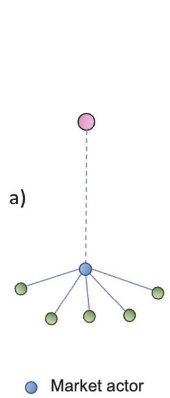

Fig. 1. Model architecture in (a) the first body of literature focusing on EC (b) the second strand of literature on system integration of prosumagers and (c) this paper.

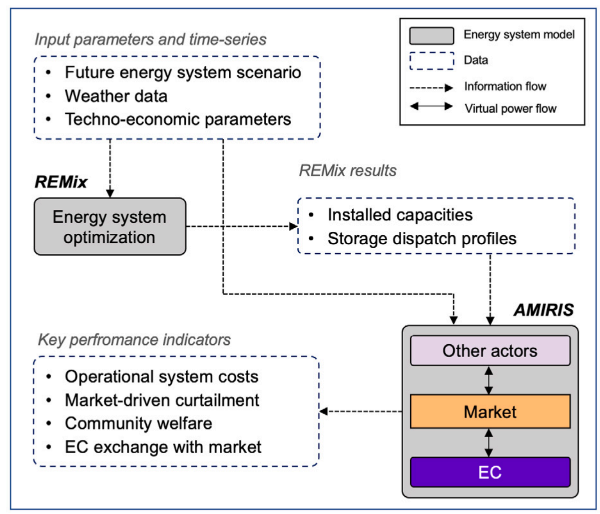

Fig. 2. Schematic overview of the overall workflow to analyze the integration of ECs in the future energy system.

- 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.

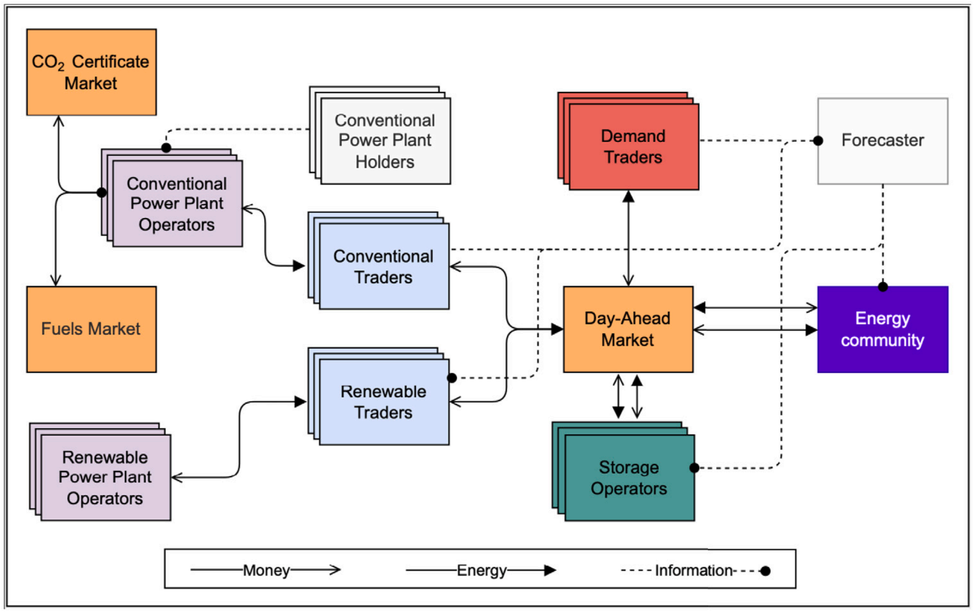

Fig. 3. Schematic structure of the basic agents in AMIRIS.

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.

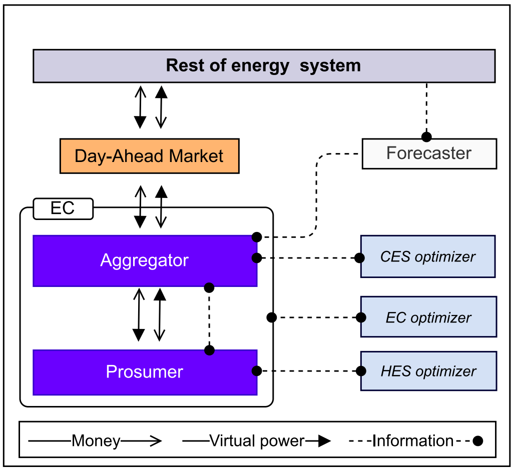

Fig. 4. Implementation of the EC models in AMIRIS.

