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Assessing the impacts of energy sharing on low voltage distribution networks: Insights into electrification and electricity pricing in Germany

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ABSTRACT

The shift towards renewable energy sources, which is especially significant in the residential sector, relies on distributed energy resources (DER) like PV systems, heat pumps, battery storage systems, and electric vehicles. Integrating DERs into low-voltage distribution networks presents challenges, including potential grid instabilities. Energy sharing is a consumer-centric market approach, allowing consumers and prosumers to establish renewable energy communities (RECs) and share energy generated via DERs. Existing literature concerning energy sharing often prioritizes highlighting the benefits it offers to participants, rather than examining its direct impacts on established system boundaries such as distribution grid infrastructure. To this end, we employ a sequential modeling approach to study the integration of energy sharing schemes facilitated by RECs and their impacts on grid performance metrics, such as component loading, voltage magnitudes, and grid reinforcement costs. We examine twelve scenarios reflecting different REC configurations, DER adoption levels, and pricing strategies for both current (2023) and future (2037) contexts in Germany. Our findings indicate that implementing energy sharing not only results in considerable cost savings at the community level (with potential savings of up to 80% compared to scenarios without energy sharing) but also brings about significant reductions in grid asset loading (with decreases in transformer loading of up to 68% and line loading of up to 62%, compared to baseline scenarios). Conversely, we show that energy sharing can significantly influence voltage magnitudes at various nodes within the grid, potentially leading to substantial increases in grid reinforcement costs in future scenarios (i.e., 2037). Our research provides valuable insights for REC participants, regulators, and DSOs to understand the impacts of energy sharing on European low-voltage distribution networks and explore mitigation options, such as grid reinforcement measures.

1. Introduction

1.1. Motivation

Current human activities, particularly the reliance on fossil fuel extraction and consumption, pose a severe threat to environmental stability [1], putting us at risk of triggering tipping points that irreversibly disrupt the Earth's system [2]. The 2023 IPCC report highlights the urgency of the situation, emphasizing *severe* risks and *high* reasons for concern, as millions of people face exposure to extreme events caused by the breach of such tipping points [2]. Consequently, there is an urgent need for action to mitigate climate change.

Recognizing this urgency, for example, the European Union (EU) has set ambitious targets for adopting RES as part of its *Fit for 55* package within the *European Green Deal*. By 2030, the EU aims for renewable energy to constitute 42.5% of its energy mix [3], signaling its pivotal role in driving the shift towards carbon neutrality by 2050 [4]. This shift will be particularly evident in the residential sector, where the majority of final energy demand is projected to be met by RES [5].

In the ongoing pursuit of decarbonizing residential building stock as one of the main polluter, the widespread adoption of DER has emerged as a promising avenue [6]. DERs describe decentralized, small-scale power generation and storage devices, such as PV systems, HPs, battery storage (BS) systems, and EVs, that are located close to the point of consumption. Initially, the adoption of DER assets was primarily driven by environmental concerns rather than economic motives [7]. However, with investment costs for DERs such as PV and BS systems declining exponentially over the recent years [8], more consumers

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are embracing DERs for self-consumption. This transition turns consumers into *prosumers*, who both generate and consume energy, actively engaging with the energy system.

Against this backdrop, the switch from fossil fuels to RES promises many benefits for consumers. However, the growing reliance on RES also presents challenges: Energy systems must undergo significant adaptations, shifting from a centralized model where electricity is generated by large-scale generators and distributed downwards to individual consumers, to a decentralized paradigm where DERs coexist with consumers across various levels of the grid. This transition poses particular challenges for the grid segments below the transmission level, in particular, the low-voltage distribution level, where much of the digital-enabled, low-carbon energy innovation is anticipated to occur [9]. Specifically, within LVDNs, the rapid increase in DERs can cause energy system instabilities [10], such as overloading of individual grid components like transformers and lines, as well as voltage issues.

Across Europe, approximately 2,400 distribution system operators (DSOs) are tasked with ensuring the stability of the distribution grid, delivering 2,700 TWh of energy to around 260 million customers [11]. Traditionally, managing emerging system instabilities has involved reinforcing the distribution grid by installing additional components (e.g., more cables, or a larger substation/transformer), which can be costly. Another approach involves optimizing the use of existing infrastructure while considering physical grid constraints [12]. So-called RECs formed at the distribution grid level can play a vital role in this regard, offering financial incentives for members to consume locally generated renewable energy, thereby maintaining a balanced local energy supply [13]. RECs are legal entities where citizens can voluntarily engage in, granting them rights to produce, consume, store, and share renewable energy within their community. In Europe, the legal framework for RECs was established in 2019 under the *European Green Deal* through the *Clean Energy for all Europeans* package, including the revised *Renewable Energy Directive (RED) II* [14], later updated as RED III [3]. This underscores the EU's commitment to empowering citizens in the energy transition.

While various services and activities align with the REC concept, not all are explicitly outlined within the EU framework. Energy sharing, for instance, emerges as a consumer-centric market approach, allowing consumers and prosumers to establish RECs and share renewable energy within the same distribution grid segment [15]. Discussions and initial steps towards implementing energy sharing frameworks are underway across various European nations. However, many countries face challenges in establishing frameworks that facilitate energy sharing beyond a single building, allowing for the sharing of renewable energy over larger distances and leveraging the public grid infrastructure. Notably, Article 22(4) of RED II outlines various elements that an enabling framework for energy sharing should encompass, stressing the necessity that the "[...] relevant distribution system operator cooperates with renewable energy communities to facilitate energy transfers within renewable energy communities" [14].

1.2. State of the art

To define a suitable legislative framework, it is crucial to assess the feasibility of widespread implementation of energy sharing RECs. The benefits of energy sharing, extensively studied, encompass improved profitability [16–20], CO_2 reductions [19], and higher levels of self-sufficiency [5,21,22]. However, the DERs involved in energy sharing can also pose challenges to the existing grid infrastructure, such as congestion and voltage issues [12]. Components of grid infrastructure, like transformers and lines, play a pivotal role in energy sharing frameworks as they facilitate the transmission of electricity from its source to its destination. Therefore, an energy sharing transaction should only be deemed valid if it considers the impacts on these infrastructure elements.

The majority of studies and pilot projects concerning energy sharing prioritize highlighting the benefits it offers to participants, rather than examining its direct impacts on established system boundaries such as distribution grid infrastructure. This is also confirmed by reviews on this topic, for example, by Dudjak et al. [23]. Recently, some first academic studies have emerged considering the technical constraints associated with energy sharing within LVDNs.

Guerrero et al. [24] evaluate the technical impacts caused by energy sharing transactions in a LVDN in the UK. Their method predicts the network state caused by each energy sharing transaction made and internalizes the extra cost associated with the violations of the physical constraints. Tushar et al. [25] use a game-theoretical approach to facilitate energy sharing transaction that can help the grid to cope with peak hour demand, while, at the same time, ensure economic benefits for all participants. Wang et al. [26] propose schemes incentivizing DER investment and peak load mitigation. Novel cost-sharing mechanisms for common infrastructure during energy sharing are also explored. Baroche et al. [27] aim to allocate costs associated with the use of shared grid infrastructure in energy sharing by introducing using exogenous network fee charges. Such an approach allows community members to anticipate the cost of participating in energy sharing transactions on the network. Almasalma et al. [12] present a grid voltage control mechanism that leverages PV inverter control, integrated into the energy sharing model. Similar voltage-based control mechanisms have been explored in Demirok et al. [28], Kabir et al. [29], and Efkarpidis et al. [30].

Further, Park et al. [31] propose an energy sharing mechanism in which the REC has an obligation to reserve some flexibility during each transaction to ensure that the distribution grid remains intact. Specifically, the DSO announces the amount of flexibility to be reserved at the appointed time and the reserved flexibility is then used to mitigate any short-term voltage issues [31]. Also following a multi-stage approach, Putratama et al. [32] present an energy sharing settlement strategy that lets participants first minimize their energy bills through energy sharing and then adjust the market results to mitigate any voltage violations. In Morstyn et al. [33] energy sharing transaction fees are defined on a day-ahead basis by the DSO and used to ensure network constraints are met. However, none of these papers delve into the actual impacts of energy sharing on the grid, as their primary focus remains on solutions derived from incorporating grid constraints into the energy sharing model.

While several studies focus on integrating grid constraints, only a limited amount of literature focuses on analyzing the direct impacts of energy sharing transactions on the distribution grid. Azim et al. [34] studied power losses in distribution grids caused by energy sharing. Specifically, they observe network losses where energy sharing participants are provided with BS systems and flexible loads. However, their study employs an algorithmic model rather than an optimization model, and does not consider additional grid parameters beyond network losses. The paper of Hayes et al. [35] presents a co-simulation approach of energy sharing transactions and power flow analysis of a local distribution grid. Simulating a typical European semi-urban LVDN, they suggest that a moderate level of energy sharing transactions does not have a significant impact on grid performance, though their analysis is limited to voltage impacts only. Similarly, Teske et al. [36] propose an algorithmic approach for energy sharing transactions. Their approach not only achieves economics benefits for both prosumers and the DSO but also avoids grid congestions in the short term and reduces the need for grid reinforcement in the long term. Although they consider both voltage and component loading as network parameters, their study lacks an evaluation of various pricing mechanisms, such as network fees.

Orlandini et al. [37] perform a power flow analysis to assess the grid impacts of energy sharing and incorporate network fees into their model. An iterative approach is proposed, in which energy sharing transactions are validated based on grid limit violations and a dynamic network fee component is adjusted accordingly to motivate participants to avoid grid congestion. However, their model uses a multi-vector energy approach, incorporating PV, wind, and combined heat and power plants, rather than focusing on PV and storage system combinations. Botelho et al. [38] improve this approach by determining which peers contribute to the violation of certain network constraints and then penalizing their transactions in an iterative approach. Similarly, Dynge et al. [8] evaluate the economic benefits of energy sharing for consumers and prosumers having PV and storage systems, while also examining the challenges these transactions pose for grid operation. Their findings indicate that while the installation of PV systems alone has negligible impacts on grid operation, the use of decentralized BS results in increased voltage fluctuations and a 14% rise in losses within the neighborhood compared to scenarios without energy sharing.

Recent studies, such as Dimovski et al. [39], conduct detailed power flow simulations to assess the performance of various REC configurations and their effects on key grid performance metrics, including losses, line and transformer loading, and voltage violations. However, their analysis is limited to medium voltage (MV) grids and does not account for external factors like pricing and network fees, which influence consumer behavior and asset configuration. Hussain et al. [40] focus on the degradation of distribution grid assets, optimizing energy sharing such that the amount of power households can draw from the grid gets limited in case potential damage to the transformer is caused. In addition, Saif et al. [15] conduct a study quantifying the impacts of energy sharing transactions on LVDN performance under different retail electricity pricing strategies and Nour et al. [41] study the impacts of energy sharing on voltage unbalance of a LVDN while comparing energy sharing to cases where each building optimizes their assets based on regular home energy management system (HEMS).

Finally, Velkovski et al. [42] recently assessed the impact of various tariff structures designed to incentivize energy sharing within RECs, examining options such as flat and dynamic tariffs tied to day-ahead market prices, along with different network tariff models like regulated charge reductions and time-of-use tariffs. However, their approach to pricing overlooks the operational state of the distribution grid in setting network fees and offers no insights into the potential costs of necessary grid infrastructure upgrades for the DSO. Consequently, many existing studies fail to adequately model differentiated pricing and network fee mechanisms, particularly dynamic network fees that encourage users to adjust not only to fluctuating electricity prices but also to the grid's real-time operational conditions. Furthermore, these analyses typically focus on the direct effects of energy sharing on specific grid parameters (e.g., voltage levels, component loading), rather than considering how such transactions indirectly drive grid expansion and the associated costs due to adverse grid impacts.

1.3. Contribution and objectives

In the early stages of studying the evolving energy system, significant research effort was directed towards analyzing the implications of integrating DERs into LVDNs [43–47]. Traditional grid reinforcement measures, along with novel power quality control strategies, external incentive mechanisms, and market signals, were proposed to support DSOs in maintaining the distribution grid. However, as the concept of energy sharing emerged, the focus shifted towards the end-user perspective rather than the implications for the grid operators [8]. Much of the current research on energy sharing has centered on the internal mechanisms governing how energy is shared among REC members [48] and the benefits it offers them [49]. Notably, only a few recent studies have examined the broader implications of energy sharing on the overall energy system, particularly its impacts on local LVDNs.

This paper aims to contribute to the state of the art by studying the impact of energy sharing on various network performance metrics. The novelty of this research lies in its examination of how different pricing strategies and pathways towards electrification shape these metrics. As demonstrated in our literature review, both of these factors play a significant role in the adoption of innovative market mechanisms like energy sharing. With regards to the pricing strategies, for example, the RED II explicitly mandates regulators to develop a framework that allows REC members to freely share energy according to internally defined rules but to also be subject to *cost-reflective network charges* that ensure their adequate contribution to the overall system cost. Hence, we address a gap in the existing literature by considering dynamic pricing strategies with (1) static network fees that take into account standard assumptions on system impacts and (2) dynamic network fees that account for the actual impact energy sharing is causing on the local LVDN. In the same vein, regulators also have to consider the future decentralized, bottom-up nature of the energy system that is largely driven by the electrification of both transportation and residential heating. Therefore we consider future uptake in DERs by integrating the adoption rates for BS systems, EVs, and HPs, outlined in the German electricity network development plan 2023–2037/2045.

Existing literature often overlooks the relationship of these factors, making it difficult for regulators to define fitting regulatory frameworks for energy sharing schemes given the external boundaries (e.g., grid characteristics, pricing strategies) of such schemes. This gap is particularly evident in Germany, where no prior study has evaluated energy sharing within the framework of the electricity network development plan or upcoming regulations on pricing, notably under §14a and §41a EnWG. To highlight how this paper differentiates from existing research, we provide a comprehensive literature overview in Table 1.1. Through our research, we seek to address the following research questions (RQs):

- RQ1: How can energy sharing schemes be integrated into LVDNs?
- RQ2: What impact does energy sharing have on LVDN performance, considering different pricing strategies and electrification pathways?

