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Advancing renewable energy community planning through integrated sector-coupling and economies of scale

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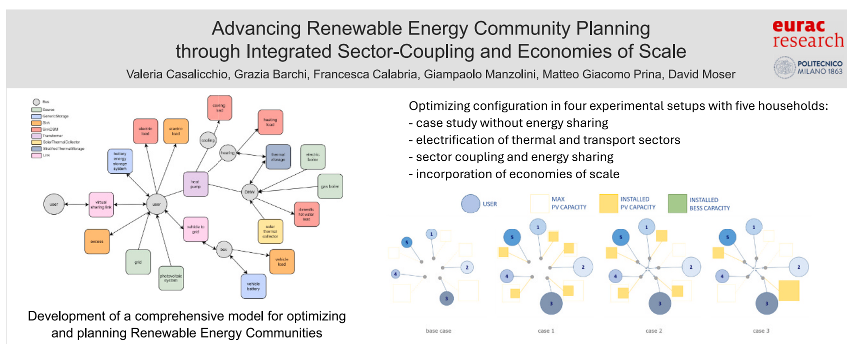
HIGHLIGHTS

- Comprehensive model to optimize Renewable Energy Communities.
- Sector coupling and economies of scale in planning Renewable Energy Communities.
- Model applied to Renewable Energy Community experimental setups in Bolzano, Italy.

GRAPHICAL ABSTRACT



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ABSTRACT

As the world transitions towards renewable energy sources, optimizing energy sharing within communities has emerged as a key strategy for sustainability and cost-efficiency. In this paper, we present a comprehensive simulation model designed to optimize energy sharing among households and municipal buildings within a renewable energy community setting. Our model integrates various energy sectors, including electricity, heating, cooling, domestic hot water, and transportation, using a bottom-up approach and linear programming. Drawing upon existing frameworks and methodologies, we conduct a case study in a hypothetical small Italian community to demonstrate the potential of our simulation model in promoting energy efficiency and sustainability. We analyze the economic and environmental impacts of different energy optimization strategies in various scenarios, including sector coupling and collaborative energy sharing. Our findings reveal that integrating various energy demands and utilizing economies of scale in energy communities can lead to significant bill savings. With sector coupling alone, savings exceed 35 %, while combining sector coupling with energy sharing results in over 43 %

Abbreviations: BEV, Battery Electric Vehicle; BESS, Battery Energy Storage Systems; CAPEX, Capital Expenditure; COP, Coefficient of Performance; DSM, Demand Side Management; DHW, Domestic Hot Water; FOP, Fuzzy Optimization Problem; GHG, Greenhouse Gas; GHI, Global Horizontal Irradiance; LP, Linear Programming; LPG, Load Profile Generator; MAS, Multi-Agent System; MILP, Mixed Integer Linear Programming; MOO, Multi-Objective Optimization; NLP, Nonlinear Programming; nZEB, Nearly Zero-Energy Buildings; OPEX, Operating Expenditure; P2P, Peer-to-Peer; PV, Photovoltaic; REC, Renewable Energy Community; SOC, State of Charge; SOO, Single-Objective Optimization; V2G, Vehicle-to-Grid; VSC, Vehicle Smart Charging.

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savings, achieved without significantly increasing installed capacity, but with a more efficient distribution, which also reduces the total investment cost by around 32 % due to economies of scale.

1. Introduction

A pivotal challenge of this century lies in orchestrating a clean energy transition. Key contributors to greenhouse gas (GHG) emissions are in particular the buildings sector representing 35 % of energy-related EU emissions and the transport sector representing around 25 % of the EU's total greenhouse gas emissions [1,2]. The European commission acknowledges the role of sector integration in the fulfilment of the objectives: "Linking sectors will allow the optimisation of the energy system as a whole, rather than decarbonising and making separate efficiency gains in each sector independently" [3].

A renewable energy community (REC) [4] can help optimize the use of the existing grid, integrating more renewable energy, electrifying transport and buildings, with an additional positive effect on household expenditures [5].

1.1. Research contribution

Despite significant advances in modeling RECs, existing studies often focus on isolated aspects like photovoltaic system sizing or economic feasibility, lacking a comprehensive framework for holistic optimization.

Our study introduces a complete simulation tool that integrates critical dimensions of RECs identified in literature. To our knowledge, it is the first to offer such a comprehensive perspective on energy communities. In summary, our simulation tool addresses a crucial gap in REC literature by integrating multiple features into a single, comprehensive framework and demonstrating its efficacy in real-world scenarios. It provides a robust solution to optimize energy communities, ensuring they are economically viable, environmentally sustainable, and socially equitable. This represents a step forward in the clean energy transition and serves as a valuable resource for researchers, policymakers, and practitioners.

1.2. Literature review

The state-of-the-art literature review provides a comprehensive overview of the research status in the field of energy communities, and they are divided per main topic. Table 1 provides the key features of analyzed models and Table 2 shows further classification according to [6].

1.2.1. Optimization and energy planning

Several studies provide valuable models to guide energy experts and urban planners in optimizing the sizing and management of Renewable Energy Communities (RECs), considering various configurations and their impacts to maximize efficiency and minimize costs.

Cielo et al. [7] propose a model which optimize size of photovoltaic (PV) system and electrochemical energy storage, demonstrating the sensitivity to energy markets and operating costs. Furthermore, they also consider the management costs of the Renewable Energy, i.e. the cost of acquiring and sharing measurements among the REC shareholders. Minuto et al. [8] develop a framework that accounts for economic and environmental indicators with the objective to maximize the economic feasibility and minimize the impact on the distribution grid, the primary energy consumption, and the emissions.

Similarly Coletta and Pellegrino [9] and Cutore et al. [10] propose an optimal design methodology for sizing a REC while comparing centralized and decentralized configurations, to assess energetic, economic, and social impacts. Pontes Luz and Amaro E Silva [11] evaluate the technical-economic feasibility of different configurations of an energy community - which integrates the city consumers and a local winery -

Table 1
Features of renewable energy community model.

	optimal design	emissions	DSM	batteries	composition	economies of scale	centralized / decentralized	fairness assessment	thermal sector	transport sector
Celik et al. [25]			x					x		
Reis et al. [29]			x		x			x	x	x
Fleischhacker et al. [21]	x	x				x			x	x
Karunathilake et al. [12]	x									
Kotarela et al. [16]	x			x					x	
Radl et al. [22]	x			x		x	x		x	x
Alnaser et al. [28]				x						
Di Lorenzo et al. [30]										
Cielo et al. [7]	x	x		x						
Minuto et al. [8]	x	x							x	x
Coletta and Pellegrino [9]	x						x			
Pontes Luz and Amaro E Silva [11]	x									
Cosic et al. [13]	x	x		x						
Alonso et al. [14]	x									
Rikkas and Lahdelma [15]									x	
Gjorgievski et al. [17]								x		
Perger et al. [18]				x				x		
Zatti et al. [19]	x		x					x	x	
Fioriti et al. [20]								x		
Wang et al. [23]		x	x	x				x		x
Bashir et al. [24]	x	x	x	x					x	
Chronis et al. [26]	x		x	x					x	x
Secchi et al. [27]	x	x		x					x	
Cutore et al. [10]	x	x		x			x			
Silvestre et al. [32]	x				x					
Elomari et al. [33]	x	x		x	x					
Minelli et al. [34]					x				x	
current study	x	x	x	x	x	x	x	x	x	x

Table 2
Renewable energy community existing methodologies.