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, $\pi \le \omega$). 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^{pr}_i). To accomplish this, the energy management system acquires the sale and purchase prices, then decides the hourly grid usage and feed-in (e^{pr+}_{it} and e^{pr-}_{it}), and the HES charge/discharge schedule (z^{pr+}_{it}, z^{pr-}_{it}). 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:

$$\underset{\psi}{\text{Minimize}}\ C^{pr}_i = \sum\nolimits_t ((P^{ag+}_t + P^{rc})e^{pr+}_{it} - P^{ag-}_t e^{pr-}_{it} + P^{ch}_i (z^{pr+}_{it} + z^{pr-}_{it})) \tag{1a}$$

$$\text{subject to: } a^{pr}_{it} = (1 - \Lambda^{pr}_i) a^{pr}_{i(t-1)} + \epsilon^{pr}_i z^{pr+}_{it} - \frac{z^{pr-}_{it}}{\varepsilon^{pr}_i} : (\lambda^a_{it}), \tag{1b}$$

$$z^{pr+}_{it} = e^{pr+}_{it} - e^{pr-}_{it} - H_{it} + z^{pr-}_{it} : (\lambda^z_{it}) \tag{1c}$$

$$0 \le a^{pr}_{it} \le K^{pr}_i F^{pr}_i : \left(\underline{\tau}_{it}, \overline{\tau}_{it}\right), \tag{1d}$$

$$a^{pr}_{i(t-1)} = A^{pr}_{i0} : \left(\lambda^{a0}_{i0}\right), t = 1, \tag{1e}$$

$$0 \le e^{pr+}_{it} \le E^{pr+}_{it} : \left(\underline{\upsilon}_{it}, \overline{\upsilon}_{it}\right), \tag{1f}$$

$$0 \le e^{pr-}_{it} \le E^{pr-}_{it} : (\underline{\mu}_{it}, \overline{\mu}_{it}), \tag{1g}$$

$$0 \le z^{pr+}_{it} \le \frac{U^{pr}_{it} K^{pr}_i}{\epsilon^{pr}_i} : (\underline{\beta}_{it}, \overline{\beta}_{it}), \tag{1h}$$

$$0 \le z^{pr-}_{it} \le U^{pr}_{it} K^{pr}_i \varepsilon^{pr}_i : (\underline{\gamma}_{it}, \overline{\gamma}_{it}), \tag{1i}$$

Eq. (1a) portrays the cost-minimizing objective function of the prosumager. The term ψ symbolizes the set of optimization variables, i.e., $\psi = \{e^{pr+}_{it}, e^{pr-}_{it}, z^{pr+}_{it}, z^{pr-}_{it}, a^{pr}_{it}\}$. In our model, t and i respectively denote the optimization time step and the user index. The terms in parentheses (i.e., λ^a_{it}, λ^z_{it}, $\underline{\tau}_{it}$, $\overline{\tau}_{it}$, λ^{a0}_{i0}, $\underline{\upsilon}_{it}$, $\overline{\upsilon}_{it}$, $\underline{\mu}_{it}$, $\overline{\mu}_{it}$, $\underline{\beta}_{it}$, $\overline{\beta}_{it}$, $\underline{\gamma}_{it}$, $\overline{\gamma}_{it}$) 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^{ag+}_t and P^{ag-}_t 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^{ch}_i 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^{pr}_i), the charged and discharged power (z^{pr+}_{it} and z^{pr-}_{it}), and the HES's charging and discharging efficiencies (ϵ^{pr}_i and ε^{pr}_i). 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

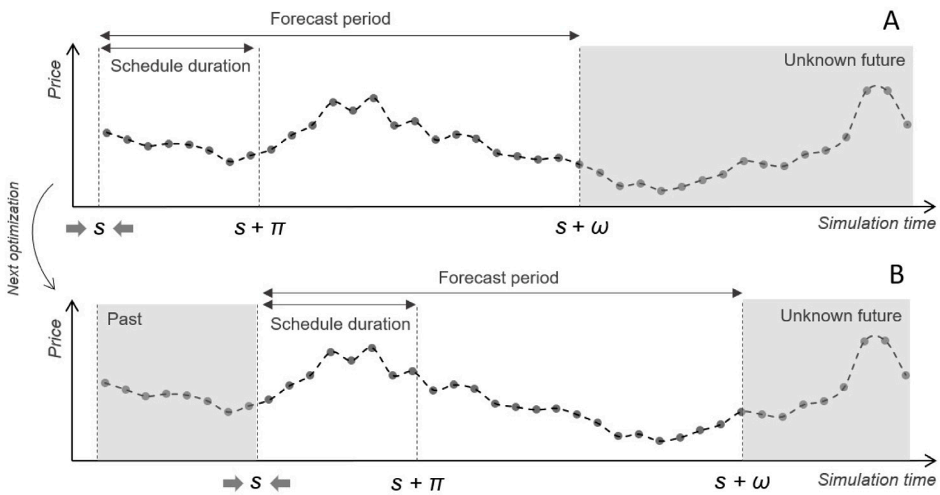

Fig. 5. Forecast period (ω) and schedule duration (π) in two consequent optimization runs A and B.