To answer the two RQs, we analyze a variety of twelve scenarios reflecting diverse REC configurations in current (2023) and future contexts (2037), encompassing PV systems, BS systems, EVs, alongside variations in pricing strategies from static to dynamic, and differing network fee components. This array of scenarios offers insights into how energy sharing impact grid performance metrics across varying conditions. To the best of our knowledge, such an multi-facet analysis of the impacts of energy sharing on LVDNs for a REC in Germany is still absent in spite the variety of existing research. To that end, this paper contributes beyond the state of the art as follows:

- Development of a sequential modeling approach for integrating energy sharing schemes into LVDNs and analyzing its impacts not only on a variety of grid performance metrics but also in terms of potential reinforcement costs.
- Consideration of varying degrees of DER adoption reflecting different electrification pathways, as outlined in the German electricity network development plan 2023–2037/2045, and forms of DER, that account for consumption, storage, and heating demands, such as PV systems, BS systems, EVs, and HPs.
- Evaluation of different pricing strategies, including comparisons between static and dynamic electricity prices, as well as static and dynamic network fees that account for the actual impact energy sharing is causing on the local LVDN.
- Simulation of a case study based on an energy sharing community in Munich, Germany, utilizing real-world household and RES data, and incorporating upcoming regulatory frameworks such as §14a and §41a EnWG.

Table 1.1
Literature review.
Source: Own illustration.

Reference	DERs				Electricity price		Network fee		Grid performance metrics			
	PV	BS	EV	HP	Static	Dynamic	Static	Dynamic	Peak demand	Comp. loading	Voltages	Reinf. cost
[12]	✓					✓	✓				✓	
[34]	✓	✓				✓	✓				✓	
[27]	✓				✓			✓		✓		
[38]	✓				✓			✓		✓	✓	
[39]	✓	✓							✓	✓	✓	
[8]	✓	✓	✓		✓	✓	✓		✓		✓	
[24]	✓	✓			✓		✓		✓		✓	
[35]	✓		✓			✓	✓				✓	
[40]	✓	✓	✓			✓	✓			✓		
[33]	✓	✓				✓		✓			✓	
[41]	✓	✓	✓			✓	✓			✓	✓	
[37]	✓				✓			✓		✓	✓	
[31]	✓	✓					✓				✓	
[32]	✓	✓			✓		✓				✓	
[36]	✓		✓	✓	✓		✓			✓	✓	✓
[25]	✓	✓				✓	✓		✓			
[42]	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	
[26]	✓	✓				✓	✓		✓			
This work	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

1.4. Outline

This paper is structured as follows: The second section covers the methodology, providing insights into the modeling approach, scenarios, and performance metrics. Section three delves into the setup of the case study used in this paper. Section four presents the study's results, beginning with an assessment of the energy community's performance to highlight the benefits of the REC setup, followed by an evaluation of network performance using the metrics from section two. In section five, the results are discussed, limitations of the approach are presented, and opportunities for further research are outlined. Section six summarizes the key findings of this research.

2. Methodology

2.1. Community architecture

In our modeling approach, we envision a REC comprising diverse buildings, each accommodating various types of households capable of acting as either traditional energy consumers or prosumers generating their own electricity using RES. These buildings are interconnected at the same voltage level, specifically within a segment of the LVDN, which may consist of a single feeder (i.e., a segment that is served by a single transformer) or a group of them. Within this network segment, the REC constitutes a subset of nodes, as depicted in Fig. 2.1. Therefore, not all buildings within the LVDN segment may take part in the REC, as some may opt for conventional grid imports and exports without engaging in energy sharing. Such buildings will operate in a so-called *business as usual (BAU)* mode, similar to conventional consumers today without involvement in local energy community initiatives. This setup aligns with the provisions outlined in the EU's RED II (Directive EU/2018/2001 [14]), which requires that participation in such schemes must be voluntary. Nevertheless, we assume all buildings in the segment possess various DERs, including PV systems, BS systems, EVs, and/or HPs.

Regarding the community itself, all buildings considered part of the REC can freely share energy with other members, thereby reducing their reliance on grid imports from traditional utilities. However, each building within the REC still has the option to procure energy from the traditional utility, which is particularly relevant during periods when the community may not be entirely self-sufficient (e.g., insufficient RES generation available to cover the entire community demand). Furthermore, we assume each building is equipped with smart metering technology, enabling real-time monitoring and measurement of energy flows. Additionally, a HEMS is installed in every building, optimizing the operation of DERs based on inputs such as load profiles and market signals. These market signals include traditional signals from the utilities (e.g., retail electricity prices, network fees, and feed-in tariffs (FITs)) and community-based prices for energy sharing transactions. Apart from consumers/prosumers, other key stakeholders in the community structure include a designated community manager (CM), the DSO, and the traditional energy utility.

Operating within a centralized community architecture, the CM acts as a third-party overseeing the coordination of HEMSs across various buildings and facilitating energy sharing among community members. Specifically, all buildings in the REC coordinate with the CM to solve a centralized optimization problem and find an optimal solution for the entire community. This centralized optimization problem addresses the first research question of this paper by effectively integrating energy sharing within the LVDN (cf. Section 2.2.1). The DSO ensures that community activities comply with technical network constraints by monitoring power flows within the LVDN. A network model is used to assess the impact of energy sharing on various LVDN performance metrics, effectively addressing the second research question of this paper (cf. Section 2.2.2). For this purpose, we assume the DSO has all relevant monitoring infrastructure in place. Finally, the traditional energy utility serves as a supplier for energy imports and exports to and from the grid, complementing energy sharing within the community. Importantly, in a real-world setting, the utility would not require direct access to households' metering data, unlike the CM and the DSO. Instead, the DSO would provide necessary billing information (e.g., total energy imported or exported to/from the grid) to the utility. This architectural framework seamlessly integrates into the existing liberalized energy market structure, where consumers retain autonomy in selecting their preferred energy utility while also having the option to participate in voluntary community-based energy initiatives like energy sharing.

2.2. Modeling approach

2.2.1. Energy sharing model

With our model we aim to facilitate energy sharing within the REC while optimizing energy procurement to satisfy the diverse household demands and DER operations. DER operations include PV system generation, BS system charging/discharging, EV charging/discharging,

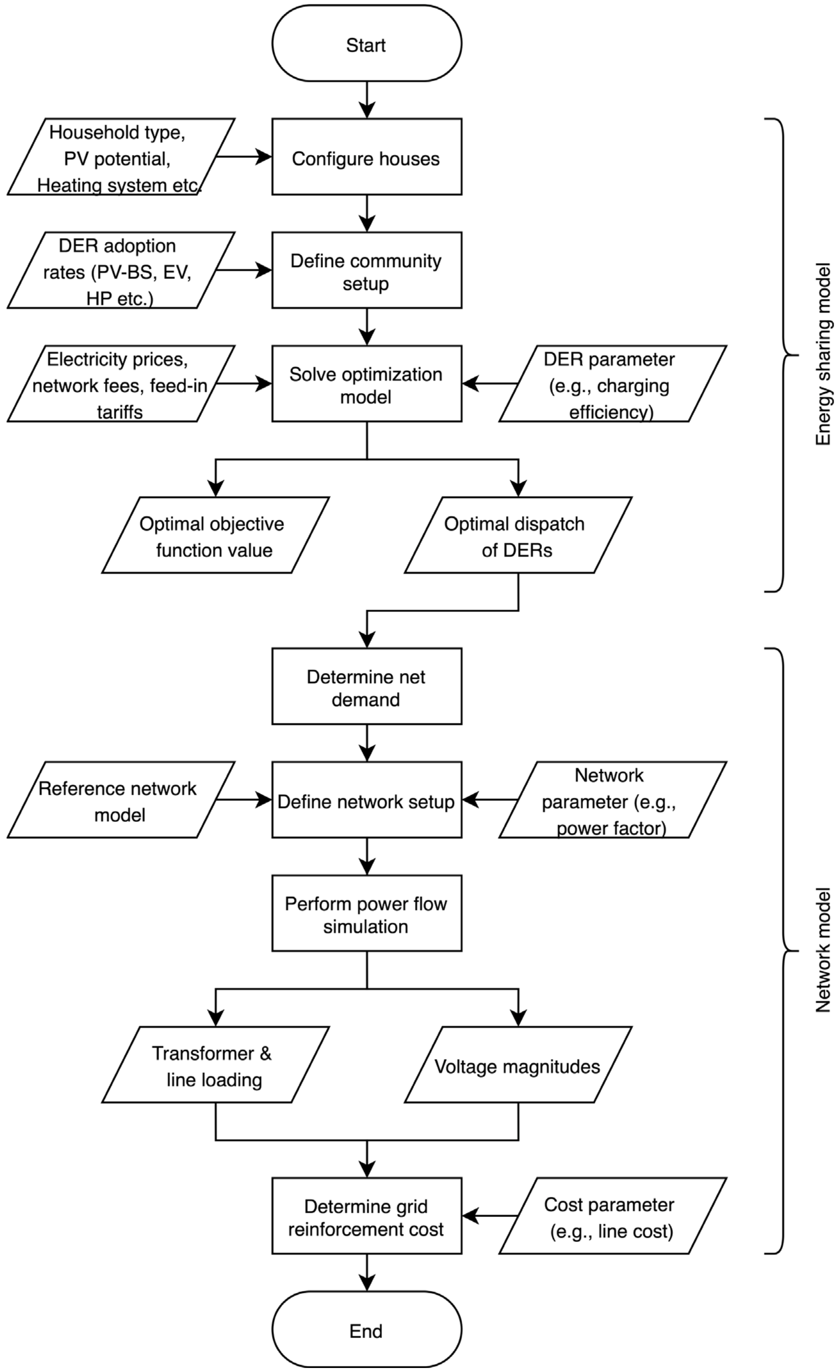

Fig. 1.1. Flow chart of the modeling approach.
Source: Own illustration.

and HP heat generation. Our mixed-integer linear programming (MILP) model is based on prior research [8,15,41,50], incorporating modifications and extensions to address diverse asset configurations (e.g., adding EVs as storage units, and HPs and gas heaters (GHs) to meet heating requirements), network demands (e.g., active and reactive power), and pricing strategies (e.g., static and dynamic pricing). We present our modeling process through a comprehensive flowchart in Fig. 1.1. The model formulation employs mathematical constructs such as sets (defining model instances like variables), parameters (model data), variables (model unknowns), an objective function (model goal), and constraints (model mathematical relationships). Specifically, we define two sets: a set of participating buildings in the REC $B = \{1, \dots, B\}$ and a time horizon representing our one-week simulation period $T = \{1, \dots, T\}$. In addition, various input data is used for our parameters (cf. Section 3). The variables represent the decisions made by the individual buildings regarding, for example, energy import/export from/to the grid or the community, BS system charge/discharge, or EV operations. Finally, the objective function seeks to minimize the REC's total electricity cost. The objective function is subject to supply, demand, storage, and energy sharing constraints.

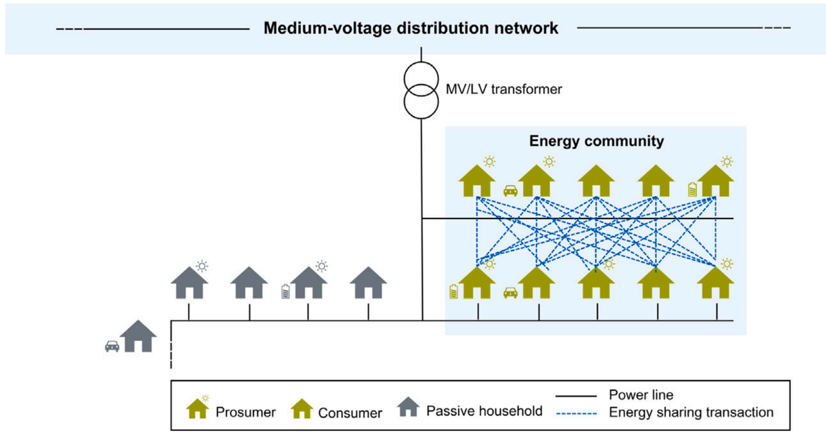

Fig. 2.1. Architecture and placement of the examined REC within the LVDN.
Source: Own illustration.

Symbol	Description
Sets and Indices	
$B/b, p$	Set/indices of buildings
T/t	Set/indices of time steps
Variables	
$q_{b,t}^{\text{gd,im}}$	Grid import by building b in time t [kWh]
$q_{b,t}^{\text{gd,ex}}$	Grid export by building b in time t [kWh]
$q_{b,t}^{\text{cm,im}}$	Total community imports by building b in time t [kWh]
$q_{b,t}^{\text{cm,ex}}$	Total community exports by building b in time t [kWh]
$q_{p\to b,t}^{\text{cm,im}}$	Import by building b from peer p in time t [kWh]
$q_{b\to p,t}^{\text{cm,ex}}$	Export by building b to peer p in time t [kWh]
$q_{b,t}^{\text{bs,ch}}$	Charging of building b's BS in time t [kWh]
$q_{b,t}^{\text{bs,dch}}$	Discharging of building b's BS in time t [kWh]
$s_{b,t}^{\text{bs}}$	SoC of building b's BS in time t [kWh]
$q_{b,t}^{\text{ev,ch}}$	Charging of building b's EV in time t [kWh]
$q_{b,t}^{\text{ev,dch}}$	Discharging of building b's EV in time t [kWh]
$s_{b,t}^{\text{ev}}$	SoC of building b's EV in time t [kWh]
Parameters	
$p_t^{\text{gd,im}}$	Price for grid import in time t [€/kWh]
$p_t^{\text{gd,ex}}$	Price for grid export in time t [€/kWh]
$q_{b,t}^{\text{el}}$	Electricity demand of building b in time t [kWh]
$q_{b,t}^{\text{th}}$	Heat demand of building b in time t [kWh]
$q_{b,t}^{\text{pv}}$	PV generation of building b in time t [kWh]
$\bar{q}^{\text{bs,ch}}$	Maximum charging power of the BS [kW]
$\bar{q}^{\text{bs,dch}}$	Maximum discharging power of the BS [kW]
$\underline{s}_{\text{bs}}$	Minimum SoC of the BS [%]
$\bar{s}_{\text{bs}}$	Maximum SoC of the BS [%]
$\eta^{\text{bs,ch}}$	Charging efficiency of the BS [%]
$\eta^{\text{bs,dch}}$	Discharging efficiency of the BS [%]
$\bar{q}^{\text{ev,ch}}$	Maximum charging power of the EV [kW]
$\bar{q}^{\text{ev,dch}}$	Maximum discharging power of the EV [kW]
$\underline{s}_{\text{ev}}$	Minimum SoC of the EV [%]
$\bar{s}_{\text{ev}}$	Maximum SoC of the EV [%]
$\eta^{\text{ev,ch}}$	Charging efficiency of the EV [%]
$\eta^{\text{ev,dch}}$	Discharging efficiency of the EV [%]
b_t^{ev}	Binary for the location of the EV [0,1]
$q_{b,t}^{\text{ev}}$	Electricity demand of building b's EV in time t [kWh]
$q_{b,t}^{\text{hp}}$	HP generation of building b in time t [kWh]
$q_{b,t}^{\text{gh}}$	GH generation of building b in time t [kWh]
η_t^{cop}	COP of the HP in time t [-]
p_t^{gas}	Gas price in time t [€/kWh]