	Objective	Energy	Spatial resolution	Temporal resolution - coverage	Modeling method	Modeling tool	Location	Year
Celik et al. [25]	Optimize REC performance	electric	20 smart homes	1 min - 1 day	SOO	JADE (Java), (MATLAB)	–	2017
Reis et al. [29]	Optimize loads and dispatch	electric thermal transport	100 households, 3 SMEs, coordinator, retailer agent	1 h - 1 wk	SOO	Anylogic (Java IDE Eclipse)	Portugal	2018
Fleischhacker et al. [21]	Assess REC capacities	electric thermal transport	–	1 h	MOO	HERO-Hybrid EneRgy Optimization	Austria	2019
Karunathilake et al. [12]	Determine ideal technology mix	electric	–	1 month - 10 years	FOP	(STELLA)	Canada	2020
Kotarela et al. [16]	Design building energy system lifecycle	electric thermal	jointly acting renewables self-consumers	1 h - 1 year	SOO	–	Greece	2020
Radl et al. [22]	Optimize PV system and energy storage	electric thermal	households and commercial consumers: 23 individuals, 11 cars	1 h - 1 year	LP SOO	HERO-Hybrid EneRgy Optimization	EU	2020
Alnaser et al. [28]	Optimize battery scheduling	electric	102 households	30 min - 1 day	SOO	AIMMS, OpenDSS	–	2020
Di Lorenzo et al. [30]	Investigate building energy community feasibility	electric	–	1 s	–	Simulink (MATLAB)	–	2020
Cielo et al. [7]	Optimize PV system and energy storage	electric	school, gymnasium, town hall, 10 households	1 h - 1 year	MILP SOO	(Python)	Italy	2021
Minuto et al. [8]	Optimize technology configuration and sizing	electric thermal	condominium with 74 households, 13 office/shop	30 min - 1 year	SOO	–	Italy	2021
Coletta and Pellegrino [9]	Assess REC capacities (centralized, distributed PV)	electric	52 households	1 h - 1 year	SOO	(MATLAB)	Italy	2021
Pontes Luz and Amaro E Silva [11]	Assess REC capacities	electric	local winery, 30 households	15 min	SOO	Calliope (Python)	Portugal	2021
Cosic et al. [13]	Minimize energy costs and CO_2 emissions	electric	local authority, fire department, bank, residential building, 3 single-family houses	1 h - 1 year	MILP MOO	–	Austria	2021
Alonso et al. [14]	Compare regulatory schemes	electric	–	1 h - 1 wk. for season	MILP SOO	–	Spain	2021
Rikkas and Lahdelma [15]	Optimize size and operation of hybrid energy solutions	electric thermal	mixed-type building	1 h - 1 year	LP/MILP SOO	–	Finland	2021
Gjorgievski et al. [17]	Real-time fair energy sharing	electric	2/15 households	15 min - 1 h	simulation	(Python)	–	2021
Perger et al. [18]	Maximize social welfare	electric	5 small medium enterprises, 10 households	1 h	LP SOO	YALMIP (MATLAB)	Austria, Germany	2021
Zatti et al. [19]	Optimize design and revenue distribution	electric thermal	6 households, 3 commercial users	1 h - 5 days	MILP SOO	–	Italy	2021
Fioriti et al. [20]	Assess REC capacities (focus on rewards and exit costs)	electric	10 households, commercial users, aggregator	15 min - 1 year	SOO	–	Italy	2021
Wang et al. [23]	Optimize REC performance	electric transport	4 households	1 h - 1 day	MINLP MOO	(Python), (GAMS)	extra UE	2021
Bashir et al. [24]	Optimize thermal storage for REC heating with renewables	thermal	100 single-family houses, district heating, aggregator with wind farm	1 h - 1 year	MILP SOO	(MATLAB), (GAMS)	Finland	2021
Chronis et al. [26]	Evaluate REC participation benefits in local market	electric thermal transport	60 households, Mayor's office	1 h - 1 year	MILP SOO	–	Greece	2021
Secchi et al. [27]	Maximize REC self-sufficiency and minimize BESS capacity	electric thermal	90 members	15 min - 1 year	MOO	OpenDSS (MATLAB)	Italy	2021

(continued on next page)

supported by collective photovoltaic self-consumption, showing the advantages and disadvantages of centralized or decentralized systems.

Cosic et al. [13] and Alonso et al. [14] contributions reside in providing mathematical frameworks for optimizing the planning and management of RECs, considering factors such as energy costs, emissions reductions, and regulatory influences. Rikkas and Lahdelma [15] and Kotarela et al. [16] focus on optimizing energy systems within communities to enhance efficiency and reduce costs. Rikkas and Lahdelma [15] devise an optimization framework targeting a building comprising residential, office, and commercial spaces, considering diverse local energy generation and storage systems for electricity, heating, and cooling, while Kotarela et al. [16] implement a collective energy consumption model typical urban multifamily nearly zero-energy buildings (nZEB) to achieve energy self-sufficiency and grid stability.

1.2.2. Equity and energy sharing

The literature extensively considers economic aspects beyond the mere dimension of renewable systems, focusing particularly on profitability for all members during the management of REC. In particular, Vladimir Z Gjorgievski et al. [17], Perger et al. [18], Zatti et al. [19], and Fioriti et al. [20] focus on promoting fair energy distribution within communities. They propose various methodologies and models aimed at ensuring that energy sharing among community members is equitable, considering individual contributions, preferences, and seasonal variations in energy demand. Profit distribution, as suggested by Zatti et al. [19], is modeled as a cooperative game, incentivizing electricity consumption shifting and encouraging active participation from all members. Fioriti et al. [20] additionally consider user cooperation and efficient operation in their tailored business model, with exit clauses and aggregator payments.

1.2.3. Economies of scale

The optimal configuration between centralized and decentralized systems is often shaped by economies of scale, a topic extensively addressed by Fleischhacker et al. [21] and Radl et al. [22] within the context of energy communities. Fleischhacker et al. [21] emphasize the importance of considering the economies of scale in energy community design to enhance the overall efficiency and their economic viability. Similarly, Radl et al. [22] introduce a linear optimization framework aimed at reducing community energy expenses by investing in PV systems, batteries, and thermal storage, while considering that the community has the advantage of investing together in assets and benefits from economies of scale and reduced grid tariffs for electric energy exchanged.

1.2.4. Storage technologies, load shifting and demand side management

Wang et al. [23] and Bashir et al. [24] Celik et al. [25], and Chronis et al. [26] explore the use of energy storage technologies, such as batteries and thermal systems, to enhance flexibility and demand side management (DSM) within communities.

Wang et al. introduce a model for a peer-to-peer energy sharing community with an internal pricing scheme, and an energy fluctuation penalty algorithm. The aim is to encourage participation from both prosumers and consumers, motivating them to adhere to the energy smart contract and engage in electricity peak-shifting activities. Similarly, Bashir et al. [24] develop a mixed integer linear programming (MILP) based model to size thermal storage for meeting community hot water demand using renewable energy. An aggregator, overseeing a wind farm and DWHP system, optimizes storage size and schedule hot water loads based on individual parameters.

Chronis et al. [26] simulate the local energy market within an energy community, optimizing energy exchanges among both residential and commercial members, some of whom possess flexible loads, such as electric boilers, battery electric vehicle (BEV) chargers. Secchi et al. [27] address the BESS sizing challenge with a prosumer-centered approach, seeking to minimize BESS capacity and highlight the effective utilization of BESS in peer-to-peer (P2P) sharing.

1.2.5. Decentralized control and optimization of energy exchanges

Celik et al. [25], Alnaser et al. [28] propose decentralized control algorithms and optimization models to manage energy sharing and consumption efficiently. Celik et al. [25] introduce a decentralized control algorithm which coordinates energy sharing among smart homes in residential areas using game theory and a multi-agent system (MAS), while Reis et al. [29] and Di Lorenzo et al. [30] include a coordinating entity managing and distributing energy resources within the community. Alnaser et al. [28] develop a residential community energy management system, where a community operator maximizes the energy sufficiency of the community over a specific operational planning period by efficiently controlling residential batteries.

Table 2 (*continued*)

	Objective	Energy	Spatial resolution	Temporal resolution - coverage	Modeling method	Modeling tool	Location	Year
Cutore et al. [10]	Maximize investment profitability of REC	electric	17 buildings	1 h - 1 year	SOO	(MATLAB R2021a)	Italy	2023
Silvestre et al. [32]	Optimize consumption or generation design	electric	households	10 min - 1 month	NLP SOO	GRG Microsoft Excel Solver	Italy	2023
Elomari et al. [33]	The system, its boundaries, and the capacity of REC system	electric	100 residential buildings	1 h - 1 year	MOO	Homer Pro (Python)	Spain	2024
Minelli et al. [34]	Evaluation of usefulness of NZEB target in REC	electric thermal	School building (consumer), newly built residential NZEB (prosumer)	1 h - 1 year	simulation	EnergyPlus, Design Builder (Python)	Italy	2024
current study	Optimize operational and expansion capacities and fair benefit distribution in REC	electric thermal transport	5 households (both prosumers and consumers) *flexible application*	1 h - 1 year	LP MOO	oemof (Python)	Italy	–

Fuzzy Optimization Problem (FOP).
Multi-Objective Optimization (MOO).
Single-Objective Optimization (SOO).
Linear Programming (LP).
Mixed-Integer Linear Programming (MILP).
Nonlinear Programming (NLP).

1.2.6. Energy community composition

As discussed in Volpato et al. [31], examining the composition of an REC is crucial for ensuring its overall effectiveness, sustainability, and economic viability before its establishment. Each consumer has distinct energy consumption patterns, peak demand times, and preferences, therefore Different types of consumers within an energy community may have complementary energy profiles. By understanding and optimizing the composition of the community, it becomes possible to match supply and demand more efficiently, reducing waste and optimizing resource utilization. These aspects are partly addressed by Reis et al. [29] and by Silvestre et al. [32].

Reis et al. [29] proposed model includes a coordinating entity that manages and distributes the community's energy resources by taking into account agent preferences, such as load usage periods and comfortable temperatures, and cross-sector activities, such as public lighting and EV charging stations.