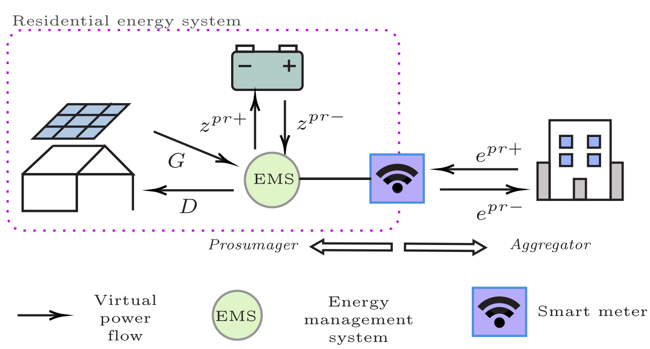

Fig. 6. Schematic overview of the prosumager's model.

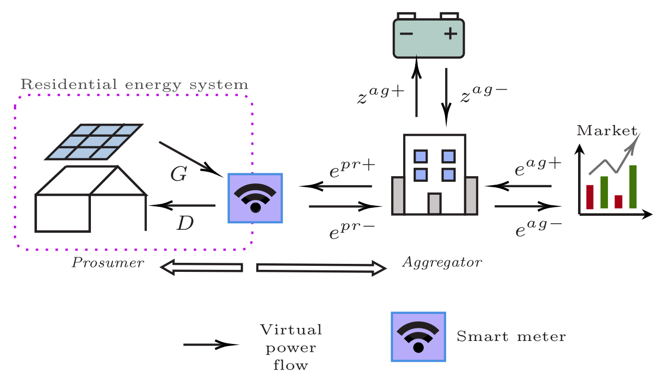

Fig. 7. Schematic overview of the CES model.

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})

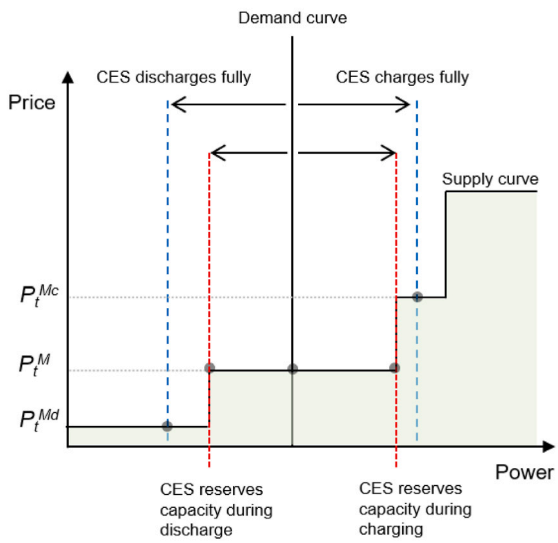

Fig. 8. Illustrative example of CES exercising market power.

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:

$$\underset{p_t^{ag+},\,p_t^{ag-}}{\text{Maximize}}\; r = \sum\nolimits_{i,t} \left(P_t^M (e_{it}^{pr-} - e_{it}^{pr+}) + p_t^{ag+} e_{it}^{pr+} - p_t^{ag-} e_{it}^{pr-}\right) \tag{5a}$$

$$\text{subject to: } P_{min}^M + \Gamma \le p_t^{ag+} \le P_{max}^M + \Gamma, \tag{5b}$$

$$P_{min}^M - \Gamma \le p_t^{ag-} \le P_{max}^M - \Gamma, \tag{5c}$$

$$\text{where } e_{it}^{pr+}, e_{it}^{pr-} \in \underset{\psi}{\text{argmin}}\; C_i^{pr} = \sum\nolimits_t \left((p_t^{ag+} + P^{rc}) e_{it}^{pr+} - p_t^{ag-} e_{it}^{pr-} + P_i^{ch}(z_{it}^{pr+} + z_{it}^{pr-})\right), \tag{5d}$$

$$\text{(1b)–(1i)}. \tag{5e}$$

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).

$$\underline{\beta}_{it}, \overline{\beta}_{it}, \underline{\gamma}_{it}, \overline{\gamma}_{it}, \underline{\mu}_{it}, \overline{\mu}_{it}, \underline{\tau}_{it}, \overline{\tau}_{it}, \underline{\upsilon}_{it}, \overline{\upsilon}_{it} \ge 0, \tag{6}$$

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).