Objective function Since we employ a centralized community architecture, the objective function minimizes the total energy procurement cost of the REC. This involves minimizing expenses incurred from grid imports and community transactions, while maximizing gains from selling excess energy to either the grid or the community. Eq. (1) outlines this objective function. We make the assumption that the collective revenue generated by buildings selling energy to the community equals the total expenditure on energy imports from the community. Hence, the costs associated with importing energy from the community and the revenue from exporting energy to the community cancel each other out.

$$\begin{aligned}\min \quad & \sum_{t=1}^{|T|}\sum_{b=1}^{|B|}(p^{\text{gd,im}} \cdot q_{b,t}^{\text{gd,im}} - p_t^{\text{gd,ex}} \cdot q_{b,t}^{\text{gd,ex}} \\ & + p_t^{\text{cm,im}} \cdot q_{b,t}^{\text{cm,im}} - p_t^{\text{cm,ex}} \cdot q_{b,t}^{\text{cm,ex}} + p_t^{\text{gas}} \cdot q_{b,t}^{\text{gh}})\end{aligned} \tag{1}$$

Constraints Various constraints are incorporated into the model to account for the unique characteristics of the REC. The energy sharing scheme within the REC allows for direct transactions between prosumers and their peers. Generally, the import of building b from peer p is equal to the export of p to b in time t (cf. Eq. (2)).

$$q_{p\to b,t}^{\text{cm,im}} = q_{b\to p,t}^{\text{cm,ex}} \qquad \forall b \neq p, t \in T \tag{2}$$

Eq. (3) states that the total amount for energy exported $q_{b,t}^{\text{cm,ex}}$ from a building b to other community members is the sum of his individual exports to each other peer p.

$$q_{b,t}^{\text{cm,ex}} = \sum_{p\neq b}^{|B|} q_{b\to p,t}^{\text{cm,ex}} \qquad \forall b \in B, t \in T \tag{3}$$

Similarly, the total received (i.e., imported) energy $q_{b,t}^{\text{cm,im}}$ for a building b is the sum of the imported energy from all the peers in the community (cf. Eq. (4)).

$$q_{b,t}^{\text{cm,im}} = \sum_{p\neq b}^{|B|} q_{p\to b,t}^{\text{cm,im}} \qquad \forall b \in B, t \in T \tag{4}$$

In addition, it is assumed that energy sharing is limited to stay within the community, i.e., buildings can only share energy with peers who decide to join the REC and not with other buildings located in the LVDN feeder that are not part of the REC. Thus, we also define a constraint that ensures that the sum of exports made by REC members equals the sum of imports (cf. Eq. (5)).

$$\sum_{b=1}^{|B|} q_{b,t}^{\text{cm,im}} = \sum_{b=1}^{|B|} q_{b,t}^{\text{cm,ex}} \qquad \forall t \in T \tag{5}$$

Another central constraint in the model is the electrical power balance equation, represented in Eq. (6), ensuring that the supply equals the demand at each building b at each time step t. Specifically, a building b's electricity demand $q^{\mathrm{el}}_{b,t}$, exports to the grid $q^{\mathrm{gd,ex}}_{b,t}$ and to the community $q^{\mathrm{cm,ex}}_{b,t}$, as well as BS $q^{\mathrm{bs,ch}}_{b,t}$ and EV $q^{\mathrm{ev,ch}}_{b,t}$ charging requirements must be equal to the sum of imports from the grid $q^{\mathrm{gd,im}}_{b,t}$ and the community $q^{\mathrm{cm,im}}_{b,t}$, as well as the BS $q^{\mathrm{bs,dch}}_{b,t}$ and EV $q^{\mathrm{ev,dch}}_{b,t}$ discharging requirements. We also integrate the electricity load of a HP that might be installed at a building b's premises to cover its thermal load. The HP's electricity demand is determined in relation to a time-varying COP η^{cop}_t (cf. Section 3.3). The power balance equation holds for buildings who have both PV and BS systems installed, and will change depending on which DERs are installed.

$$q^{\mathrm{el}}_{b,t} + q^{\mathrm{gd,ex}}_{b,t} + q^{\mathrm{cm,ex}}_{b,t} + q^{\mathrm{bs,ch}}_{b,t} + q^{\mathrm{ev,ch}}_{b,t} + \frac{q^{\mathrm{hp}}_{b,t}}{\eta^{\mathrm{cop}}_t} = q^{\mathrm{pv}}_{b,t} + q^{\mathrm{gd,im}}_{b,t} + q^{\mathrm{cm,im}}_{b,t} + q^{\mathrm{bs,dch}}_{b,t} + q^{\mathrm{ev,dch}}_{b,t} \qquad \forall b \in B, t \in T \tag{6}$$

Similarly, we employ a thermal power balance equation, represented by Eq. (7), to ensure that the heat demand $q^{\mathrm{th}}_{b,t}$ of each building b is fulfilled either by a conventional GH $q^{\mathrm{gh}}_{b,t}$ or HP $q^{\mathrm{hp}}_{b,t}$ at every time step t. We incorporate heating requirements into our model to accommodate the anticipated transition to electric heating in the residential sector (cf. Section 2.3).

$$q^{\mathrm{th}}_{b,t} = q^{\mathrm{hp}}_{b,t} + q^{\mathrm{gh}}_{b,t} \qquad \forall b \in B, t \in T \tag{7}$$

For prosumers who have BS systems installed, the following constraints govern the charging/discharging processes. Each building's BS should operate within its ratings. That is, the charging $q^{\mathrm{bs,ch}}_{b,t}$ and discharging $q^{\mathrm{bs,dch}}_{b,t}$ of building b's BS in time step t is limited by the power rating of the converter that connects the BS to the LVDN. The lower limit is set at 0, while the upper limit is set to $\bar{q}^{\mathrm{bs,ch}}$ and $\bar{q}^{\mathrm{bs,dch}}$, respectively (cf. Eq. (8) and Eq. (9)).

$$0 \le q^{\mathrm{bs,ch}}_{b,t} \le \bar{q}^{\mathrm{bs,ch}} \qquad \forall b \in B, t \in T \tag{8}$$

$$0 \le q^{\mathrm{bs,dch}}_{b,t} \le \bar{q}^{\mathrm{bs,dch}} \qquad \forall b \in B, t \in T \tag{9}$$

In addition, the state of charge (SoC) of building b's BS in time step t $s^{\mathrm{bs}}_{b,t}$ has a lower limit of $\underline{s}_{\mathrm{bs}}$ and an upper limit of $\bar{s}_{\mathrm{bs}}$ (cf. Eq. (10)).

$$\underline{s}^{\mathrm{bs}} \le s^{\mathrm{bs}}_{b,t} \le \bar{s}^{\mathrm{bs}} \qquad \forall b \in B, t \in T \tag{10}$$

Eq. (11) states the update of the BS SoC from time step $t-1$ to t. Specifically, the SoC of a building b's BS $s^{\mathrm{bs}}_{b,t}$ is a function of the SoC of the previous time step $t-1$ and the charge/discharge in the current time step t. The charging/discharging thereby depends on the charging efficiency $\eta^{\mathrm{bs,ch}}$ and discharging efficiency $\eta^{\mathrm{bs,dch}}$, respectively. All BS systems are initialized with an empty SoC (i.e., $s^{\mathrm{bs}}_{b,0} = 0$) and the SoC update function in the first time step $t = 0$ refers to this initial SoC. It is important to note that, in real-life scenarios, maintaining an SOC above 0% is generally preferred to optimize battery longevity and ensure overall system reliability.

$$s^{\mathrm{bs}}_{b,t} = s^{\mathrm{bs}}_{b,t-1} + \eta^{\mathrm{bs,ch}} \cdot q^{\mathrm{bs,ch}}_{b,t} + \frac{1}{\eta^{\mathrm{bs,dch}}} \cdot q^{\mathrm{bs,dch}}_{b,t} \qquad \forall b \in B, t \in T, t \neq 0 \tag{11}$$

For the EVs we use similar charging/discharging constraints as for the BS systems. First, the charging $q^{\mathrm{ev,ch}}_{b,t}$ and discharging $q^{\mathrm{ev,dch}}_{b,t}$ of building b's EV in time step t is limited by the power rating of the wall box that connects the EV to the LVDN. We apply the same lower and upper limits as in the case of a building's BS (cf. Eq. (12) and Eq. (13)).

$$0 \le q^{\mathrm{ev,ch}}_{b,t} \le \bar{q}^{\mathrm{ev,ch}} \cdot b^{\mathrm{ev}}_t \qquad \forall b \in B, t \in T \tag{12}$$

$$0 \le q^{\mathrm{ev,dch}}_{b,t} \le \bar{q}^{\mathrm{ev,dch}} \cdot b^{\mathrm{ev}}_t \qquad \forall b \in B, t \in T \tag{13}$$

Second, the SoC of building b's EV in time step t $s^{\mathrm{ev}}_{b,t}$ has a lower limit of $\underline{s}_{\mathrm{ev}}$ and an upper limit of $\bar{s}_{\mathrm{ev}}$ (cf. Eq. (14)).

$$\underline{s}^{\mathrm{ev}} \le s^{\mathrm{ev}}_{b,t} \le \bar{s}^{\mathrm{ev}} \qquad \forall b \in B, t \in T \tag{14}$$

Notably, we specifically govern the charging/discharging activity of an EV based on its location, as detailed in Eq. (15). This means that an EV can only be charged during time step t if it is connected to a wall box within the LVDN, and not while it is in transit. Consequently, b^{ev}_t is assigned a value of 1 when the EV is connected to the LVDN at time step t, and 0 otherwise.

$$b^{\mathrm{ev}}_t = \begin{cases} 1, & \text{if EV is connected to the LVDN in time step } t \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

Finally, Eq. (16) states the SoC update function of the EV from time step $t-1$ to t, adhering to the identical criteria defined in the SoC update process of the BS systems.

$$s^{\mathrm{ev}}_{b,t} = s^{\mathrm{ev}}_{b,t-1} + \eta^{\mathrm{ev,ch}} \cdot q^{\mathrm{ev,ch}}_{b,t} + \frac{1}{\eta^{\mathrm{ev,dch}}} \cdot q^{\mathrm{ev,dch}}_{b,t} - q^{\mathrm{ev}}_{b,t} \qquad \forall b \in B, t \in T, t \neq 0 \tag{16}$$

It is important to note that our model relies on deterministic profiles for load, generation, and mobility. In other words, we assume perfect foresight of the exact realization of all parameters, even if their actual realization occurs in the future.

2.2.2 Network model

In our study, we utilize the IEEE European reference network model (RNM) [51], which depicts a European three-phase low voltage (LV) feeder with a radial topology. Fig. 2.2 provides a schematic representation of the studied IEEE European LVDN. Generally, the feeder encompasses various electrical elements. These include, for example, nodes (referred to interchangeably as buses), loads (buses that are characterized by electrical demand), lines (connecting buses in the network), a transformer (serving as the slack bus connecting the feeder to the upstream grid). The used IEEE European RNM consists of a total of 906 buses, 55 loads, 905 lines, and a single MV/LV transformer. While the line and bus elements in the studied RNM remain unchanged, we modify loads and the transformer to align with the outputs of our energy sharing model. In the following we give a detailed overview on these modifications. The parameterization details for all individual network elements (including buses and lines) are discussed in Section 3.1.

Load elements In our LVDN feeder, we accommodate all 55 loads from the RNM, each representing a unique building housing specific household loads (cf. Section 3.2). As previously mentioned, our REC comprises only a subset of these loads, as not all buildings within the LVDN segment participate in the REC; some may prefer conventional grid imports and exports without engaging in energy sharing. Therefore, the loads of buildings participating in the REC require further adjustments based on the outputs of our energy sharing model.

Specifically, we use the set of decision variables $\left\{ q^{\mathrm{gd,im}}_{b,t}, q^{\mathrm{gd,ex}}_{b,t}, q^{\mathrm{cm,im}}_{p\to b,t}, q^{\mathrm{cm,ex}}_{b\to p,t} \right\}$ of our energy sharing model for each buildings b, to determine its individual active and reactive load profile. The net active power demand is computed as the sum of the energy imported to building b (comprising grid imports $q^{\mathrm{gd,im}}_{b,t}$ and community imports $q^{\mathrm{cm,im}}_{b,t}$) minus the energy exported from building b (comprising grid exports $q^{\mathrm{gd,ex}}_{b,t}$ and community exports $q^{\mathrm{cm,ex}}_{b,t}$) (cf. Eq. (17)). Importantly, charging/discharging activities of BS systems and EVs are disregarded,

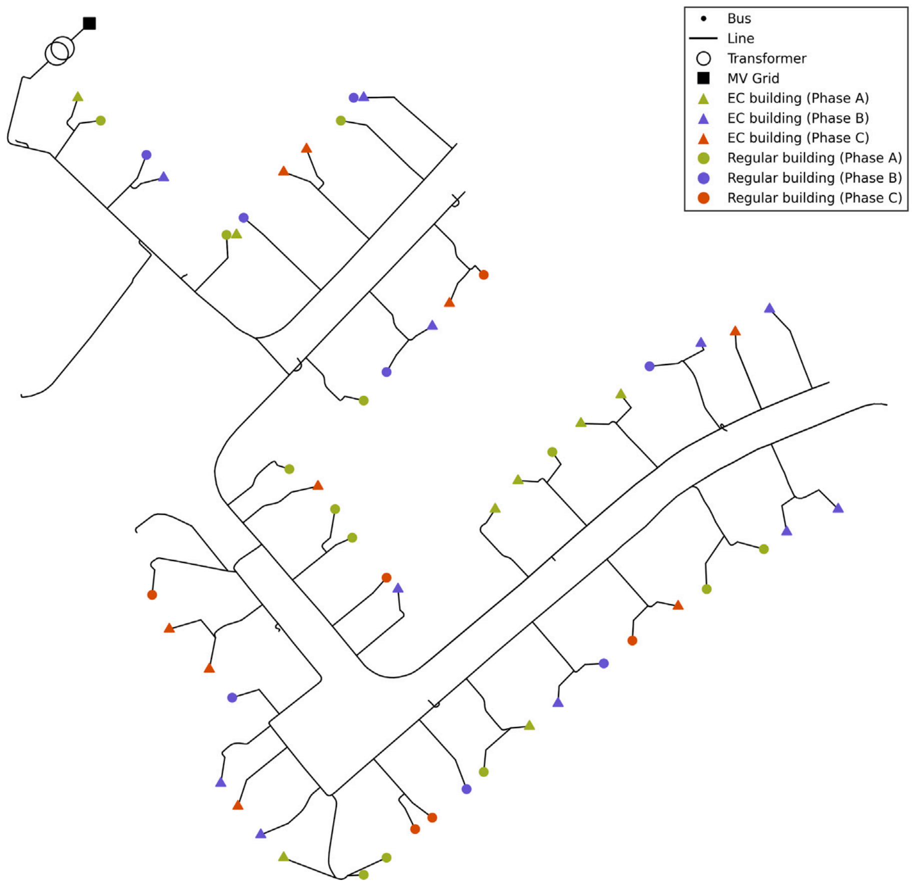

Fig. 2.2. Schematic representation of the studied IEEE European LVDN.
Source: Own illustration based on data of [51].