Silvestre et al. [32] introduces an algorithm designed to optimize the composition of consumers within an energy community with the objective to maximize the economic advantages derived from self-consumption of a specified PV plant, but also, to determine the ideal size of the PV system for a specific group of consumers. In this context, Elomari et al. [33] developed a model that uses a multi-objective optimization algorithm to estimate future costs and levelized cost of energy as the main objective, with environmental impact as a secondary objective. This method provides valuable insights into various renewable energy community configurations, aiding decision-makers in selecting the most appropriate options. Minelli et al. [34] also demonstrated that complementarity between prosumers is key for effective renewable energy use, showing that coupling an NZEB with a neighboring building can reduce grid overload, especially with time-shifted energy loads.

As outlined in the literature review, all stakeholders involved in establishing a REC encounter numerous challenges in addressing specific queries, such as determining the appropriate capacity for installation and identifying the optimal number of members and energy consumption patterns. Additionally, they need to evaluate the significance of including residential, commercial, and industrial profiles, and devise effective strategies for managing energy flows to maximize revenue and minimize costs. At the same time, they select members based on specific objectives and needs, plan infrastructure according to building availability and consumption profiles, and evaluate management strategies to optimize production and consumption. Considering local laws and regulations to ensure community compliance is essential, as is ensuring that community participation and the benefits of renewable energy are equally distributed among all members, thus avoiding socio-economic disparities. Lastly, conducting environmental impact assessments is crucial to the overall success of the REC. It is therefore possible to confirm the growing need for updated mathematical models characterized by the most relevant features to interpret increasingly intricate regulatory guidelines.

Building on key insights from our literature review, this work distinguishes itself by integrating valuable elements from existing researches while introducing advancements in the optimization and energy planning of RECs. Our model leverages linear programming techniques to optimize energy flows by focusing on cost minimization, efficiency maximization, demand management, sector coupling, and economies of scale.

In terms of equity and energy sharing, our model incorporates cooperative game theory to fairly allocate the economic benefits of energy sharing, based on each participant's contribution, as detailed in our previous work [35]. This alignment of individual contributions with community-wide benefits, combined with demand management strategies, enhances overall system effectiveness.

We address the often-overlooked concept of economies of scale by developing a comprehensive framework that optimizes both the design and the management of energy systems within RECs, ensuring cost-effectiveness and improved economic outcomes for community members.

Our model integrates energy storage and demand management to balance supply and demand optimally, enhancing the reliability and sustainability of the energy community.

Additionally, our model accommodates both centralized and decentralized systems, allowing for a thorough analysis of each. This flexibility enables the exploration of diverse configurations and the identification of optimal solutions.

Finally, our model is designed to evaluate various configurations, including prosumers, consumers, and producers of different types, within regulatory constraints. This ensures the potential to maximize self-consumption while assessing the relative benefits of different configurations.

Broadening the existing integrated REC model described in Casalicchio et al. [35,36], this study aligns with the objective of supporting the decision-making process by incorporating the following features –optimization and sector coupling- and ensuring that every aspect identified in the literature analysis is comprehensively addressed within a single framework.

- Optimization: The model is tailored to optimize the dispatch and design of the REC system, taking into consideration economies of scale, costs, and emissions.

- Sector coupling: The model enables the evaluation of potential synergies among the electric, thermal, and transportation sectors within the energy system.

This work is organized as follows. Section 2 presents the methodology adopted to implement the additional features and the overall characteristics of the proposed model.

Section 3 provides detailed information on the case study and its tests. Section 4 discusses the detailed results and finally the main findings and observations are summarized in Section 5.

2. Methodology

This section describes the adopted methodology and the model characteristics and structure.

The model developed in this work builds on Casalicchio et al. [35,36] and is based on a bottom-up approach and a linear programming, which implements a static approach focusing on a short-term target period of one year.

2.1. Objective function formulation

Our model is implemented using the Open Energy Modeling Framework, oemof [37] which casts both objectives and constraints as linear functions, enabling optimization through linear programming techniques. The oemof framework supports optimizing both the operational dispatch of energy resources and the expansion of system capacity within a REC, providing a comprehensive approach to cost minimization and efficient energy planning.

It is an open-source, modular, and flexible software that represents energy systems as networks of nodes and links, offering high adaptability for modeling diverse configurations. Its continuous updates and active development ensure it remains a robust and current tool for energy system analysis. For instance, Fig. 1 illustrates the interactions among model components.

Oemof offers essential components for constructing energy system models. Here is a concise overview of these linear components:

Bus - Balancing object ensuring flow balance at each timestep.

Sink - Single-input-flow object.

Source - Single-output-flow object.

Transformer - Linear object with multiple inputs and outputs, defined by input and output conversion factors.

Link - Connects two buses with specific conversion factors and capacity limits, regulating flow direction.

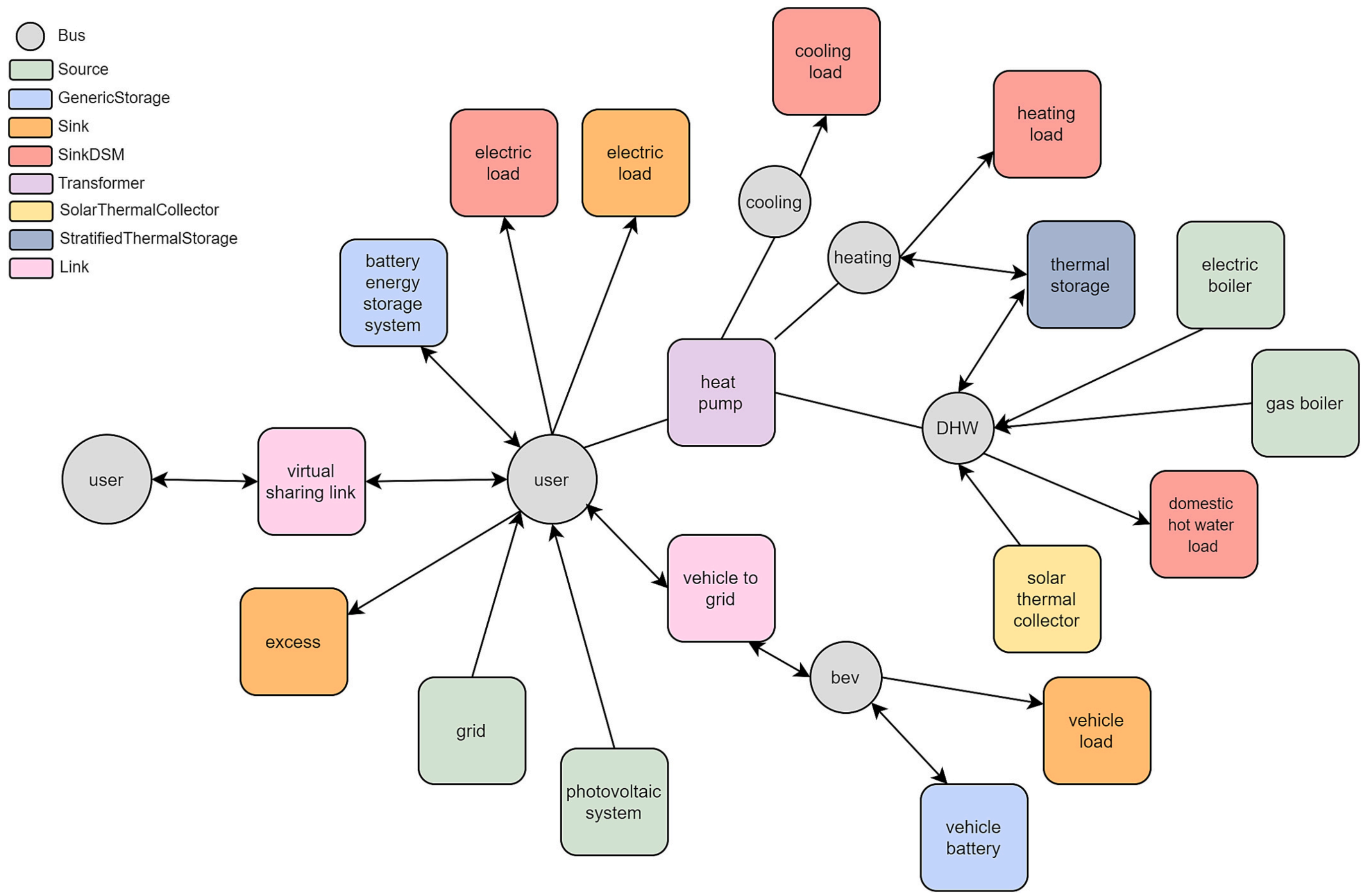

Fig. 1. Streamlined illustration of a renewable energy community as an oemof-network (sector coupling).

GenericStorage - Models various storage types, considering capacity, energy loss, and charging/discharging efficiencies.

SinkDSM - Facilitates consumption flexibility through load shifting or shedding strategies, with options for upper and lower bounds, shift interval, and associated costs.