$$p_t^{ag+} + P^{rc} + \lambda_{it}^z + \overline{\upsilon}_{it} - \underline{\upsilon}_{it} = 0 : e_{it}^{pr+}, \tag{7a}$$

$$-p_t^{ag-} - \lambda_{it}^z + \overline{\mu}_{it} - \underline{\mu}_{it} = 0 : e_{it}^{pr-}, \tag{7b}$$

$$-\lambda_{it}^a + (1 - \Lambda_i^{pr}) \lambda_{i(t+1)}^a - \underline{\tau}_{it} + \overline{\tau}_{it} = 0 : a_{it}^{pr}, \tag{7c}$$

$$(1 - \Lambda_i^{pr}) \lambda_{i1}^a - \lambda_{i0}^{a0} = 0 : a_{it}^{pr}, t = 1, \tag{7d}$$

$$P_i^{ch} - \frac{1}{\epsilon_i^{pr}} \lambda_{it}^a + \lambda_{it}^z - \underline{\gamma}_{it} + \overline{\gamma}_{it} = 0 : z_{it}^{pr-}, \tag{7e}$$

$$P_i^{ch} + \epsilon_i^{pr} \lambda_{it}^a - \lambda_{it}^z - \underline{\beta}_{it} + \overline{\beta}_{it} = 0 : z_{it}^{pr+}. \tag{7f}$$

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:

$$-\sum\nolimits_t \left(p_t^{ag+} e_{it}^{pr+} + P^{rc} e_{it}^{pr+} - p_t^{ag-} e_{it}^{pr-} + P_i^{ch}(z_{it}^{pr+} + z_{it}^{pr-})\right) = \sum -\lambda_{i0}^{a0} A_{i0}^{pr} + \sum\nolimits_t \Big(\overline{\tau}_{it} K_i^{pr} F_i^{pr} + \overline{\mu}_{it} E_t^{ag-} + \overline{\upsilon}_{it} E_t^{ag+} + \lambda_{it}^z H_{it} + \overline{\beta}_{it} \frac{U_{it}^{pr} K_i^{pr}}{\epsilon_i^{pr}} + \overline{\gamma}_{it} U_{it}^{pr} K_i^{pr} \epsilon_i^{pr}\Big) \tag{8}$$

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:

$$p_t^* e_{it}^{pr*} = \bigvee\nolimits_{k=1}^{n} P_{kt}^* e_{it}^{pr*} \tag{9}$$

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 $\bigvee_{k=1}^{n} P_{kt}^* e_{it}^{pr*}$.

$$-M^* b_{tk}^* \le h_{itk}^* \le M^* b_{tk}^*, \forall itk \tag{10a}$$

$$-M^*(1 - b_{tk}^*) \le h_{itk}^* - P_{kt}^* e_{it}^{pr*} \le M^*(1 - b_{tk}^*), \forall itk \tag{10b}$$

$$\sum\nolimits_{k=1}^{n} b_{tk}^* = 1 \tag{10c}$$

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:

$$\bigvee\nolimits_{k=1}^{n} P_{kt}^* e_{it}^{pr*} = \sum\nolimits_{k=1}^{n} h_{itk}^*, \tag{11a}$$

$$p_t^* = \sum\nolimits_{k=1}^{n} P_{kt}^* b_{tk}^*. \tag{11b}$$

Consequently, the original bilevel optimization problem in (5) can be reformulated with additional constraints derived in (10) and (11) as:

$$\underset{\xi}{\text{Maximize}}\; r = \sum_{t,i} \left(P_t^M (e_{it}^{pr-} - e_{it}^{pr+}) + \sum\nolimits_{k=1}^{n} h_{itk}^+ - \sum\nolimits_{k=1}^{n} h_{itk}^-\right)$$

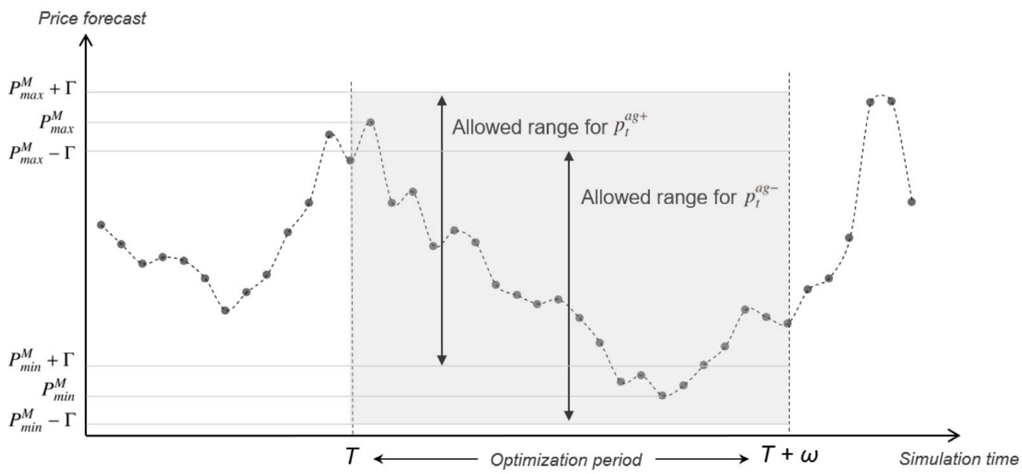

Fig. 9. Sale and purchase price limits for one exemplary optimization period.