assuming these occur beyond the meter, i.e., behind the building's connection point to the LVDN.

$$q^{\text{net}}_{b,t} = q^{\text{gd,im}}_{b,t} + q^{\text{cm,im}}_{b,t} - q^{\text{gd,ex}}_{b,t} - q^{\text{cm,ex}}_{b,t} \qquad \forall b \in B, t \in T \tag{17}$$

While the energy sharing model primarily considers active power, the network model incorporates changes in reactive power, for example, caused by the energy sharing transactions. As reactive power plays a crucial role in maintaining voltage quality within the LVDN, alterations in active power flows impact the distribution and magnitude of reactive power [52]. For simplicity, we calculate the net reactive power at each building's connection point for every time step t by transforming the active power demand $q^{\text{net}}_{b,t}$ using a constant power factor $\cos(\theta)$ [15] (cf. Eq. (18)).

$$q^{\text{net,reactive}}_{b,t} = \sqrt{\left(\frac{q^{\text{net}}_{b,t}}{\cos(\theta)}\right)^2 - \left(q^{\text{net}}_{b,t}\right)^2} \qquad \forall b \in B, t \in T \tag{18}$$

Transformer element Furthermore, adjustments are made to the local transformer to accommodate building energy requirements. The transformer size $\bar{q}^{\text{transformer}}$ is determined based on [53], considering both the annual power peak demand $\bar{q}^{\text{net}}$ and anticipated future demand growth f^{safety} of the entire feeder (cf. Eq. (19)). An additional power oversize capacity p^{over} is also incorporated to ensure that the chosen capacity aligns with commercially available transformer standard sizes [54].

$$\bar{q}^{\text{transformer}} = \frac{\bar{q}^{\text{net}}}{\cos(\theta)} \cdot f^{\text{safety}} + q^{over} \tag{19}$$

After creating the net active and reactive load profiles for each building and determining the optimal transformer size, the power flow simulation can be executed using *Pandapower*.

2.3 Scenarios

The rise of residential electrification, especially the widespread integration of DERs and novel market mechanisms like energy sharing, pose significant challenges to LVDNs. Additionally, the adoption of digital-enabled, low-carbon energy innovations at consumers' connection points, such as HEMSs, further strains distribution grids due to consumers adjusting their consumption patterns based on market signals [19,55]. Hence, this paper evaluates the performance of an REC and its impact on an LVDN, considering various electrification pathways (to accommodate the evolving DER landscape) and electricity pricing strategies (to address external market signals). Specifically, we analyze the performance of our methodology across two electrification pathways (for 2023 and 2037) and three pricing strategies (static pricing, dynamic pricing, and dynamic pricing incorporating a dynamic network fee component). Furthermore, each scenario encompasses two operational modes for the LVDN: a baseline scenario (BAU), where buildings optimize their assets independently using their HEMSs, and a collaborative energy sharing scenario (REC), where buildings participate in the centralized REC and engage in energy sharing. In total, we explore 12 scenarios, as outlined in Table 2.1.

2.3.1 Electrification pathways

We establish two electrification pathways to account for a future uptake of DERs (cf. Table 2.2). The German electricity network development plan 2023–2037/2045 identifies a significant uptick in various

Table 2.1
Studied scenarios.
Source: Own illustration.

ID	Electrification pathway	Operating mode	Pricing strategy	Scenario name
s0	2023	BAU	SP	2023_BAU_SP
s1			DP	2023_BAU_DP
s2			DN	2023_BAU_DN
s3		REC	SP	2023_REC_SP
s4			DP	2023_REC_DP
s5			DN	2023_REC_DN
s6	2037	BAU	SP	2037_BAU_SP
s7			DP	2037_BAU_DP
s8			DN	2037_BAU_DN
s9		REC	SP	2037_REC_SP
s10			DP	2037_REC_DP
s11			DN	2037_REC_DN

Table 2.2
Electrification pathways. Percentage of households adopting various RES.
Source: Own illustration based on data of [56].

Year	EVs [%]	EVs bidi. [%]	HPs [%]	PV-BS [%]
2023	2.0	0	6.0	1.0
2037	65.0	65.0	76.0	71.0

renewable energy capacities by 2037: a 4.8-fold increase in total PV system capacity (reaching 345 GW), a 51-fold increase in PV-BS system capacity (totaling 67.4 GW), alongside substantial rises in the number of EVs (a 20-fold increase, totaling 25.2 million) and HPs (an 11-fold increase, totaling 14.3 million) [56]. For this reason, our analysis will encompass both a current *2023* electrification scenario and a future *2037* electrification pathway for the uptake in electric mobility demand, the electrification/decarbonization of heating demand, and the demand for BS systems. Further specifics on the calculation of the different adoption rates are discussed in Section 3.4.

2.3.2 Pricing strategies

To uncover how different market signals impact the model's outputs, we investigate three pricing strategies. We examine these strategies in light of current and anticipated electricity pricing regulations in Germany, encompassing diverse frameworks for both electricity rates and network charges. The *Static Pricing — SP* strategy maintains static electricity prices and network fees over time, providing minimal encouragement for consumers to change their consumption habits. Here, the operation of DERs is mainly driven by immediate energy needs. For those with PV installations, there is some slight flexibility to align consumption with solar production, showcasing a limited form of flexibility inherent in this strategy. This pricing strategy serves as a baseline, illustrating a situation without significant economic incentives to modify energy usage based on pricing signals.

Moving towards more dynamic market signals, the *Dynamic Pricing — DP* strategy introduces dynamic electricity prices while keeping network fees unchanged. This variability aims to influence users to consume more energy when prices are low, often during times of high RES availability, and less when prices are high. Notably, this strategy aligns with Germany's forthcoming regulation §41a EnWG that mandates electricity suppliers to offer dynamic pricing models from January 1, 2025 [57].

As the most advanced among the examined strategies, the *Dynamic Network Fee — DN* strategy integrates dynamic electricity prices with dynamic network fees. Such a structure not only encourages users to adapt to varying electricity prices but also to consider the network's current state, promoting adjustments in energy usage to avoid potential overloads of network infrastructure. Specifically, we establish periods with dynamic network fee rates based on our LVDN's current condition. The price levels for the dynamic network fee must be set in coordination with the dynamic electricity market prices to be impactful; such a network fee must offset any reduction in electricity market prices to foster grid-supportive behavior. Moreover, the scheduling for lower and higher network fee intervals must accurately reflect the grid's condition. We determine these intervals using historical data on the transformer load in our LVDN feeder. During periods of high transformer load, the network fee should increase, whereas it should decrease when the load is lighter. Further specifics on the chosen price levels and time intervals are discussed in Section 3.4. This approach also aligns with the impending regulations under §14a EnWG in Germany, mandating network operators to offer dynamic network fees to owners of flexible consumption units starting April 1, 2025 [58].

2.4 Performance metrics

2.4.1 Energy community performance

While our primary focus lies in evaluating how energy sharing affects network performance, we also delve into assessing its impact on energy community performance. Therefore, we verify the functionality of our optimization model through analysis of different technical performance aspects, including grid and community interactions, as well as DER operation within our energy sharing framework. Furthermore, we quantify the costs associated with the REC operation, specifically measuring the total electricity costs resulting from grid and community interactions, encompassing both imports and exports.

2.4.2 Network performance

Transformer and line loading The assessment of the transformer and line loading relies on the power flow simulation. The loading of each element is always based on the current. For the transformer, loading on each side (i.e., LV and MV) is computed using the actual and rated currents. We assume the maximum of both loading values to determine the overall transformer loading. Line loading, on the other hand, is evaluated at both ends of the lines (i.e., starting and ending bus in the LVDN) by comparing the magnitude of the current with the rating. Again, the maximum value is adopted. In both cases, the loading must not exceed 100% to avoid power disruptions, curtailment of DER units at associated buses, or necessitate network reinforcement measures.

Voltage deviations This performance metric quantifies how much voltage occurs at each connection point in the LVDN, reflecting both demand and RES generation. Changes in voltage generally occur depending on the direction of current flow, resulting in drops during periods of high demand and increases during times of high generation. Excessive demand/generation can thus cause deviations from the nominal voltage, leading to deteriorating voltage quality and necessitating costly voltage compensation measures. To mitigate these issues, we adhere to voltage limits set at +/−6% of the nominal voltage, deviating from the current standard DIN 50160 [59], which allows for a range of +/−10% at both LV and MV grid levels. By utilizing a voltage range of [0.94, 1.06] pu, we maintain a safety margin of ±4% for higher grid levels above the LVDN, accounting for the possibility of already elevated voltage levels in the upstream network. [15,60–62]. Additionally, we quantify over- and under-voltage hours by counting the total number of time steps where voltage limits are exceeded.

Grid reinforcement costs We also evaluate the costs related to grid reinforcement. Should certain grid performance benchmarks be breached, the DSO is obligated to implement grid reinforcement measures, which may involve installing extra lines or adding a larger transformers to the LVDN feeder. Accordingly, the DSO monitors metrics such as transformer loading, the load on all LVDN lines, and voltage limits to identify potential bottlenecks and make necessary investments in grid reinforcement. For lines, it is assumed that the DSO installs parallel lines, while for transformers, new units with greater rated capacity are installed [36,63]. We follow an iterative heuristic similar to that in [64]: initially, we examine line overloading and add parallel lines alongside existing ones, starting from the transformer. Next, we evaluate transformer loading, upgrading it to the next available standard size if overloading is detected [54]. Subsequently, we search for any voltage violations in the grid. Specifically, we examine the voltage magnitudes at all 906 buses, and if violations are identified, we reinforce the lines connecting to the affected buses by adding parallel lines starting from the transformer. It is important to highlight that no explicit limit is imposed on the number of parallel lines that can be installed in the feeder. This represents a limitation in the current methodology, as it may not fully capture real-world operational constraints. After each step in the heuristic, we re-run the power flow simulation to verify if any grid constraints persist, repeating the necessary step (i.e., adding additional lines/transformer capacity) as required. Once all reinforcement measures are implemented, a final power flow simulation is conducted to ensure that the upgrades have not compromised existing reinforcements made to the lines and transformer, thereby ensuring no instances of overloading or voltage violations remain. It should also be noted that the heuristic procedure used here, while computationally efficient, may not yield optimal solutions. As such, the calculated grid reinforcement costs should be regarded as indicative estimates. The associated costs for all reinforcement measures are described in Section 3.4.

3 Case study setup and data

3.1 Network characteristics

As described earlier, for our network model we modify loads and the transformer to align with the outputs of our energy sharing model, keeping the line and bus elements unchanged. The sizing of the transformer is based on our baseline BAU scenario, by adding a margin of 20% to the scenario's peak load and taking the corresponding standard power rating for LV transformers starting from 150 kVa, provided by [54]. The transformer is stepping down the voltage from 11 kV, typically found in MV networks, to the lower voltage level of 416 kV, which is standard for residential and small commercial consumers in the LVDN. The transformer features delta windings on the MV side and grounded star windings on the LV side, with respective resistance and reactance of 0.4% and 4% [51]. This mitigates problems like ground faults and voltage imbalance while guaranteeing appropriate voltage transformation [65]. Table 3.1 provides an overview of all network parameters used. In total, 55 buses are representing buildings with respective consumer and prosumer loads. Out of these 55 buses, a subset of 50% is randomly chosen to be part of our REC, facilitating energy sharing with each other. Fig. 2.2 illustrates the network configuration, with triangular patches indicating the households within our REC.

Table 3.1
Network parameters.
Source: Data based on [51].

Parameter	Value
Apparent power of trafo $\bar{q}^{\text{transformer}}$ [kVA]	{150, 250, 400, 630, 800, 1000}
Primary voltage level [kV]	11
Secondary voltage level [kV]	0.416
Connection types [-]	Delta, Wye
Reactance, Resistance [%]	4, 0.4
Power factor $\cos(\theta)$ [%]	0.95

3.2 Household characteristics

To provide each of the 55 buildings with an individual load profile, we assign to each building a specific household type and corresponding three-phase load profile. To preserve privacy, we consider eleven representative household types, as identified in a study by the Forschungsstelle für Energiewirtschaft (FfE) [66], which analyzed the real-life settlement patterns of 940 households in Germany. Table 3.2 shows these household types in detail and the corresponding load profiles are displayed in Fig. 3.1(a). Thermal and EV load profiles were also included in the data of the FfE (cf. Fig. 3.1(b) and (c)). We use these profiles to model future energy demands, especially in scenarios with increased adoption of HPs and EVs (i.e., 2037 scenarios). Specifically, for the EV load modeling, the EV load is aggregated to the time step in which the EV commences its journey, considering the demand as the required SoC at the start of the trip. Our eleven household types are randomly assigned to the 55 consumer and prosumer buses situated within the LVDN.

3.3 DER characteristics

Moreover, each building may possess various DER, such as a PV and BS system, a HP, and/or an EV. To simulate scenarios with varying DER adoption rates, we follow the projections from the German electricity network development plan 2023–2037/2045 [56]. Consequently, we assume various adoption levels for these technologies in both current (2023) and future (2037) contexts. The projected adoption rates for EVs, HPs, and BS systems are calculated by dividing the projected numbers of these assets in each scenario, as detailed in the development plan, by Germany's total number of passenger vehicles (48.4 million [67]) and residential buildings (18.9 million [68]). In addition to the data from the network development plan, we assume that 65% of EVs will have bidirectional charging capability by 2037 [69], i.e., owners can temporarily store energy and discharge it at a later time. We model the EV characteristics based on the Tesla Model S Plaid 2022 specifications [70], assuming a 100 kWh battery and setting charging/discharging efficiencies to 90%. Any EV demand exceeding the specified battery capacity is ignored and assumed to be charged during the trip. For the PV system, we assume that all buildings that are part of the REC own PV systems, making it attractive to them to share their excess energy with others in the community. The peak output of PV systems ranges randomly between 0 kWp and 5 kWp, with hourly solar radiation data sourced from the EU's Photovoltaic Geographical Information System (PVGIS) [71]. Here, we based our calculation on the solar radiation database PVGIS-SARAH2 [71] and assumed a PV system consisting of crystalline silicon (CAS) cells that have a fixed mounting type, a slope of 40°, an azimuth of 0°, and a loss rate of 14%.