StratifiedThermalStorage - Represents simplified large-scale sensible heat storage with ideal stratification.

The general dispatch optimization problem entails determining the best utilization of resources to meet demand while minimizing expenses and encompasses two main aspects:

- operational optimization: this focuses on minimizing the daily operational costs by optimizing the dispatch of energy resources.
- expansion capacity optimization: this involves determining the optimal expansion of system capacity, including investments in new generation units, storage solutions, or other infrastructure components. The goal is to identify the most efficient capacity expansion strategy that minimizes long-term costs while ensuring adequate supply to meet the demand.

The objective function OF_{EC} in Eq. 1 reflects these dual goals by incorporating both operational costs and capacity expansion costs. Eq. 1, expresses the overall cost of purchased energy u, by member m, at time t, times its variable cost $vc_{m,u,t}$ [€/kWh] and the investment, and operations and maintenance costs epc_u of optimized systems capacity C_u. We denote with U the set of all purchased energy flows, with M the set of all the members and with T the set of all timesteps.

The hourly power balance in each Bus, and the maximum deliverable power from all sources govern the goal function.

$$\text{minimize} \qquad OF_{EC} = \sum_{m\epsilon M}\sum_{u\epsilon U}\sum_{t\epsilon T} E_{m,u,t} \bullet vc_{m,u,t} + C_m \bullet epc_m \tag{1}$$

The model is flexible enough to implement any type of REC, given the defined component configuration, as it allows for a potentially unlimited number of nodes. In practice, the number of nodes is constrained by the computational capabilities and available resources.

2.2. Electric sector modeling and improvements

The Sink and SinkDSM components, as shown in Fig. 1, are used to model fixed and flexible loads with load profiles for users represented by $L_{fix,m}$ [kWh], $L_{flex,m}$ [kWh]. In particular, the SinkDSM component allows for the modeling of both load shifting and load shedding. In our model, we focus specifically on load shifting, and we introduce upper and lower bounds that enable demand to vary within these limits. This component ensures that any upward shift in demand is balanced by a corresponding downward shift, maintaining overall system stability. Both flexible and fixed electric load profiles of residential users are obtained using the LoadProfileGenerator (LPG) application [38]. Based on the load type, we determine whether the demand is shiftable or not, enabling the modeling of load shifting in the optimization process.

While Sink components were already introduced in Casalicchio et al. [36], in this work, the electrical section is further expanded to incorporate economies of scale for both photovoltaic (PV) and battery components, including both electric and thermal storage systems. The economies of scale costs are considered by setting both a variable capital expenditure of investment $CAPEX_u$ [€/kW] a fixed capital expenditure of investment $CAPEX_{offset,u}$ [€] to approximate the economies of scale curve and the operating expenditure of investment $OPEX_{PV}$ [€/year].

These costs are given as an input to oemof to calculate the equivalent periodical costs epc_u [€/y] and $epc_{offset,u}$ [€/y] and perform the capacity optimization of the PV system as shown in Eqs. 2 and 3, together with the life expectancy of investment $lifetime_u$ and the weighted average cost of capital (WACC).

A maximum limit is also set for the capacity $C_{max,PV}$ [kW] that can be built in case of limited available area or other constraints to be taken into account.

$$epc_m = CAPEX_m \bullet \text{wacc} \bullet \frac{(1+\text{wacc})^{lifetime_m}}{(1+\text{wacc})^{lifetime_m}-1} + OPEX_m \tag{2}$$

$$epc_{offset,m} = CAPEX_{offset,m} \bullet \text{wacc} \bullet \frac{(1+\text{wacc})^{lifetime_m}}{(1+\text{wacc})^{lifetime_m}-1} + OPEX_{offset,m} \tag{3}$$

The economies of scale stem from the simple fact that larger elements are more cost-effective. Therefore, one or more stores that are responsible for the installation of the components under analysis are analyzed to collect turnkey costs, i.e. system costs that include the cost of inverters, switchboards, cables, support structures, the cost of labor, and so on. Once these costs for different size systems are obtained, an interpolation curve is created for each system to identify the average variable costs (value dependent on the installed capacity) and the average fixed costs (value not dependent on the size of the installed capacity).

2.3. Thermal sector

Three SinkDSM components are introduced to model heating, domestic hot water (DHW), and cooling demands. Shedding and shifting are two demand response strategies aimed at managing energy consumption during peak periods. Gils [39] recommends prioritizing the shifting strategy over shedding due to its lower impact on comfort and productivity. Gils [39] provides data on shifting periods and limitations, including the percentage reduction in load $s_{reduction}$ [%] and its impact on comfort and routines.

In this work, the "oemof" model is chosen for the SinkDSM object due to its computational efficiency and simplicity, requiring fewer parameters while still being adequate for the task.

This component ensures that the total electricity demand remains constant over time (Eq. 7). A portion of the flexible load E [kWh] can be shifted, as long as it stays within the defined upper bound cap_{up} [%] and the lower bound cap_{down} [%]. The shifting occurs within the shift interval t_{shift} [h] where the upward-shifted demand $\mathrm{DSM}_t^{\mathrm{up,shift}}$ [kWh] is balanced by the downward- shifted demand $\mathrm{DSM}_t^{\mathrm{do,shift}}$ [kWh].

$$\mathrm{E}_{\mathrm{after},t} = E_{before,t} + \mathrm{DSM}_t^{\mathrm{up,shift}} - \mathrm{DSM}_t^{\mathrm{do,shift}} \tag{4}$$

$$\mathrm{E}_{\mathrm{after},t} = E_{before,t} + \mathrm{DSM}_t^{\mathrm{up,shift}} - \mathrm{DSM}_t^{\mathrm{do,shift}} \tag{5}$$

$$\mathrm{DSM}_t^{\mathrm{do,shift}} \leq cap_{down} \bullet E_{before,t} \tag{6}$$

$$\sum_{t\in t_{shift}} \mathrm{DSM}_t^{\mathrm{up,shift}} = \sum_{t\in t_{shift}} \mathrm{DSM}_t^{\mathrm{do,shift}} \tag{7}$$

Both air heat pumps and water heat pumps are examined and modeled through a Transformer in oemof to provide space heating and cooling as well as residential hot water demands.

The oemof component takes as input the electricity flow and gives as output the heat flow according to the coefficient of performance (COP) of the heat pump $COP_{HP,t}$ [−] which varies every time step and is assessed by a dedicate oemof function by setting the 'compression heat pump' or 'chiller' mode.

It increases the temperature of a flow using a compressor that consumes electric power. The inlet heat flux comes from a low temperature source T_{low} [°C] and the outlet has the temperature level of the high temperature sink T_{high} [°C]. The same cycle can be used for heating (heat pump) or cooling (chiller).

The COP formulation incorporates the Carnot cycle efficiency and is adjusted by a correction factor φ [−] to accommodate real-world performance [40], as depicted in Eq. 8, 9, 10.

$$COP = \varphi \cdot COP^{Carnot} = \varphi \cdot \frac{T_{sink}}{T_{sink} - T_{source}} \tag{8}$$

$$COP_{HP}^{Carnot} = \frac{T_{high}}{T_{high} - T_{low}} \tag{9}$$

$$COP_{chiller}^{Carnot} = \frac{T_{low}}{T_{high} - T_{low}} \tag{10}$$

The COP is affected by the source temperature [40], hence an hourly ambient temperature $T_{amb,t}$ [°C] is supplied corresponding to the location of the EC.

It is essential to assess the system type, along with the assumptions and implemented functions, to determine the input temperatures:

Air systems – heating and cooling.

Residential comfort temperatures, corresponding to the T_{sink} of the COP, are reported for both summer and winter season in UNI EN ISO 7730 [41].

Water systems - cooling.

The model addresses the need to maintain minimum floor temperatures in homes, as specified by 'UNI EN ISO 7730' [41], to prevent discomfort and humidity condensation, incorporating insights from [42]. It examines various heat gain configurations affecting interior ambient temperature, adjusting supply cold water temperatures for floor systems accordingly to ensure floors remain within acceptable temperature ranges.

Water systems - heating.

Hot water temperatures - supplied to the radiators for heating the rooms - vary depending on the system in place using a thermoregulation approach based on a climatic curve as reported in (Eq. 11). It determines the hourly supply water temperature $T_{set\ point}$ [°C] based on outdoor temperatures, ensuring continuous adjustment for optimal comfort. It depends on the maximum $T_{\mathrm{max}flow}$ [°C] and minimum supply flow temperature $T_{\mathrm{min}flow}$ [°C], the minimum temperature outside $T_{\mathrm{min}amb}$ [°C] and the outdoor temperature threshold $T_{\mathrm{max}amb}$ [°C] for which there is no demand for heat output.

$$T_{set\ point} = \frac{T_{\mathrm{max}flow} - T_{\mathrm{min}flow}}{T_{\mathrm{min}amb} - T_{\mathrm{max}amb}} \bullet (T_{amb} - T_{\mathrm{min}amb}) + T_{\mathrm{max}flow} \tag{11}$$

2.4. Heating and cooling load profiles

Space heating demand profiles are generated using the EN 15316–4-2:2018 regulation [43] and a custom function, based on a stationary bin-method approach that considers ambient temperature trends and building energy labels to determine annual heating and cooling profiles.