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.

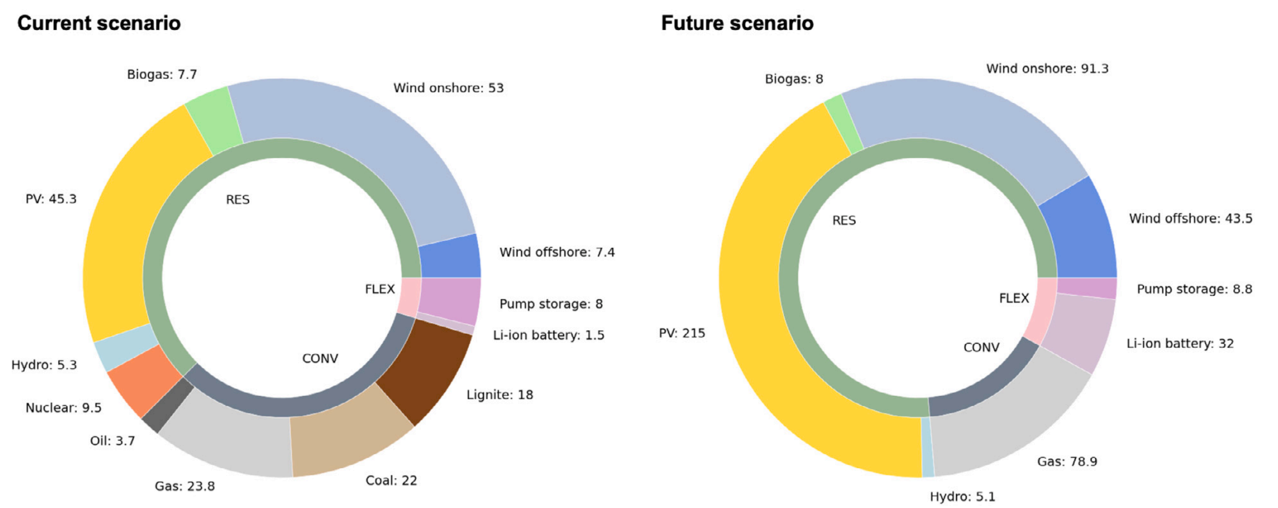

Fig. 10. Installed power plant capacities in the current and future scenarios.

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.

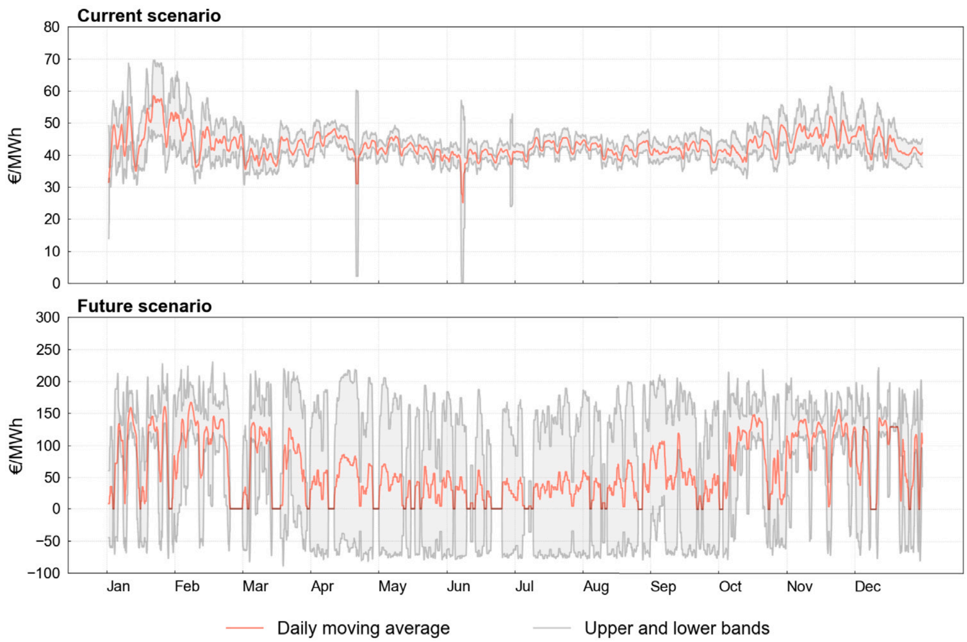

Fig. 11. Bollinger bands chart for the market prices in current and future scenarios. The chart illustrates two standard deviations, both above and below, from the 24-hour moving average trend.