For the power flow simulation, we assume that the adoption rate of PV systems in the rest of the LVDN feeder is equivalent to the one of BS systems that we determined based on the electricity network development plan 2023–2037/2045 (cf. Table 2.2), i.e., 1% for all 2023 scenarios and 71% for all 2037 scenarios. All BS systems are assumed

Table 3.2
Household parameters, including annual electricity and heat load.
Source: Data based on [66].

ID	Description	El. load [kWh]	Th. load [kWh]
h0	One full-time working person	1449.43	20 389.38
h1	One pensioner	1111.83	12 905.48
h2	Two full-time working persons	2170.98	18 327.37
h3	Two pensioners	2766.3	16 878.92
h4	One full-time & one part-time working person	2928.34	18 168.21
h5	Two full-time working persons, one child	2309.92	21 621.94
h6	One full-time & one part-time working person, one child	3372.81	18 299.41
h7	Two full-time working persons, two children	3216.66	18 435.46
h8	One full-time & one part-time working person, two children	4122.96	18 426.61
h9	Two full-time working persons, three children	4866.53	18 627.63
h10	One full-time & one part-time working person, three children	5508.36	21 640.86

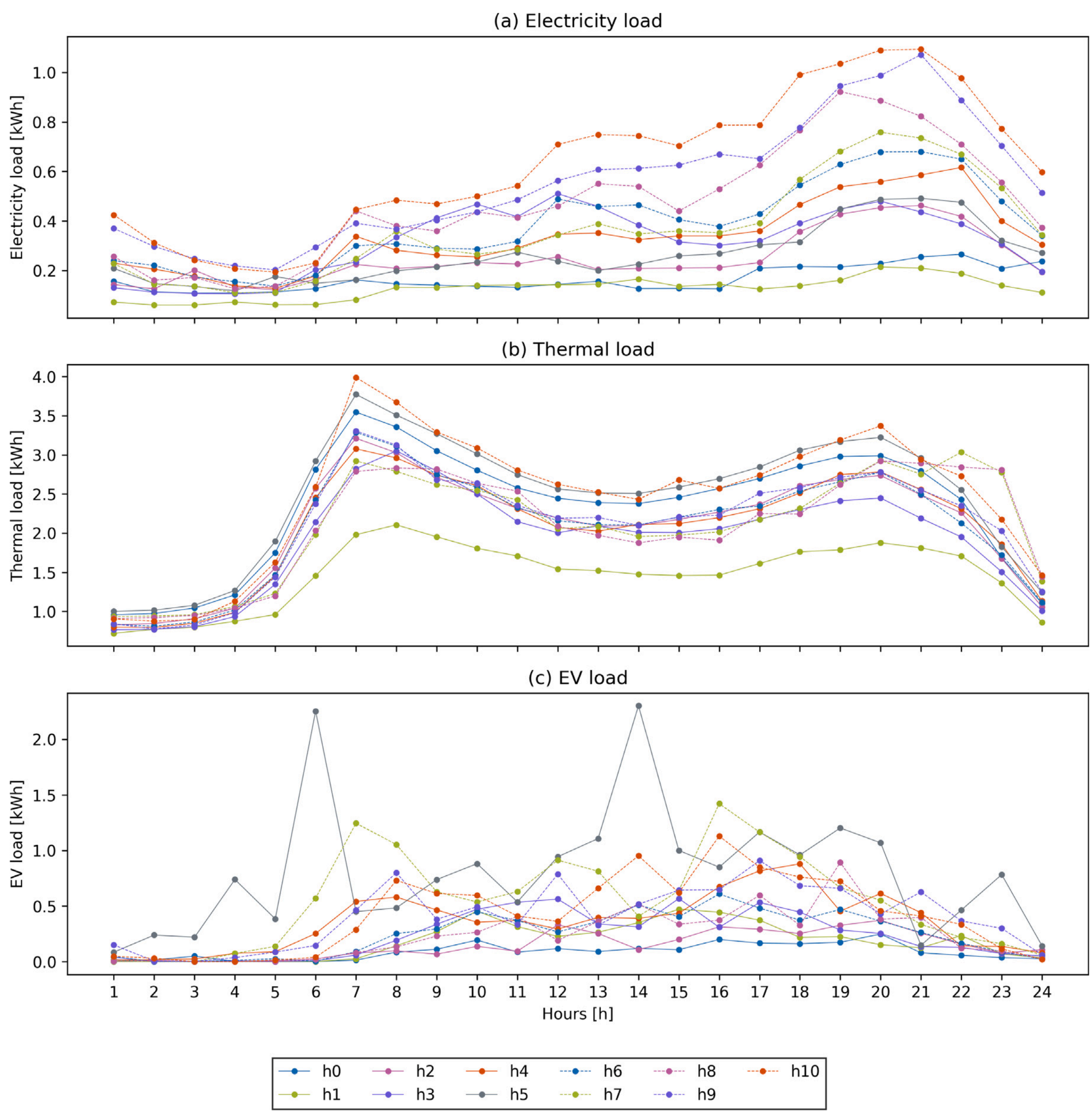

Fig. 3.1. Load profiles. (a) Annual hourly average electricity load profiles for different household types. (b) Annual hourly average thermal load profiles for different household types. (c) Annual hourly average EV load profile.
Source: Own illustration based on data of [66].

to have a capacity of 13.5 kWh, with charging and discharging power being set to 5 kW, and charging and discharging efficiencies set to 90%, modeled after the Tesla Powerwall specifications [72]. For the heating, we consider GHs as the conventional method of heat generation across all scenarios, reflecting their dominant role in Germany's current heating landscape (33.7% [73]). For scenarios where the adoption rate of HPs is > 0, we size the HP to meet the building's thermal demand at every time step. The operational efficiency of the HP is determined

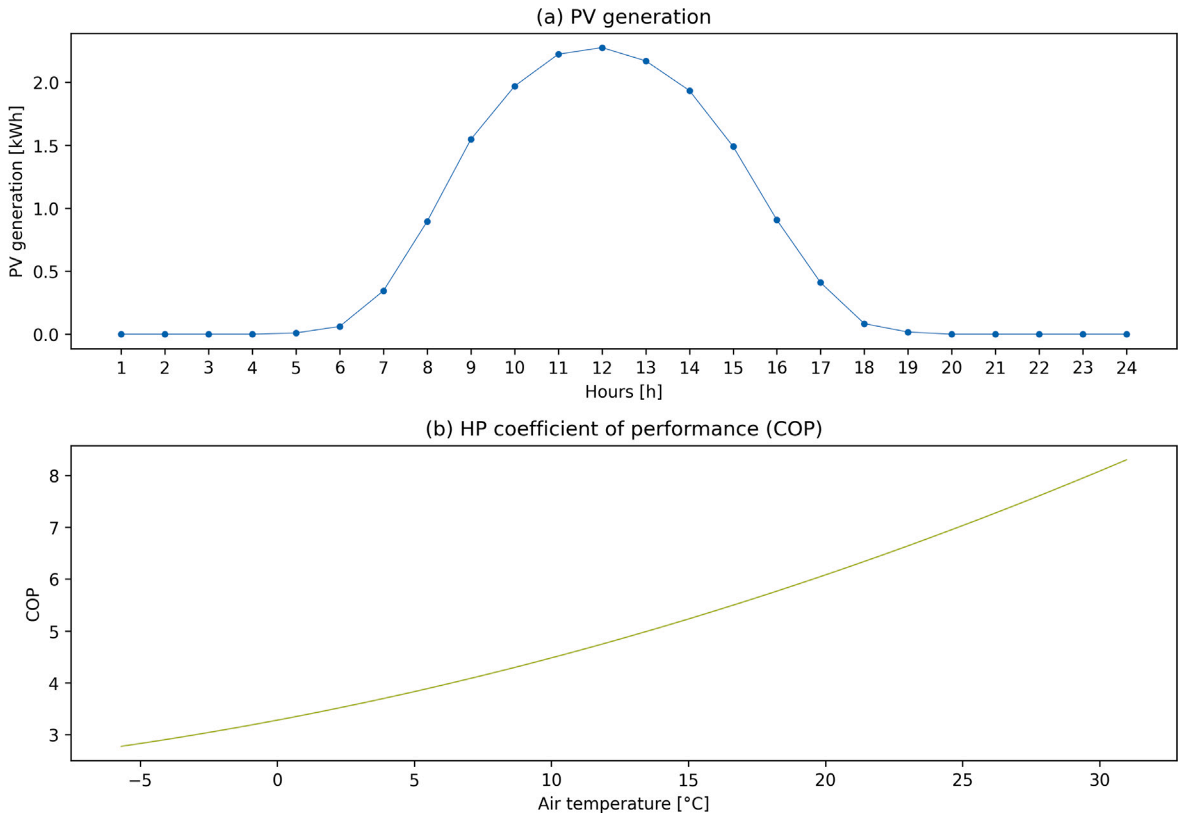

Fig. 3.2. Generation profiles. (a) Annual hourly average PV generation profile for a 5 kWp PV system located in Munich, Germany. (b) COP as function of the air temperature estimated for a HP located in Munich, Germany.
Source: Own illustration based on data of [71].

Table 3.3
DER parameters.
Source: Own illustration.

Parameter	Value
PV peak output [kWp]	[0, 5]
PV slope [°]	40
PV azimuth [°]	0
PV loss rate [%]	14
PV mounting type [-]	Fixed
PV material [-]	CAS
BS storage capacity $\overline{c}_b^{\mathrm{bs}}$ [kWh]	{0; 13.5}
BS maximum charging power $\overline{q}^{\mathrm{bs,ch}}$ [kW]	5
BS maximum discharging power $\overline{q}^{\mathrm{bs,dch}}$ [kW]	5
BS charging efficiency $\eta^{\mathrm{bs,ch}}$ [%]	0.9
BS discharging efficiency $\eta^{\mathrm{bs,dch}}$ [%]	0.9
BS minimum state of charge $\underline{s}^{bs}$ [%]	0
BS maximum state of charge $\overline{s}^{bs}$ [%]	100
EV storage capacity $\overline{c}_b^{\mathrm{ev}}$ [kWh]	{0; 100}
EV maximum charging power $\overline{q}^{\mathrm{ev,ch}}$ [kW]	22
EV maximum discharging power $\overline{q}^{\mathrm{ev,dch}}$ [kW]	22
EV charging efficiency $\eta^{\mathrm{ev,ch}}$ [%]	0.9
EV discharging efficiency $\eta^{\mathrm{ev,dch}}$ [%]	0.9
EV minimum state of charge $\underline{s}^{ev}$ [%]	0
EV maximum state of charge $\overline{s}^{ev}$ [%]	100

by its COP. The COP is calculated for each time step based on [5], who related the COP to the ambient air temperature. To obtain air temperature data, we again utilize PVGIS [71], focusing on Munich, Germany, which has an average temperature of 9.6 °C. The calculated HP COP values vary between 2.776 and 8.298. Fig. 3.2 presents both (a) an exemplary PV generation profile and (b) the HP COP as function of the air temperature for Munich, Germany. Table 3.3 summarizes the chosen parameters of our DERs.

3.4 Electricity prices, network fees, and costs

The optimal dispatch of consumer/prosumer DERs is determined based on import/export prices for grid and community interactions. For imports from the grid, we utilize dynamic electricity prices for $p^{\mathrm{gd,im}}$ based on publicly available data of the German day-ahead market from 2023 sourced from ENTSO-E [74]. In our analysis, we distinguish between dynamic and static pricing by setting the static price at the average of the day-ahead prices, ensuring the observed impacts stem solely from the pricing structure rather than overall price levels. Fig. 3.3(a) illustrates the comparison between these dynamic and fixed electricity prices. Additionally, exports to the grid (i.e., feed-in of PV energy) benefit from a fixed FIT $p^{\mathrm{gd,ex}}$ defined according to the EEG 2023 regulation in Germany, which sets it to 8.11 ct./kWh for all PV systems with less than 10 kWp capacity [75]. For imports/exports from/to the community (i.e., energy sharing), we set community prices $p^{\mathrm{cm,im}}$ and $p^{\mathrm{cm,ex}}$ to 50% of the $p^{\mathrm{gd,im}}$, making community sales more appealing compared to grid exports, aligning with existing research findings [16,76].