The amount of heat needed and the heat present in the environment are related in a linear manner, taking into account factors such as the maximum energy required during extreme temperatures Q_{max}[kWh], the annual energy demand of the house based on its energy class Q_y [kWh], whether the system should be activated or deactivated δ_i[−] according to regulations and climatic conditions, and the design temperature representing the desired room temperature T_{design}[K] for each season, as well as the outdoor temperature T_{bil} [K] at which space heating or cooling is no longer required (Eqs. 12 and 13).

Additionally, the yearly energy requirements for each user are determined based on the European Union energy label $Q_{EUlabel}$ [kWh/m^2], the percentage of energy allocated for space heating EP_{SH} [%], and the total surface area S [m^2] (Eq. 14).

$$Q_{SH,t} = Q_{max} \cdot \delta_t \cdot \frac{T_{bil} - T_{amb,t}}{T_{bil} - T_{design}} \quad (12)$$

$$Q_{max} = \frac{Q_y}{\sum_t \delta_t \cdot \frac{T_{bil} - T_{amb,t}}{T_{bil} - T_{design}}} \quad (13)$$

$$Q_y = Q_{EUlabel} \cdot EP_{SH} \cdot S \quad (14)$$

European Union energy labels, which outline energy consumption including heating, cooling, hot water production, lighting, and ventilation requirements, are assigned to users probabilistically using reference area statistics. The area allocation is based on the number of users in each utility and regional housing standard.

The method employed to create space heating demand profiles is also applied to generate the cooling load profile, adjusting parameters, and utilizing data from LPG on appliance activation and deactivation times.

Water systems - Domestic hot water.

In domestic hot water systems, Legionella contamination poses a risk, especially in centralized setups like hospitals and residential complexes. To prevent this, thermal treatments, such as maintaining water temperatures above 50 °C continuously or recirculating water at 60 °C for 30 min daily, are commonly used [44]. A periodic treatment is preferred, maintaining water at 40 °C when untreated, thus a function is created to return the hourly hot water supply temperature, impacting energy requirements.

2.5. Domestic hot water load profiles

The LPG application is also used to collect the hourly load profile for the DHW peculiar to the household under consideration, which provided the demand in liters of DHW.

A function takes hourly DHW demand profiles expressed in liters V_{DHW} [l] as input and returns the hourly DHW demand Q_{DHW} [kWh].

2.6. Thermal energy storage

Additional Source components are integrated for each member to simulate both an electric boiler and a gas boiler, with costs associated, reflecting the electricity and gas prices as well as the efficiencies of the systems. The StratifiedThermalStorage component is utilized twice to model thermal energy storage (TES) for space heating and a storage tank for DHW, allowing for precise temperature settings and detailed evaluation of losses.

The TES module models a cylindrical storage system composed of two distinct temperature zones: a hot region and a cold region. These zones are characterized by constant temperatures corresponding to the feed-in and return temperatures of the connected heating system. Charging or discharging the storage causes the thermocline—the boundary between the two zones—to shift downward or upward, respectively.

The TES is defined by its autonomy duration, its maximum storage capacity and heat losses to the environment. Eq. 22 outlines the energy balance of the storage at each timestep t, accounting for constant heat losses through the top and bottom surfaces δ [kWh], losses through the lateral surface proportional to the state of charge βQ_{t-1} [kWh], and overall lateral surface losses γQ_N [kWh]. These losses depend on the storage's thermal transmittance u_{value} [W/m2/K], which is is assumed to be uniform and influenced by material properties, also assumed constant throughout the system, such as the insulation layer thickness s_{iso} [mm], the insulation material conductivity λ [W/m/K], and the internal and external heat transfer coefficients α_i [W/m2/K] and α_o [W/m2/K]. The relationships governing these dynamics are presented in Eq. 16. Input data for this study are drawn from Raccanello et al. [45], whose recommended values for single-tank thermal energy storage systems align with the modeling framework adopted here.

$$Q_t = Q_{\{t-1\}}(1-\beta) - \gamma Q_N - \delta + \dot{Q}_{in,t}\eta_{in}\Delta t - \frac{\dot{Q}_{out,t}}{\eta_{out}}\Delta t \quad (15)$$

$$u_{value} = \frac{1}{\frac{1}{\alpha_i} + \frac{s_{iso}}{\lambda_{iso}} + \frac{1}{\alpha_o}} \quad (16)$$

Furthermore, the TES system includes equivalent periodic costs epc_u [€/y] and $epc_{offset,u}$ [€/y], which are provided during the capacity optimization process. The investment mode outputs the optimal storage capacity, the optimal dispatch, and the loss values.

2.7. Modeling of the transport sector

An additional Bus is introduced for each member to incorporate a Sink, a GenericStorage, and a Link oemof components, aiming to simulate a battery BEV. The Sink component represents the vehicle's load during operation, with the associated profile $L_{bev,i}$ [kWh]. The GenericStorage (described by Eq. 17) receives as inputs the capacity of the battery C_{bev} [kWh], the efficiencies ($\eta_{bev,charge}$ [%], $\eta_{bev,discharge}$ [%]), and a minimum storage level depending on the hour which is provided to guarantee a minimum charge $SOC_{bev,t}$ [kWh] (Eq. 18). The primary component here is the Link, offering two distinct configurations. This Link establishes a connection between the vehicle Bus and the user Bus, enabling energy flow sharing when the input efficiency equals 1. It is necessary to provide the conversion factor for flow in both directions, namely from the user to the vehicle $CF_{V2G,BEVcharge}$ [%] and from the vehicle to the user $CF_{V2G,BEVdischarge}$ [%]. The CF varies according to the chosen configuration, with two possibilities: vehicle-to-grid (V2G) and vehicle smart charging (VSC). With V2G active, the vehicle can function as a battery, allowing connection to the grid while parked, facilitating energy flow bidirectionally between the user and the vehicle, as expressed in Eqs. 19 and 20.

$$C_t = C_{t-1} + E_t^{charge} \bullet \eta_{bev,charge} - \frac{E_t^{discharge}}{\eta bev,_{discharge}} \quad (17)$$

$$SOC_{bev,t} \leq C_t \leq C_{nom} \quad (18)$$

$$CF_{V2G,BEVcharge,t} = \begin{cases} 1 \text{ } if \text{ } L_{bev,i} = 0 \\ 0 \text{ } if \text{ } L_{bev,i} > 0 \end{cases} \quad (19)$$

$$CF_{V2G,BEVdischarge,t} = \begin{cases} 1 \text{ } if \text{ } L_{bev,i} = 0 \\ 0 \text{ } if \text{ } L_{bev,i} > 0 \end{cases} \quad (20)$$

On the contrary, in VSC mode, the car battery can only be charged when parked, and no energy flow from the vehicle to the user bus is permitted, as illustrated in Eqs. 21 and 22.

$$CF_{VSC,BEVcharge,t} = \begin{cases} 1 \text{ } if \text{ } L_{bev,i} = 0 \\ 0 \text{ } if \text{ } L_{bev,i} > 0 \end{cases} \quad (21)$$

$$CF_{VSC,BEVdischarge,t} = 0 \quad (22)$$

In the case of a non-electric vehicle, the Link and GenericStorage components are replaced by a Source representing the fuel source for a typical gasoline vehicle.

In the study by Secchi et al. [46], various methodologies for optimizing V2G systems are explored. These methodologies aim to enhance charging processes while addressing diverse objectives, including maximizing the exploitation of renewable energy sources, reducing peak load demand through scheduling strategies, balancing the net grid load, and minimizing net-load variance. In this paper, we focus on a cost reduction approach as the primary objective for both VSC and V2G systems. The charging and discharging functions aim at minimizing the overall system costs, according to PV production and grid costs. This approach aligns with the findings of Jadoun et al. [47] and Shi et al. [48] which, however, also associate system cost minimization with NLV minimization. Other studies consider cost minimization by targeting electric vehicle charging costs, as García-Villalobos et al. [49], or focus on electric vehicle grid services revenue as Englberger et al. [50].

The RAMP mobility tool [51] is employed to create consumption and charging models for BEVs based on assumed BEV usage patterns.

The RAMP mobility tool, an open-source bottom-up stochastic model, necessitates the specification of BEV share, battery capacity ranges, maximum charging and discharging power, and charging-discharging efficiency. Subsequently, exclusively utilizing publicly available data, it simulates the temporal series of mobility and charging for BEVs with high temporal resolution.