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,

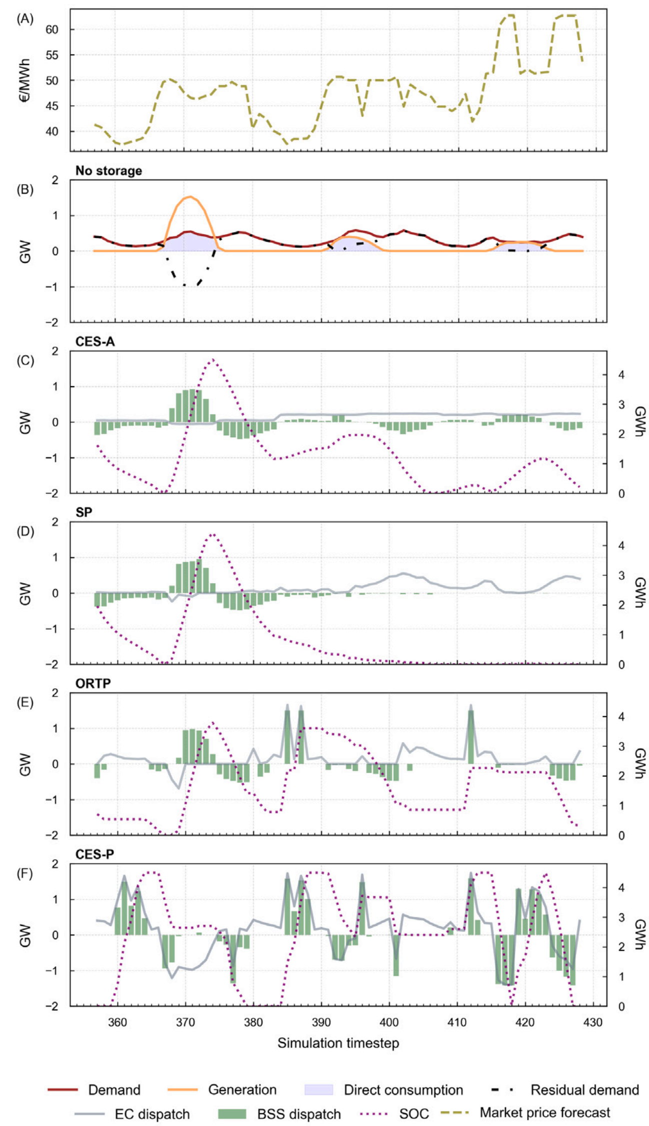

Fig. 12. EC dispatch in different use-cases over three exemplary days. Market price forecast is shown in A. User's direct consumption and residual demand are presented in B. subplots C, D, E, F respectively show the EC dispatch in the *CES_A*, *SP*, *ORTP* and *CES_P* use-case (as described in Table 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).

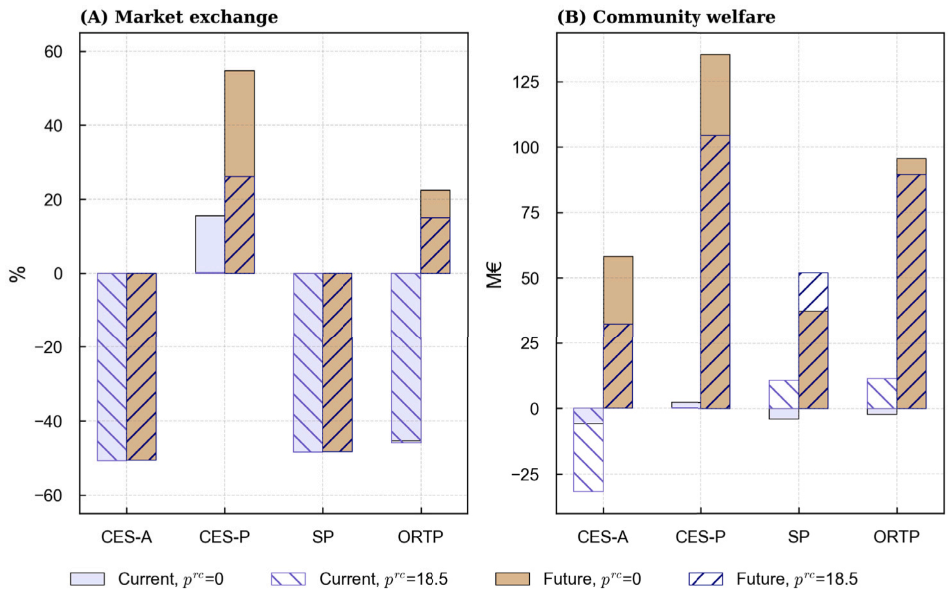

Fig. 13. Community level KPIs: market exchange (A) and community welfare (B) in the *CES_A*, *SP*, *ORTP* and *CES_P* relative to the *No_stor*(as described in Table 3). Note that subplots are scaled differently.