Moreover, we incorporate a static network fee component of 8.08 ct./kWh, based on the average 2022 network fee component in Germany [77]. Our calculation of dynamic network fees align with the requirements of §14a EnWG, which mandates that network operators declare such fee adjustment periods annually, ensuring these periods remain unchanged throughout our simulation horizon. According to §14a EnWG, there should be three fee levels available: a standard fee (i.e., equivalent to our static network fee), a reduced fee (10% to 80% of the standard fee), and an increased fee (up to double the standard fee). We adjust the network fees based on historical data of the transformer load in our baseline pricing strategy (i.e., *2023_BAU_SP*). Specifically, we analyze the average transformer load for each weekday

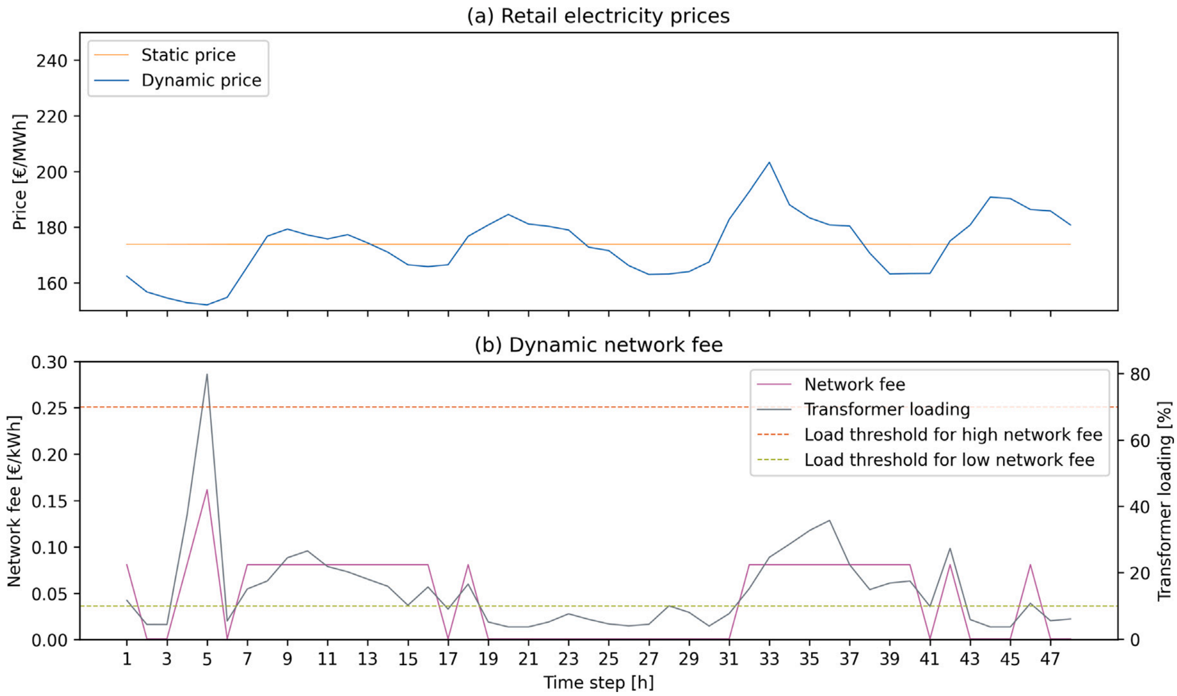

Fig. 3.3. Prices. (a) Static and dynamic electricity price. (b) Transformer loading and network fee adjustments.
Source: Own illustration based on data of [74].

Table 4.1
Energy community performance metrics, including grid/REC interaction, DER operation, and costs for each scenario. Each row corresponds to a decision variable derived from the energy sharing model. Values rounded to the nearest whole kWh.
Source: Own illustration.

Performance metric	Scenario											
	2023						2037					
	BAU			REC			BAU			REC		
	SP	DP	DN	SP	DP	DN	SP	DP	DN	SP	DP	DN
Grid import [kWh]	629	661	675	133	133	133	1731	1790	1809	1365	1420	1419
Grid export [kWh]	626	626	626	70	70	70	350	350	350	0	0	0
REC import [kWh]	0	0	0	4172	4026	4013	0	0	0	7465	7416	7480
REC export [kWh]	0	0	0	4172	4026	4013	0	0	0	7465	7416	7480
BS charging [kWh]	560	728	802	877	877	877	547	855	914	450	624	574
BS discharging [kWh]	453	590	649	710	710	710	443	693	740	365	505	465
EV charging [kWh]	0	0	0	0	0	0	1305	1307	1350	1296	1390	1483
EV discharging [kWh]	0	0	0	0	0	0	102	103	137	116	210	245
REC costs [€]	107	106	104	23	21	21	295	288	281	232	225	221

and weekend day. When the load on the transformer surpasses or falls below certain thresholds, the network fee adjusts accordingly: it increases if the load is above 70% and decreases if below 10%. The network fees are depicted in a detailed manner in Fig. 3.3(b). For grid reinforcement, we use the 2023 cost estimates outlined in [54]. Given the urban nature of our LVDN, we only consider the installation of underground cables, priced at 58 € per meter [54], covering both material and installation expenses such as cable laying and surface restoration. Transformer investment cost are set to 8.5 k€ for 150 kVa, 9.6 k€ for 250 kVa, 11.5 k€ for 400 kVa, 15.2 k€ for 630 kVa, 18.6 k€ for 800 kVa, and 23.7 k€ for 1000 kVa, respectively [54]. All simulations were conducted for a single representative summer week, beginning on 1st July, 2023, which was carefully selected to capture key dynamics, including typical variations in load, generation, and pricing.

4 Results

4.1 Energy community performance assessment

Table 4.1 presents the grid and REC interaction for each scenario. Comparing scenarios with and without energy sharing, we expect reduced reliance on the grid in REC scenarios. Such grid interactions encompass both imports during periods of low RES generation and exports during surplus RES generation. Importantly, REC scenarios demonstrate a potential for up to 78% reduction in grid imports and complete elimination of exports to the grid. At times, there are no imports from the utility at all, as REC members prioritize self-consumption of their own RES generation or opt for energy sharing within the community. This occurs due to the community price being set to 50% of the regular retail electricity price, making energy sharing within the community more economically viable and promoting local consumption.

Table 4.2
Network performance metrics, including maximum transformer and line loading, along with voltage magnitudes of phases A, B, and C, and grid reinforcement measures for each scenario. Values rounded to the nearest whole kWh.
Source: Own illustration.

Performance metric	Scenario											
	2023						2037					
	BAU			REC			BAU			REC		
	SP	DP	DN	SP	DP	DN	SP	DP	DN	SP	DP	DN
Max. trafo loading [%]	29	70	91	25	27	29	251	256	256	108	124	124
Max. line loading [%]	15	34	45	12	13	14	124	126	126	54	61	61
Max volt. phase A [pu]	1.06	1.06	1.06	1.07	1.07	1.07	1.07	1.07	1.07	1.09	1.07	1.07
Max volt. phase B [pu]	1.07	1.07	1.07	1.07	1.08	1.07	1.07	1.07	1.06	1.10	1.09	1.07
Max volt. phase C [pu]	1.06	1.06	1.06	1.06	1.07	1.07	1.06	1.06	1.06	1.07	1.07	1.08
Overvolt. hours phase A [%]	2	2	2	2	7	4	2	1	1	1	2	3
Overvolt. hours phase B [%]	10	9	8	8	8	8	2	3	2	7	4	7
Overvolt. hours phase C [%]	0	1	0	2	4	4	1	0	1	10	14	11
Min volt. phase A [pu]	1.03	1.02	1.01	1.02	1.01	1.02	0.92	0.90	0.94	0.87	0.87	0.87
Min volt. phase B [pu]	1.03	1.00	0.99	1.02	1.02	1.02	0.92	0.85	0.84	0.93	0.91	0.91
Min volt. phase C [pu]	1.04	1.03	1.03	1.04	1.03	1.02	0.84	0.83	0.83	0.99	0.99	0.99
Under. hours phase A [%]	0	0	0	0	0	0	1	1	1	1	1	1
Under. hours phase B [%]	0	0	0	0	0	0	1	1	1	1	1	1
Under. hours phase C [%]	0	0	0	0	0	0	1	1	1	0	0	0
Trafo capacity added [kVa]	0	0	0	0	0	0	630	630	630	250	250	250
Lines added [km]	1.7	1.3	1.3	1.6	2.1	1.6	3.3	3	3	5.9	4.1	3.4
Trafo costs [k€]	0	0	0	0	0	0	15.2	15.2	15.2	9.6	9.6	9.6
Lines costs [k€]	95.6	76.8	76.8	92.1	123	93.4	189	176	176	342	240	196

In the 2037 scenarios, with a higher installation of DERs, energy sharing within the community is even more pronounced compared to 2023 scenarios. This setup accommodates increased electricity demands while enabling energy storage in BS systems and EVs for later exports to the community. Specifically, households charge their assets during periods of high solar radiation (resulting in higher PV generation) and sell excess energy to other community members at a later point in time.

Regarding pricing strategies, minor variations in grid imports are observed across the scenarios, mainly due to our decision to maintain a static FIT while introducing variability in prices through dynamic electricity prices and network fees. Scenarios employing dynamic electricity prices witness higher grid import peaks, especially during periods of low retail electricity prices and when numerous DERs are installed (as seen in the 2037 scenarios). However, community interactions appear unaffected by the chosen pricing strategy, irrespective of the electrification pathway (2023 vs. 2037), since the community price is consistently set at 50% of the retail price across all strategies. In terms of costs, the impact of energy sharing on electricity costs is significant, showcasing savings of up to 80% for our REC scenarios. This reduction can be primarily attributed to decreased reliance on regular utility imports, coupled with the community price being set substantially lower than the retail electricity price.

4.2 Network performance assessment

4.2.1 Transformer and line loading

We compare the outcomes of our network model across twelve scenarios concerning their impacts on the loading of individual grid assets, specifically, the transformer and the line directly connected to the transformer. Table 4.2 presents maximum values for both the transformer and line loading for each scenario. Additionally, Figs. 4.1 and 4.2 show multiple subplots, depicting the detailed transformer and line loading for the 2023 and 2037 scenarios over a 48-hour period. Comparing scenarios with and without energy sharing, we find a substantial reduction in the loading of individual grid assets with the implementation of energy sharing. Looking at the hour of the simulation period with the highest transformer loading, energy sharing can lead to a 68% reduction in transformer loading compared to BAU scenarios. While transformer loading reaches up to 91% in BAU scenarios, the maximum transformer loading in REC scenarios does not exceed 29%. In the 2037 scenarios, the transformer is loaded to more than 100% in all scenarios, necessitating grid reinforcement measures such as the installation of a transformer with a larger capacity, due to a higher installation of DERs and energy sharing within the community being more pronounced. Nevertheless, when compared to the BAU mode in these scenarios, energy sharing mitigates transformer loading impacts by up to 56%, illustrating its positive influence on transformer loading compared to scenarios where buildings do not engage in energy sharing. However, with the anticipated rise in DER in 2037, it becomes evident that energy sharing alone cannot fully resolve transformer loading issues. Although it reduces the loading compared to BAU scenarios, the transformer loading still exceeds 100%, highlighting the need for additional grid reinforcement. Notably, any observed transformer overloading stems from short-term peaks occurring a few times a day, with the remainder of the day exhibiting transformer loading to be below 50% across all scenarios. In many instances, these peaks align with the charging of individual DER assets like BS systems and EVs during periods of low electricity prices. Regarding pricing strategies, significant variations in transformer loading are observed in the 2023 BAU scenarios, with dynamic pricing and dynamic network fees leading to higher loading. Conversely, only minor variations are observed in all other scenarios.

For the line loading, similar trends are observed as with transformer loading. To quantify the impacts of energy sharing on line loading in the LVDN, we measure the loading of the line connected to the LV side of the MV/LV transformer. Again, REC scenarios demonstrate lower loading values compared to BAU scenarios. Notably, we find the reduction in line loading to be more significant for cases with dynamic pricing being enabled. For example, in the 2023 scenarios energy sharing with dynamic pricing leads to a 62% reduction in line loading compared to energy sharing with static pricing (14%). In the 2037 scenarios, across both operating modes significant higher line loading values can be observed compared to the 2023 scenarios. However, persistent asset overloading (i.e., line loading > 100%) is only observed for the BAU mode, emphasizing the positive impact of energy sharing on line loading in future LVDNs. Again, strong line loading stems from short-term peaks that occur a few times a day and mostly align the charging of individual DERs. To provide a broader perspective on line loading, Fig. 4.3 visualizes the line loading of all the lines within the LVDN for the 2037 energy sharing scenario during the peak demand hour. Examining the individual feeder segments, varying loading levels can be observed, with some segments experiencing heavier loading than others, potentially indicating areas for targeted infrastructure upgrades.

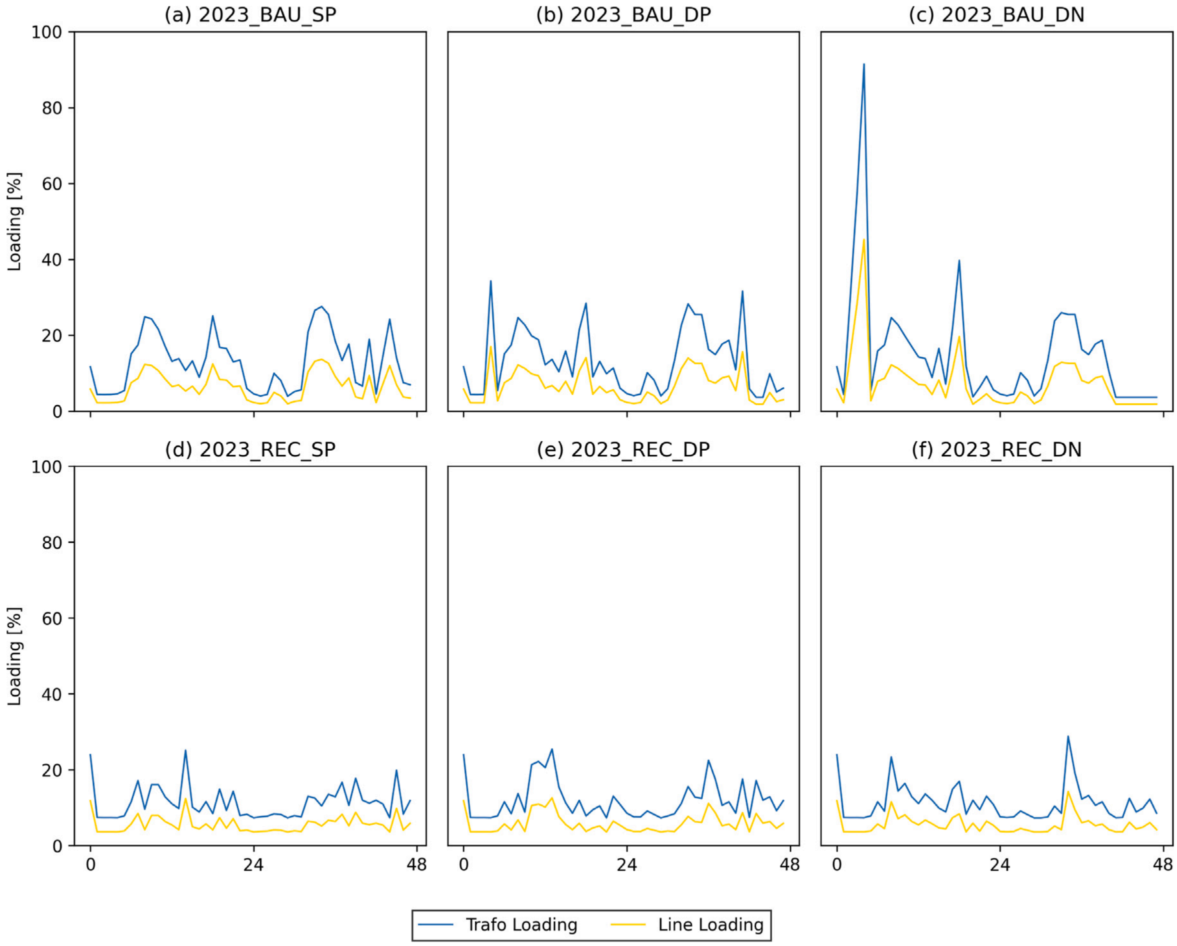

Fig. 4.1. Transformer and line loading for each 2023 scenario over a 48-hour period.
Source: Own illustration.