2.8. Economic and environmental outputs

The economic costs considered inside the model to run the optimization are revised through implemented functions in order to obtain the provide the cashflow CF by taking into account investment $CAPEX_m$ and operational and maintenance costs $OPEX_m$, incentives of the REC from sharing valorization $opt(EC)$, savings in the bills S_m, revenues from energy injection into the grid R_m, and deductions D_u: Eq. 23 and 24 respectively show the yearly cash flow and the NPV.

$$CF = \sum_{m \epsilon M} S_m + R_m + opt(EC) - OPEX_m \tag{23}$$

$$NPV = -\sum_{m \epsilon M} CAPEX_m + D_m + \sum_{t \epsilon T} \frac{CF}{(1 + wacc)^t} \tag{24}$$

Annual CO_2 emissions are computed by multiplying the energy purchased across all sectors by the corresponding emission factor, as depicted in Eq. 25. Additionally, constraints on emissions can be established during operational and expansion capacity optimization, as illustrated in Eq. 26.

$$CO_2 = \sum_{m \epsilon M} L_m^{el} \bullet CO_2^{el} + \sum_{m \epsilon M} L_m^{th} \bullet CO_2^{th} + \sum_{m \epsilon M} L_m^{tr} \bullet CO_2^{tr} \tag{25}$$

$$CO_2 \leq limit_{CO_2} \tag{26}$$

3. Case study

We designed a hypothetical small Italian community with five households to showcase the potentialities of the simulation model in optimizing energy sharing for sustainability and cost-efficiency. This case study aims to demonstrate the model's predictive capabilities in assessing strategies for promoting energy efficiency within communities.

The decision to focus on a small community was made to simplify the model's presentation, highlight its potential more clearly, and ensure that results, such as tables and images, are easily interpretable. Additionally, regulatory requirements do not impose strict limitations on community configurations, other than the need for at least two members (either consumers or producers) and two distinct connection points—one for consumption and one for production. The model is flexible and can be applied to any community structure, with computational time being the main constraint.

The REC is located in Bolzano (Italy) in 2019, focusing solely on photovoltaic sources. Key data includes an average annual Global Horizontal Irradiance (GHI) of 1434 kWh/m2, an average temperature of 12.4 °C, and geographic coordinates of 46.4936 latitude and 11.3346 longitude. The radiation database used is CMSAF from 2007 to 2016 [52], with PV systems positioned at a 30° tilt and facing south.

For this research, we adopted transitional phase measures for RECs in Italy [53]. The regulatory framework adopted in Italy operates as a virtual model, offering incentive mechanisms for RECs. These incentives comprise the cost of energy not used within the shared energy pool and a specific tariff applied solely to shared energy. Table 4 outlines the value and origins of these balance components for the two configurations utilized in this context. Essentially, members maintain their full electricity billing arrangements with suppliers but receive periodic payments from the community for energy sharing, effectively serving as a tax-free bill reduction.

In our simulations, we use data from 2019 to get aligned with the transitional phase regulations of RECs. Furthermore, most profiles in our model are synthetic and thus less reliant on specific years. Using more recent data would not significantly impact on the robustness of our methodology.

3.1. Load profiles

Table 3 provides an overview of the primary data and tools utilized to derive synthetic electrical demand profiles, heating and cooling loads (National guidelines [54], Italian regulations [55]), domestic hot water ("UNI 9182" [56]), and electric vehicles, aligning with national guidelines and standards to ensure accuracy in representing the Italian scenario.

Regarding the load profiles, it is important to highlight that sector coupling increases overall electricity demand by incorporating the energy needs of additional sectors. This rise in demand enhances the cost-effectiveness of photovoltaic systems, as it creates more opportunities for self-consumption. Specifically, if the electricity demand profile better aligns with the photovoltaic generation profile, it optimizes the balance between supply and demand, making photovoltaic generation

Table 3
Overview of data and tools for deriving energy consumption profiles.

Category	Description	Values	Profile generator/ Source
Electric load	Electric load profiles (max/min/average values)	4.02/0.02/0.27 kWh	LoadProfileGenerator [38]
Domestic hot water	DHW load profiles (max/min/average values)	670/0.00/10 l/h	LoadProfileGenerator [38]
	Temperature assumption for DHW conversion from l to kWh	48 °C	"UNI 9182" [56]
Heating and cooling loads	Climatic zone	E	ENEA [57]
	Heating load profiles (max/min/average values)	5.53/0.00/0.70 kWh	–
	Thermal performance index for winter heating EPHtot	~103 kWh/m2/y	ENEA [57]
	Cooling load profiles (max/min/average values)	43.20/0.00/0.22 kWh	–
	Thermal performance index for summer air conditioning EPCtot	~5 kWh/m2/y	ENEA [57]
Battery electric vehicle loads	BEV load profiles (max/min/average values)	8.93/0.00/0.16 kWh	RAMP mobility tool [51]
	Average annual energy consumption per BEV charging station	1.1 MWh/y	Eurostat [58]
	Average distance covered by BEV per day	11.4 km/day	Eurostat [58]
	BEV consumption	0.23 kWh/km	De Cauwer et al. [59]
	Battery capacities	30–80 kWh, peak ~50 kWh	'EV Database' [60]
	Maximum charging/discharging power	3.7 kW	Fachrizal et al. [61]
	Estimated charging efficiency	~0.9	Fachrizal et al. [61]

more efficiently utilized within the community.

3.2. Costs and parameters

Key techno-economic factors associated with both PV and battery energy storage systems (BESS) in 2021 include a PV system lifetime of 25 years and a BESS system lifetime of 15 years. The BESS has a maximum state of charge (SOC) of 0.8 and a minimum SOC of 0.2, along with charging and discharging efficiencies of 99 % and 98 % respectively. Additionally, the wacc is 0.05, and there is a tax deduction of 50 % spread over 10 years for expenses incurred in system installation.

Fig. 2 and Fig. 3 depict the economies of scale profiles for PV and storage systems, based on data from Enel X ([62,63] respectively). Additionally, the PV system's operating expenditure (OPEX) is €19 per kW per year [64], while for the BESS, it amounts to €9 per kWh per year [65].

We outline essential parameters and temperatures for heat pumps, incorporating correction factors—dependent on the heat/cool source—from oemof documentation [66], validated by Patteeuw et al. [67]: for example, ranging from 0.4 for air source HPs to 0.5 for HPs utilizing groundwater as a source.

Comfort temperatures, as defined by 'UNI EN ISO 7730:2006' [41], are set at 21 °C for winter and 25 °C for summer. To accommodate additional radiation heat gain in summer, an extra 3 °C adjustment is applied, bringing the summer comfort temperature to 28 °C.

The TES system is characterized by a 20-year lifetime [68], 90 % efficiency [68], 6-h autonomy [66], 100 mm insulation thickness s_{iso}, a thermal conductivity λ of 0.039 W/m/K [69], and internal α_i and external α_o heat transfer coefficients of 7 and 4 W/m2/K respectively [66].

Fig. 4 depicts the profile of economies of scale for the TES system derived from the data in Cordivari [70].

The energy tariffs, encompassing incentives, are comprehensively outlined in Table 4. The procurement expenses for energy is acquired from the Italian Regulatory Authority for Energy, ARERA [71]. Correspondingly, selling costs are retrievable from the GME website [72]. Gas costs associated with relevant flows in the absence of thermal sector electrification are obtained from the ARERA website [71]. Furthermore, annual fuel prices [73] are employed to compare internal combustion engine vehicles with BEVs, with the latter's specifications including a 40 kWh battery capacity [60], a 3.7 kWh charging power [60], a charging efficiency of 99 % [61], and a discharge efficiency of 98 % [61].

3.3. Simulation setup

We describe our experimental setup, which entails the analysis of five households. The base case is provided by the case where the five households are independent and only account for their individual electric demand, without accounting for the electrification of thermal and transportation demands.

We then consider three incremental experimental setups that builds on the base case:

Case 1. - We incorporate thermal, and transportation demands in the scenario (sector coupling).

Case 2. - The households participate to an energy community.

Case 3. - The energy community invests based on economies of scale.

To provide a comprehensive perspective on the possible energy profiles, we consider a set of diverse nodes/households:

Node 1 – a couple, with both members working.
Node 2 – a family with 2 children, where both parents work.
Node 3 – a family with 3 children, where both parents work.
Node 4 – a single working man.
Node 5 – a family with 1 child, where both parents work.

The reference year is 2019: for each simulation, energy costs for the reference year can be entered as tariffs have a strong impact on shared energy management.

Table 5 presents the key details of the five households included in the case studies. It includes their electricity, heating, and transportation demands, along with the maximum capacity for installing PV systems. These data are consistent across all scenarios, although some may focus solely on electricity demand.

Fig. 5 exemplifies the annual demand profiles of a single user (Node 1) across various sectors—electricity, heating, cooling, domestic hot water, and electric vehicles—presented seasonally using box plots.