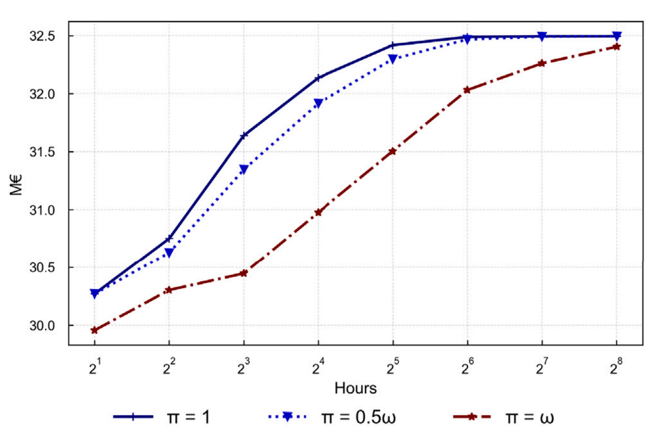

Fig. 14. Sensitivity analysis regarding the impact of the schedule duration (π) and forecast period (ω) on the community welfare (Φ).

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.

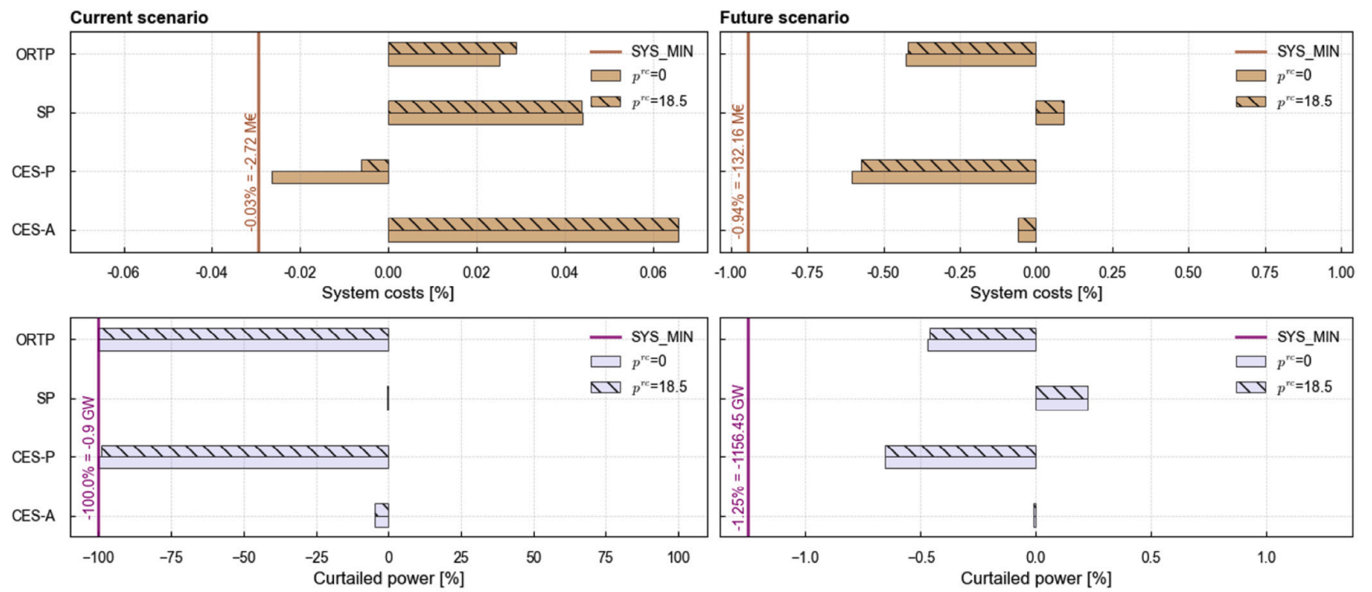

Fig. 15. Changes in system costs and RES generation curtailment in both energy system scenarios and in the *CES_A*, *SP*, *ORTP* and *CES_P* (as described in Table 3). Note that subplots are scaled differently.