4.2.2 Voltage deviations

We also quantify the network performance in terms of voltage magnitudes. Specifically, we analyze the voltage magnitudes at the three representative buses within the LVDN — one for each phase: A, B, and C — that demonstrate the most significant voltage deviation throughout the simulation period. Table 4.2 presents the minimum and maximum voltage values, along with the corresponding percentage of hours exhibiting under- or overvoltage, for each scenario. Figs. 4.4 and 4.5 show the voltage magnitudes for the three buses for each scenario over a 48-hour period. We present the voltage magnitudes for each phase individually, since our LVDN is unbalanced, with prosumers with varying characteristics (i.e., consumption and DER adoption) not being distributed in balanced way across the feeder segment. Generally, smooth voltage profiles (i.e., minimal variations across time steps), indicate stable voltage conditions at the connection point. Conversely, larger fluctuations suggest instability at the connection point, as voltage should not surpass defined voltage limits [59]. The specific voltage magnitudes are influenced by both consumption and generation. Increased levels of RES generation and additional energy being fed into the grid typically raise voltage levels, while increased consumption (e.g., due to electrification and DER adoption) often leads to decreased voltage levels due to heightened resistance in distribution grid lines [78].

In all scenarios, notable voltage deviations occur across the three phases. For instance, in the most extreme 2023 scenarios, voltage ranges from 0.87 pu to 1.07 pu (Phase A), 0.86 pu to 1.06 pu (Phase B), and 0.83 pu to 1.06 pu (Phase C). Many hours in the simulation periods surpass the predefined upper voltage limit of 1.06 pu and even dip below the lower limit of 0.94 pu, particularly evident in the 2037 scenarios. These deviations primarily result from increased demand (e.g., due to storage) causing voltage drops and heightened RES generation leading to voltage spikes. When comparing the metrics for minimum/maximum voltage and under-/overvoltage hours across all scenarios, we note minimal differences in the absolute values of minimum and maximum voltage magnitudes between scenarios with and without energy sharing. Similarly, the occurrence of under- and overvoltage hours over the simulation periods shows only slight variation, with the REC mode displaying the highest number of overvoltage hours across all three phases in both 2023 and 2037 scenarios.

However, when analyzing voltage profiles for all three phases within a 48-hour timeframe, we observe significantly more pronounced fluctuations in scenarios with energy sharing compared to those without. For example, in the 2023 scenarios, voltage profiles of all three phases in BAU mode exhibit a relatively consistent pattern, while voltage profiles for the REC mode display a more inconsistent pattern. While the heights and frequencies of voltage peaks are largely the same, it is clear that the spread of the voltage profile for cases with energy sharing is broader, deteriorating further than for cases without energy sharing. This trend likely stems from the additional degrees of freedom REC participants have compared to regular buildings in the LVDN. They can import/export energy from/to each other member in the community in each time step, leading to more energy exchanges across the entire feeder. To provide a broader perspective on voltage magnitudes, Fig. 4.3 also visualizes the voltages of all buses within the LVDN for the 2037 energy sharing scenario during the peak demand hour. Examining the individual feeder segments, varying voltage levels can be observed,

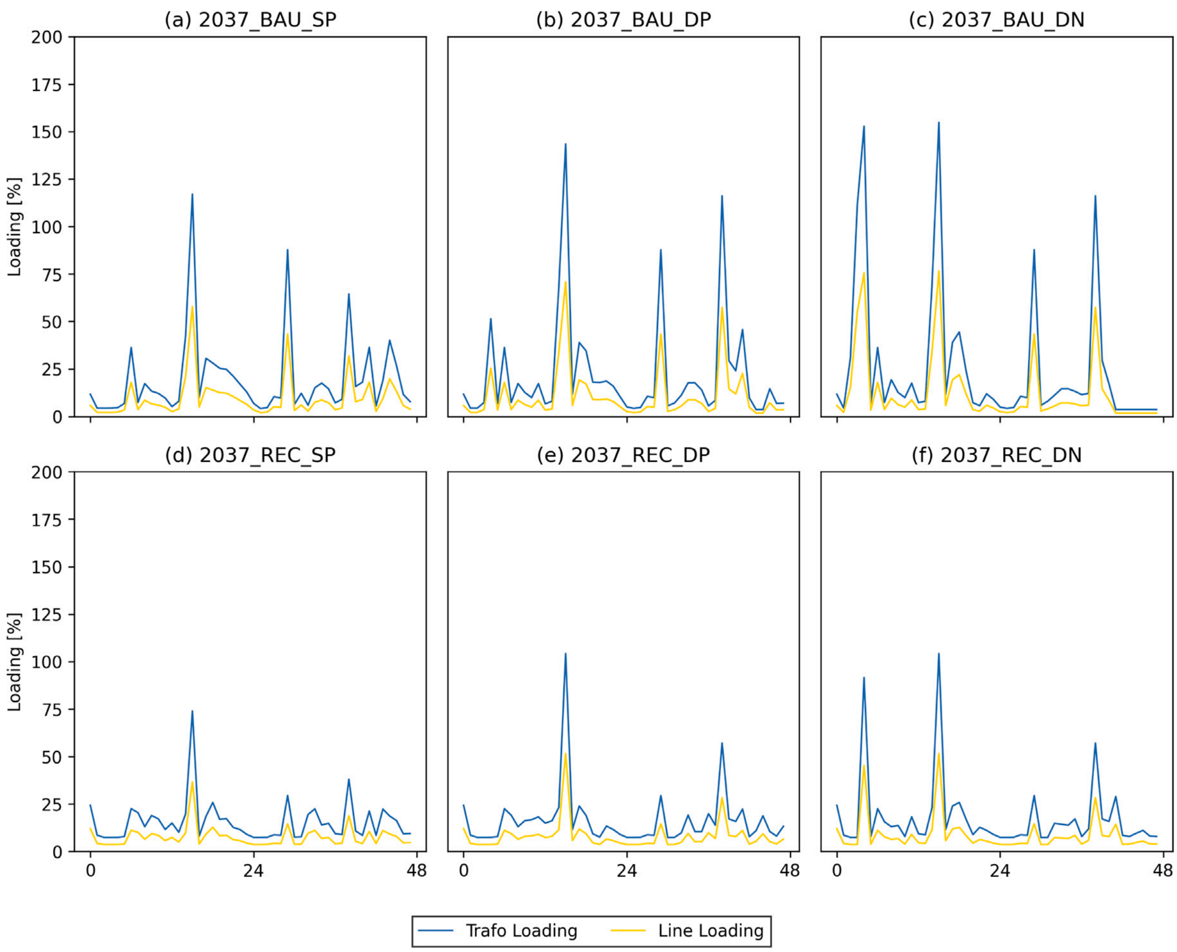

Fig. 4.2. Transformer and line loading for each 2037 scenario over a 48-hour period.
Source: Own illustration.

with some segments of buses experiencing heavier voltage magnitudes than others. Finally, regarding the pricing strategies, observations from the three representative buses suggest that the chosen strategies do not significantly impact voltage deviations, regardless of whether energy sharing is enabled. This is notable considering dynamic pricing led to adaptations in the consumption behavior, resulting in additional demand peaks during times of low electricity prices.

4.2.3 Grid reinforcement costs

To gain a comprehensive understanding of how energy sharing impacts an entire LVDN, rather than isolating individual components, our analysis extends to evaluating grid reinforcement expenses. This entails examining the transformer load, the load of the 905 lines, and the voltage levels across all 906 buses. This broader scope builds upon the previous sections, where we only investigated the line loading of the line connected to the LV side of the MV/LV transformer and the voltage levels at three representative buses. Examining the entire feeder segment presents a nuanced perspective compared to our prior findings. While energy sharing does not necessitate extensive grid reinforcement in terms of transformer and line loadings, significant measures are required due to breaches in voltage limits at various buses within the LVDN.

Table 4.2 presents the grid reinforcement measures for each scenario detailing upgrades to transformer capacity and the length of lines added to the LVDN, along with their associated costs. When comparing scenarios with and without energy sharing, we observe higher overall grid reinforcement costs across all scenarios with energy sharing. However, these costs primarily arise from installing additional lines to address under- and overvoltage at various buses, rather than from lines installed due to overloading. In terms of overall reinforcement expenses, in the most extreme case, energy sharing incurs grid reinforcement costs of €342,273, requiring the addition of over 5.9 km of new lines across the entire feeder by 2037. In contrast, for the same year, we estimate costs 44.9% lower (€188,580) for scenarios where energy sharing is not employed. Regarding transformer reinforcement, the situation is reversed, with scenarios without energy sharing requiring larger transformer extensions due to transformer overloading. In 2037 scenarios, we need to upgrade to a 630 kVa rated transformer for BAU scenarios, while only a 250 kVa rated transformer is necessary for REC scenarios.

It is worth noting, however, that the costs associated with added transformer capacity are largely negligible when compared to the expenses for line reinforcement measures. The expenses for line reinforcement incurred due to under- and overvoltages at a significant number of the 906 buses in our feeder are substantially higher and likely stem from the previously observed trend in voltage profiles of the three representative buses within a 48-hour timeframe. In contrast, buildings operating in BAU mode tend to adhere to a more consistent pattern, such as injecting surplus energy when a lot of RES generation is available. Conversely, REC mode buildings hold additional flexibility, including the option to sell excess RES generation to fellow participants instead of simply injecting it into the grid, enabling energy arbitrage among members. Remarkably, regarding pricing strategies, dynamic pricing notably reduces grid reinforcement costs, particularly evident for the 2037 REC mode, where it leads to a 42.7% reduction compared to static electricity pricing. Interestingly, when dynamic network fees

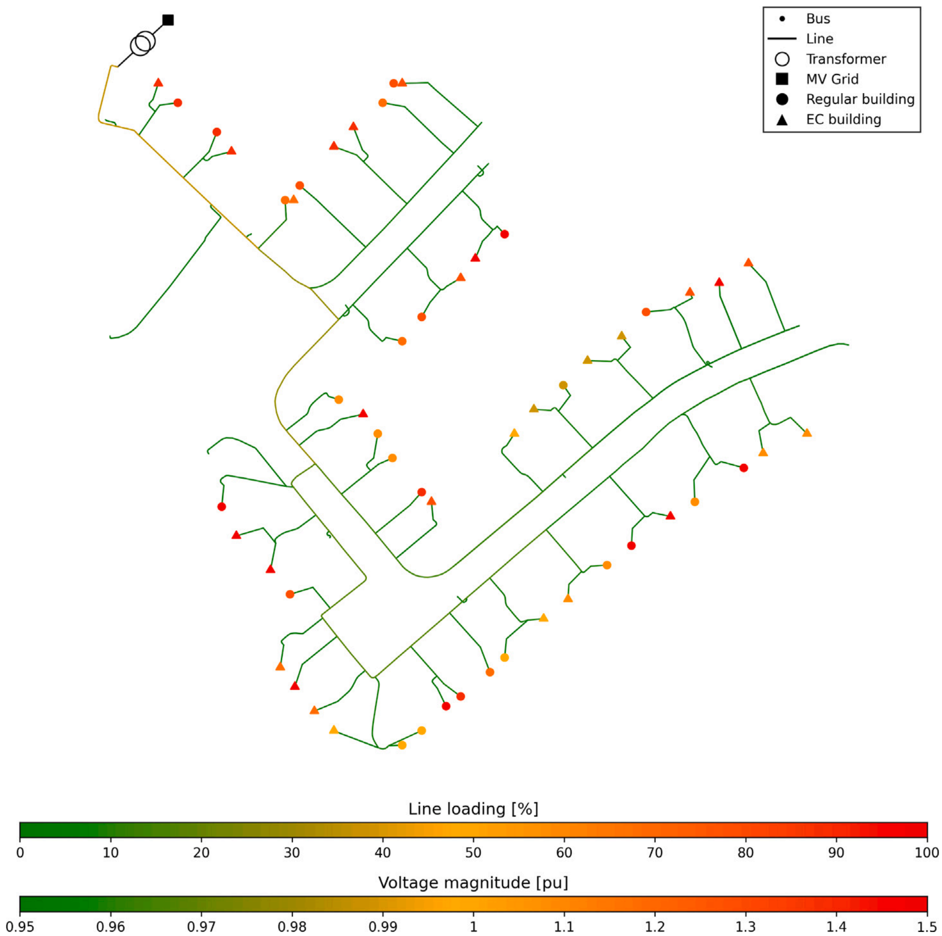

Fig. 4.3. Line loading and voltage magnitudes of phases A, B, and C for the 2037 energy sharing scenario during the peak hour of maximum overall line loading. *Source:* Own illustration.

are enabled, the difference in grid reinforcement costs between cases with and without energy sharing is less significant than previously observed, rendering the future grid reinforcement costs for energy sharing less significant.

5 Discussion

Discussions and initial steps toward implementing energy sharing frameworks are underway across various European nations. However, most countries primarily focus on establishing a broad framework for RECs, driven by the deadline to transpose the EU's RED II (Directive EU/2018/2001 [14]) provisions by June 30, 2021. Regulators encounter difficulties in implementing consumer-centric market approaches like energy sharing, as analyses of actual system impacts are largely still pending [48,79]. Consequently, setting appropriate incentives is hindered by insufficient data and analysis. Evaluating the feasibility of widespread energy sharing implementation within RECs and understanding its impacts on distribution grids are pivotal for shaping an effective legislative framework. Against this backdrop, we presented an effective methodology for integrating energy sharing schemes within RECs situated in LVDNs by employing a sequential modeling approach, which encompasses an energy sharing model and a network model. Subsequently, we assessed the impacts of energy sharing within LVDNs on various network performance metrics. Our findings reveal that while energy sharing has minimal effects on transformer and line loading, it significantly influences voltage magnitudes at various buses within the LVDN, potentially leading to substantial increases in grid reinforcement costs in future scenarios (i.e., 2037).