In the previous section, we discussed the key turnkey cost curves for PV and battery systems. For scenarios that do not incorporate economies of scale, we adopt a linear cost model.

4. Results

In this section, we present the outcomes of our simulation setups, starting with the base case scenario where only electrical demand is considered and then progressing through the three incremental setups outlined. We analyze the impacts of incorporating thermal and transportation demands, participating in a REC, and leveraging economies of scale within the community.

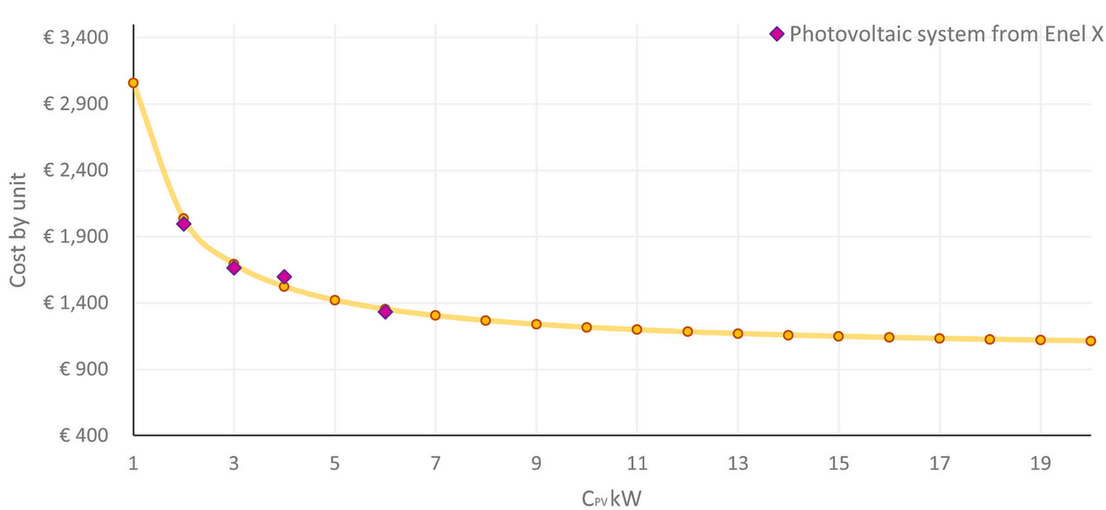

Fig. 2. Economies of scale curve of PV system (Enel X [62] - 2021).

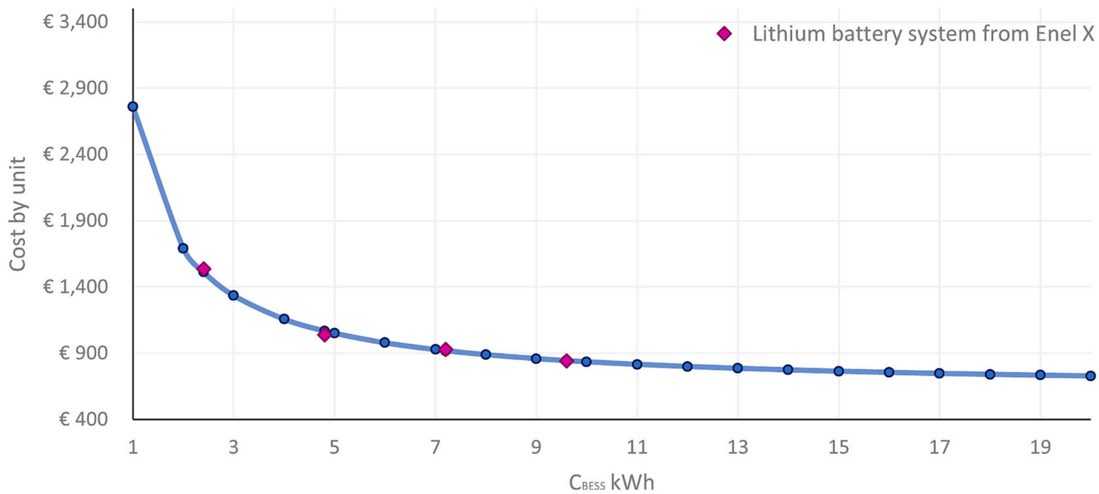

Fig. 3. Economies of scale curve of lithium battery energy storage system (Enel X [63] - 2021).

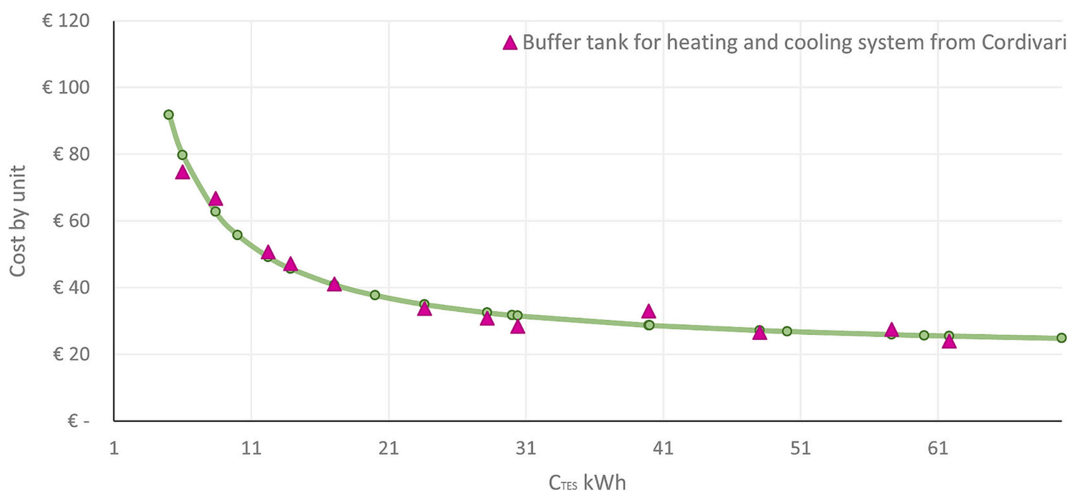

Fig. 4. Economies of scale curve of thermal energy storage (Cordivari [70] - 2022).

Table 4
Italian incentives for energy sharing through two eligible configurations.

	Arera Resolution of August 4, 2020 [74]	Ministerial Decree of September 16, 2020 [75]
Jointly acting renewables self-consumers	not applicable transmission and distribution network charges and extra revenue for avoided network losses	100 €/MWh
Renewable energy community	not applicable transmission and distribution network charges	110 €/MWh

Table 5
General information of the five households in the case studies.

	Node 1	Node 2	Node 3	Node 4	Node 5
Electric load kWh	2304	3294	3898	1506	2334
Heating load kWh	4389	8609	10,761	1050	5852
Cooling load kWh	1390	2719	3398	331	1848
DHW l	56,390	77,035	190,850	38,170	75,740
EV load kWh	1386	1406	1428	1422	1334
Max installable PV kWp	3	10	8	3	3

4.1. Base case

In this scenario, which considers only electricity demand, each household operates independently, installing PV systems according to individual preferences solely to meet their own energy needs. The optimization result (Table 6) clearly shows that installing PV systems without additional incentives is not economically viable. This is primarily because the electricity demand—excluding the electrification of the thermal and transport sectors—is not sufficiently high to justify the investment. As a result, the households would not recover the installation costs, at least in the case under study. This dynamic changes in the subsequent scenarios analyzed, where the inclusion of thermal and transport electrification increases overall energy demand, enhancing the economic feasibility of PV system installations.