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

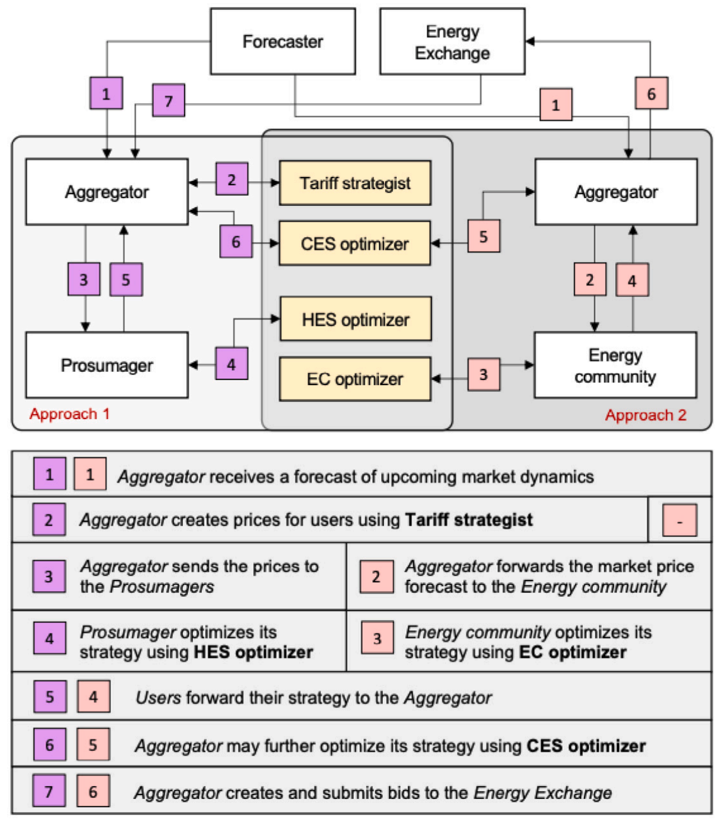

Fig. 16. Interaction among AMIRIS agents in one simulation step: Purple and pink boxes respectively correspond to information flows in the first and second approaches.

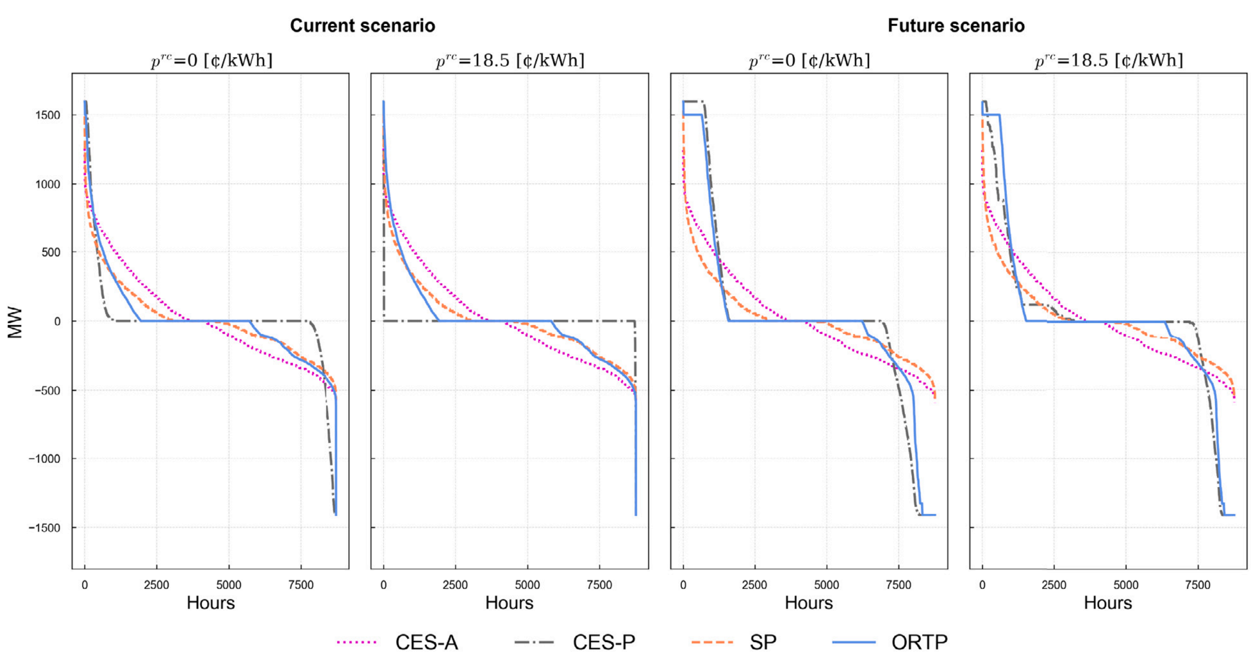

Fig. 17. BSS usage duration curves for different use-cases and scenarios. Positive and negative values respectively indicate charging and discharging of the BSS.

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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