Our findings offer valuable insights for a variety of stakeholders in the energy sector, including REC participants (REC planners, consumers/prosumers, and CMs), regulators, and DSOs. For REC participants, the study unveils significant advantages during the operational phase of energy sharing schemes. It demonstrates substantial cost reductions compared to scenarios lacking a community setup, alongside the potential for achieving self-sufficiency, thereby reducing reliance on conventional energy utilities and grid interactions. Regulators stand to gain invaluable insights from our approach too, enabling them to assess network performance under various setups during the planning phase of REC initiatives. This includes anticipating future pricing strategies, especially in light of forthcoming regulations such as those outlined in §14a and §41a of the German EnWG, as well as forecasting bottlenecks arising from the escalating adoption of DERs as highlighted in the German electricity network development plan 2023–2037/2045. Furthermore, our research offers valuable insights for DSOs in planning energy sharing schemes within LVDNs. It allows them to evaluate the impacts of such schemes on individual network assets and assess potential grid reinforcement measures accordingly. Additionally, the introduction of dynamic network fees creates a mechanism for DSOs during the operational phase of REC initiatives to provide feedback to the community on the utilization of distribution grid assets.

Nevertheless, it is essential to acknowledge several limitations present in our study. First, the findings are significantly influenced by the energy sharing model used, particularly in relation to the community's structure, including its size and the number of assets available (specifically, PV and storage systems). Future research should therefore include sensitivity analyses that account for variations in factors like the number of individual RES. Regarding our network model, it is

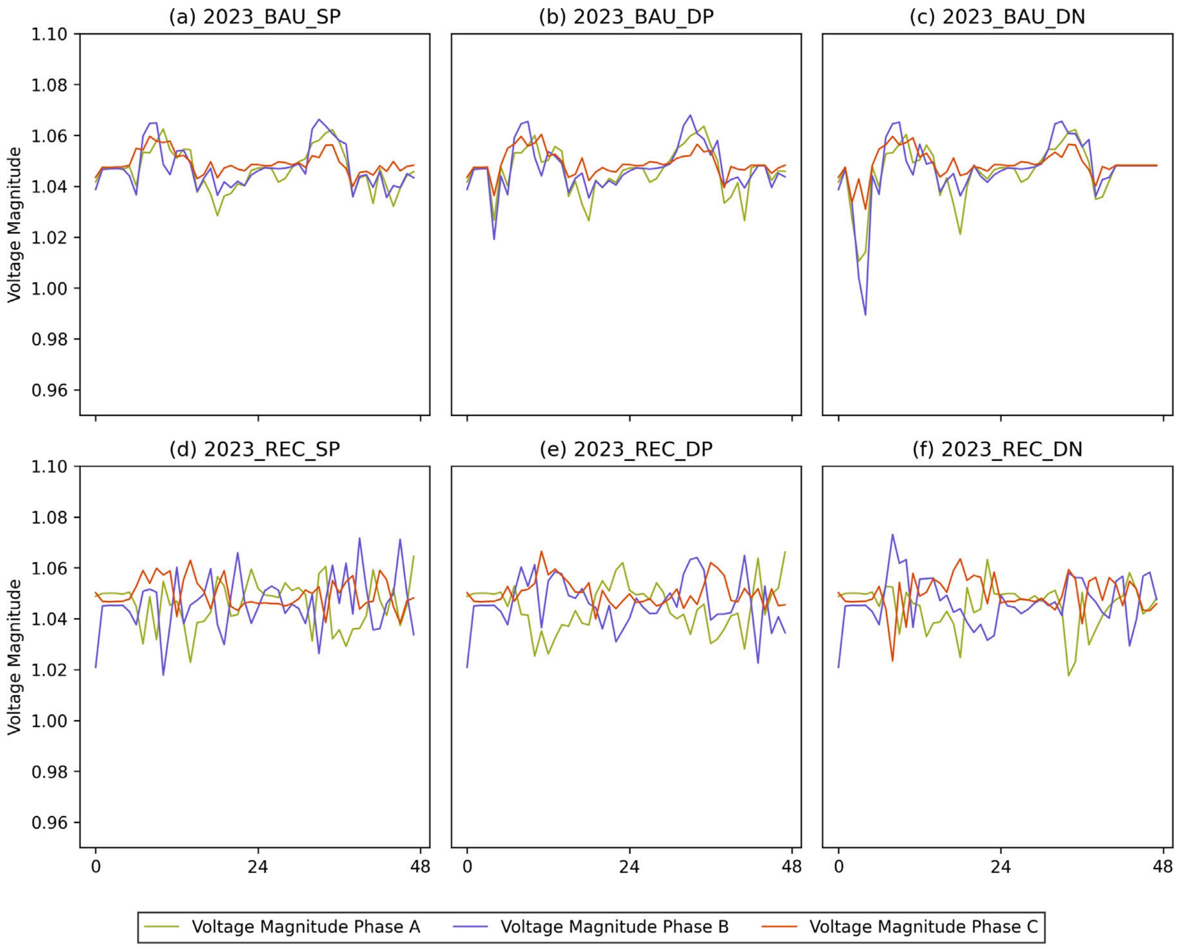

Fig. 4.4. Voltage magnitudes of phases A, B, and C for each 2023 scenario over a 48-hour period.
Source: Own illustration.

important to highlight that our power flow simulation is based on our modeling and parameterization of the European three-phase LV test feeder, whose diverse characteristics (e.g., topology, transformer capacity, etc.) may differ from other (real-world) LVDNs. Additionally, although our study effectively demonstrates the impacts of energy sharing on a LVDN feeder, we have not yet assessed its scalability. Specifically, our modeling of a local LVDN feeder only encompasses a small-scale REC where neighboring buildings are located nearby. We do not account for large-scale RECs that may be integrated in a cross-feeder fashion, spanning several LVDN feeder segments or even across different hierarchical grid levels. In such scenarios, adjustments to the selected performance metrics would be necessary, particularly because our allowed voltage deviation range does not accommodate the full ±10% from the nominal voltage, thereby affecting the determination of when the DSO would incur grid reinforcement costs. A broader range would be required when both LV and MV levels are involved. Hence, the impacts of energy sharing on network performance must be investigated when applied to larger, and more diverse energy systems involving different topologies, a greater number of REC members, and more diverse types of DERs. Moreover, we only utilize input data from the year 2023 and present a snapshot of a single, representative week in our analysis. Future research should expand this scope by extending the analysis from single years (2023 and 2037) with a representative week to a longer timeframe, potentially covering an entire year. Finally, the heuristic procedure used to determine grid reinforcement measures, while computationally efficient, may not yield the most cost-effective solutions. This approach does not account for the uncertainty inherent in future grid conditions, such as fluctuating demand or generation from distributed energy resources. More sophisticated optimization techniques, such as robust optimization, could be explored in future work to address these uncertainties and ensure a more optimal design of the grid reinforcement strategy. In this context, this study does not present direct control mechanisms for DSOs to manage the impacts of DERs and innovative market mechanisms like energy sharing. Instead, it serves as an initial step in quantifying these impacts on the grid, aiming to assess the costs associated with potential grid reinforcement measures. However, before considering the reinforcement options discussed in this paper, DSOs could explore alternative solutions, such as tap-changing transformers or real-time adjustable network fees that reflect the instantaneous impact of grid-connected entities.

6 Conclusion

Through our study, we addressed the two RQs outlined earlier. Initially, we presented an effective methodology for integrating energy sharing schemes within RECs situated in LVDNs by employing a sequential modeling approach, which encompasses an energy sharing model and a network model. Subsequently, we assessed the impacts of energy sharing within LVDNs on various network performance metrics. The key findings of the study are:

- The implementation of energy sharing schemes led to cost savings of up to 80% compared to BAU scenarios. These savings are mainly due to reduced dependence on the traditional grid, with REC members favoring internal energy transactions. At times, the REC operates independently of external electricity utilities. Dynamic pricing further enhances savings, although the introduction

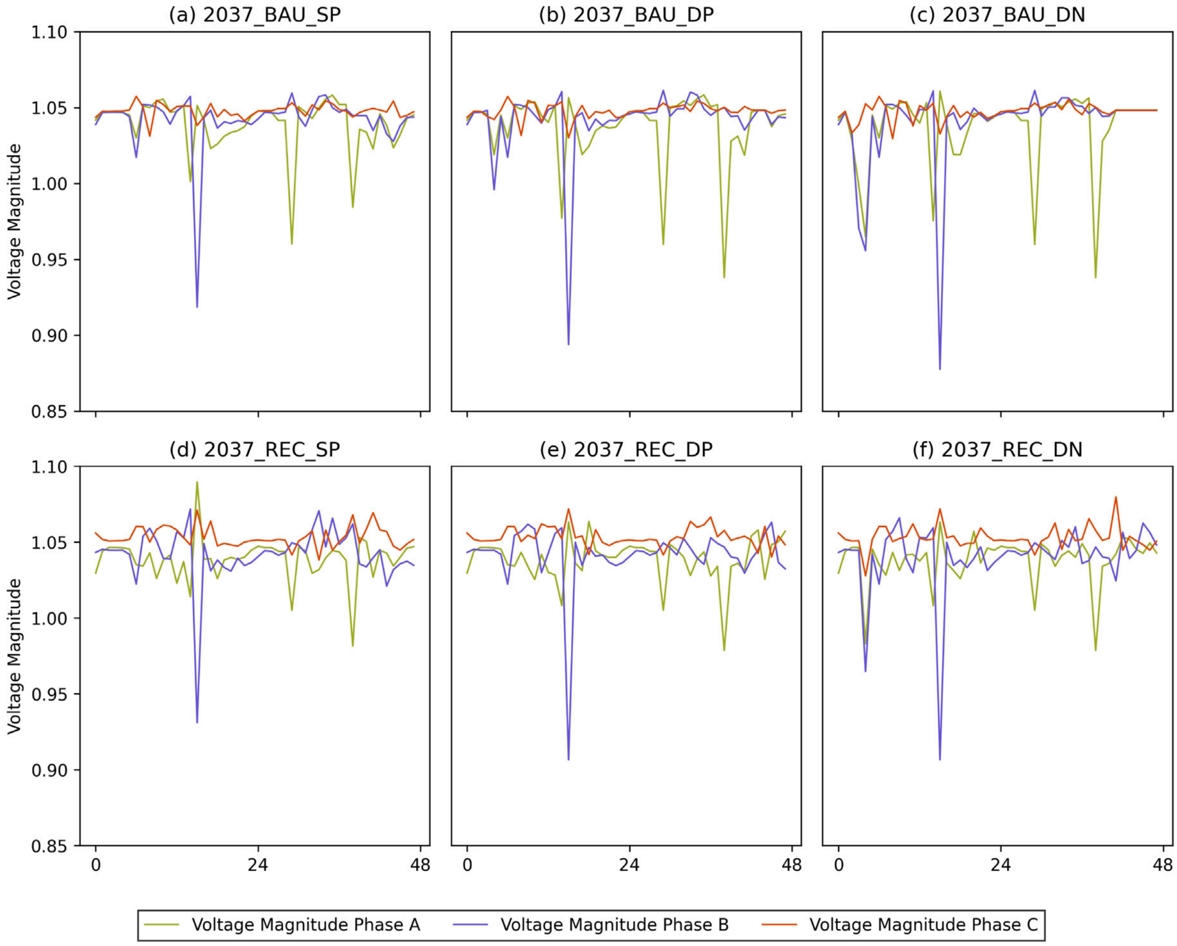

Fig. 4.5. Voltage magnitudes of phases A, B, and C for each 2037 scenario over a 48-hour period.
Source: Own illustration.

of additional DER, particularly by 2037, does not significantly increase cost benefits compared to current scenarios.

- Energy sharing effectively decreases grid asset stress, reducing transformer loading by up to 68% and line loading by up to 62% compared to BAU. This result is also supported by previous research (e.g., [40,42]). In 2037, however, energy sharing may not fully alleviate transformer overloading, highlighting potential future challenges with the deployment of additional DERs.
- While energy sharing lowers asset loading, it does not substantially reduce the frequency of loading peaks, particularly those associated with DER storage operations and energy procurement during periods of lower retail electricity prices. This indicates that while energy sharing alleviates general asset strain, peak demand periods remain a challenge for grid stability.
- Scenarios featuring dynamic pricing and network fees tend to increase grid asset loading, especially in the 2023 BAU case. Instead of encouraging consumer behavior shifts to reduce grid stress, dynamic network fees can marginally increase loading, suggesting a need for more refined pricing mechanisms to effectively manage grid utilization.
- Voltage fluctuations and violations of upper and lower voltage limits are common across all scenarios. In energy sharing scenarios, RECs exhibit more inconsistent voltage profiles due to the flexibility in energy trading and arbitrage within the community. This observation is consistent with findings from prior studies (e.g., [8,15,39]). In consequence, this results in more variable voltage magnitudes, necessitating higher grid reinforcement costs to address voltage issues.
- While energy sharing increases overall grid reinforcement costs, primarily due to the need for additional line installations to address voltage issues, transformer upgrade costs remain relatively low. Upgrades do not exceed 630 kVA, indicating that transformer capacity is generally sufficient, but line reinforcement remains a significant expense in energy sharing scenarios.

Overall, the results of our study imply that implementing energy sharing not only results in considerable cost savings at the community level (with potential savings of up to 80% compared to scenarios without energy sharing) but also brings about significant reductions in grid asset loading (with decreases in transformer loading of up to 68% and line loading of up to 62%, compared to baseline scenarios). Conversely, we show that energy sharing can significantly influence voltage magnitudes at various buses within the LVDN, potentially leading to substantial increases in grid reinforcement costs in future scenarios (i.e., 2037).

Despite these contributions, our findings are notably influenced by the energy sharing model, including community size and asset availability. Our approach also uses static community prices without individual transaction pricing, suggesting a need for future research into various REC configurations and pricing mechanisms. Additionally, our power flow simulation is based on a specific European three-phase LV test feeder, which may not fully represent other real-world LVDNs. We have not assessed scalability beyond a small-scale REC or considered large-scale RECs spanning multiple feeder segments or grid levels. Our voltage deviation range does not accommodate the broader ±10% needed for such scenarios. Future studies should explore the impacts of energy sharing in larger and more diverse systems, over extended time frames, and across different topologies and DERs. Finally, while this study quantifies the impacts on the grid and estimates potential reinforcement costs, it does not offer direct control mechanisms for DSOs. Alternative solutions, such as tap-changing transformers or real-time adjustable network fees, should be considered before implementing reinforcement measures.

CRediT authorship contribution statement

Jonathan Lersch: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation. **Rui Tang:** Writing – review & editing, Methodology, Supervision, Funding acquisition, Conceptualization. **Martin Weibelzahl:** Writing – review & editing, Supervision, Conceptualization. **Jan Weissflog:** Writing – review & editing, Validation, Methodology. **Ziyan Wu:** Investigation, Data curation.

Declaration of competing interest

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

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Data availability

The data used can be obtained by the sources stated in the article.

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