4.2. Case 1

We now revisit the same households analyzed in the base case study, extending our analysis beyond electrical loads, to include sector coupling, therefore thermal and mobility sector electrification (smart charging strategy is considered). The households demonstrate diverse energy requirements, encompassing heating, cooling, DHW, and BEVs charging, as outlined in Table 7. By incorporating a broader spectrum of energy demands, we attain a more comprehensive understanding of

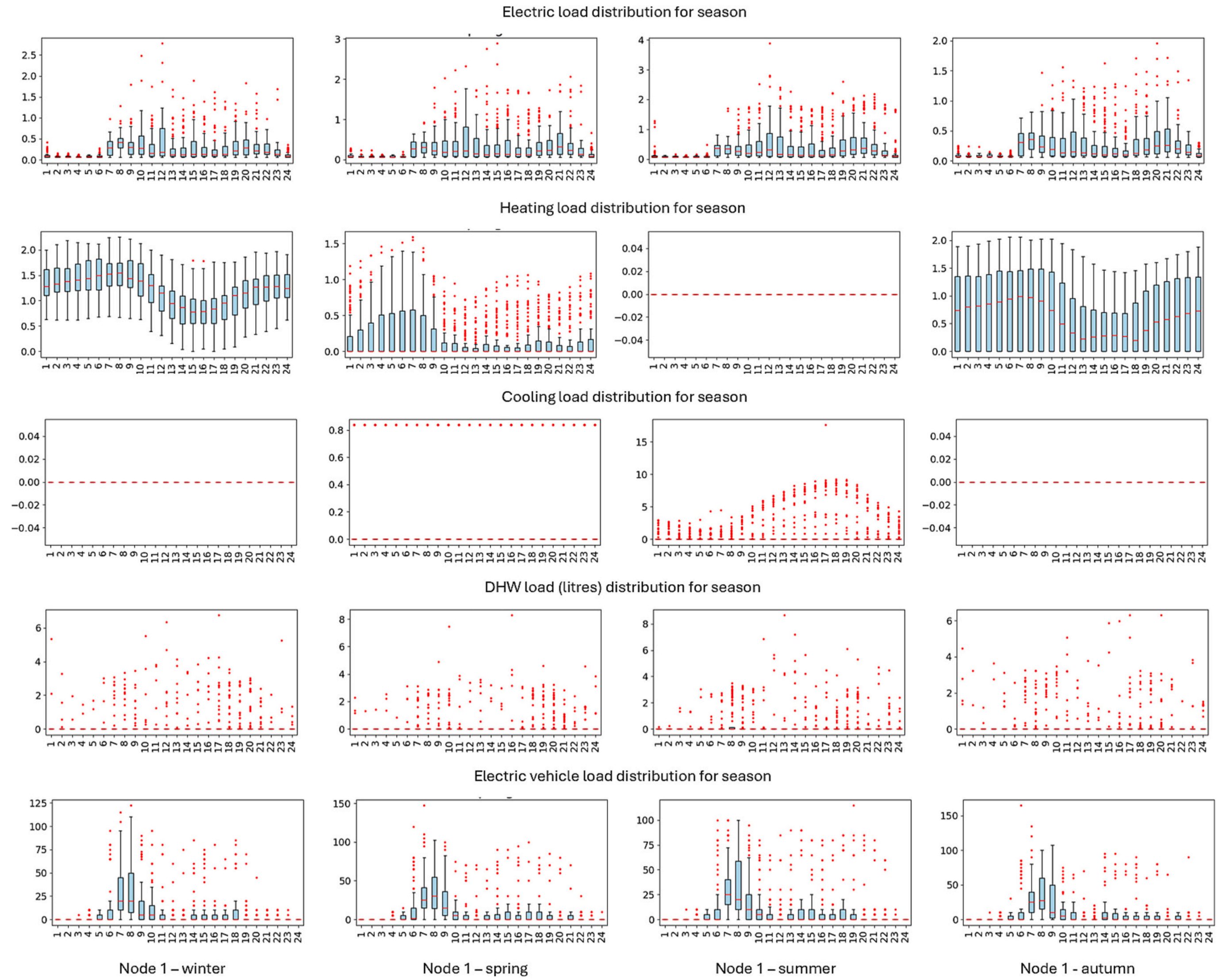

Fig. 5. Load profiles node 1.

Table 6
Base case settings.

	Node 1	Node 2	Node 3	Node 4	Node 5
Optimized PV kW	0	0	0	0	0
Self-consumption	0	0	0	0	0
Self sufficiency	0	0	0	0	0
Shared energy consumption kWh	0	0	0	0	0

Table 7
Case 1 settings.

	Node 1	Node 2	Node 3	Node 4	Node 5
Optimized PV kW	2.2	2.4	2.4	2	2.2
Self-consumption	93 %	97 %	95 %	83 %	96 %
Self sufficiency	46 %	31 %	30 %	58 %	46 %
Shared energy consumption kWh	0	0	0	0	0
Base bill €	991	1426	1779	668	1096
Self-consumption savings €	−463	−436	−534	−388	−506
Sharing incentives €	0	0	0	0	0
Grid feed-in revenue €	−10	−8	−8	−22	−6
Net total €	518	1237	1237	258	584

consumption patterns within each household.

The integration of different sectors, known as sector coupling, contributes to an increase in electrical demand. Consequently, the viability of installing a PV system significantly improves: each user independently installs a PV system with a capacity of around 2 kWp.

The optimization results are depicted in Table 7, while the energy flow data is illustrated in Fig. 6.

Here's a concise breakdown of its economic components:

1. Base Bill: Initial electric energy cost before any adjustments.

2. Self-consumption Savings: Savings achieved through consuming self-generated energy.

3. Sharing Incentives: Benefits from sharing energy resources within the community (if any).

4. Grid Feed-in Revenue: Revenue from feeding excess energy back into the grid from renewable sources.

5. Net Total: The final adjusted electric energy cost, considering all factors.

4.3. Case 2

We now present the results of the base case scenario within the energy community framework, where incentives for energy sharing are anticipated. The results are presented in Table 8, energy flow data are

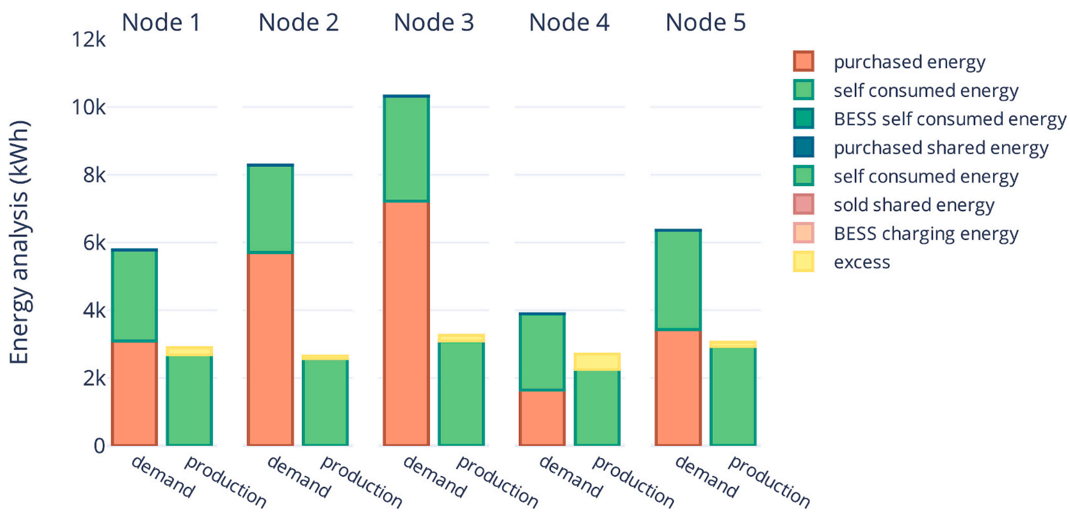

Fig. 6. Electric demand fulfilment and photovoltaic production utilization among users – case 1.

Table 8
Case 2 settings.

	Node 1	Node 2	Node 3	Node 4	Node 5
Optimized PV kW	3	0	3	2.5	3
Self-consumption	77 %	–	84 %	65 %	68 %
Self sufficiency	64 %	–	47 %	68 %	70 %
Shared energy consumption kWh	131	2710	250	53	90
Base bill €	991	1426	1779	668	1096
Self-consumption savings €	−524	0	−580	−394	−560
Sharing incentives €	−58	−160	−54	−60	−58
Grid feed-in revenue €	−48	0	−31	−51	−43
Net total €	361	1266	1114	163	435

shown in Fig. 7.

Despite Node 2 having the highest installable capacity (10 kWp), its energy production at the same capacity is lower, making shared energy utilization more favorable. This user opts not to install their own system, instead relying on the energy shared by other participants within the energy community, each installing approximately 3 kWp. As result of energy sharing, the collective photovoltaic capacity increases: in comparison to the previous scenario, there's roughly a 6 % boost in production. Self-consumption, which was solely physical before, now encompasses both physical and virtual aspects, rising from 39 % to 44 %.

Considering the collective savings for all users, it's evident that, after factoring in savings and incentives, they pay approximately 7 % less annually, translating to over €240 less than the previous scenario, and accumulating to a total annual savings surpassing €2600. Although the initial investment is marginally higher, the return on investment occurs approximately 2 years earlier.

For simplicity, the incentive derived from shared energy within the energy community is allocated among users based on their contribution to energy sharing. Thus, those who contribute more receive a greater incentive. It is worth noting that this allocation method may not necessarily be the fairest, but for the purposes of this paper, it suffices.

4.4. Case 3

In this scenario, we evaluate the impact of the economy of scale on the energy community. The results are presented in Table 9, while, for a comprehensive view of the energy flows and costs in this scenario, refer to Fig. 8.

A first evident qualitative result is that the installed capacity does not change significantly compared to Case 2, but is distributed differently among users. Notably, only 2 out of 5 users install systems, in contrast to the previous case where 4 out of 5 users do so.

Fewer installations results in roughly 4 % less production. While self-consumption, both physical and virtual, reaches approximately 62 %,

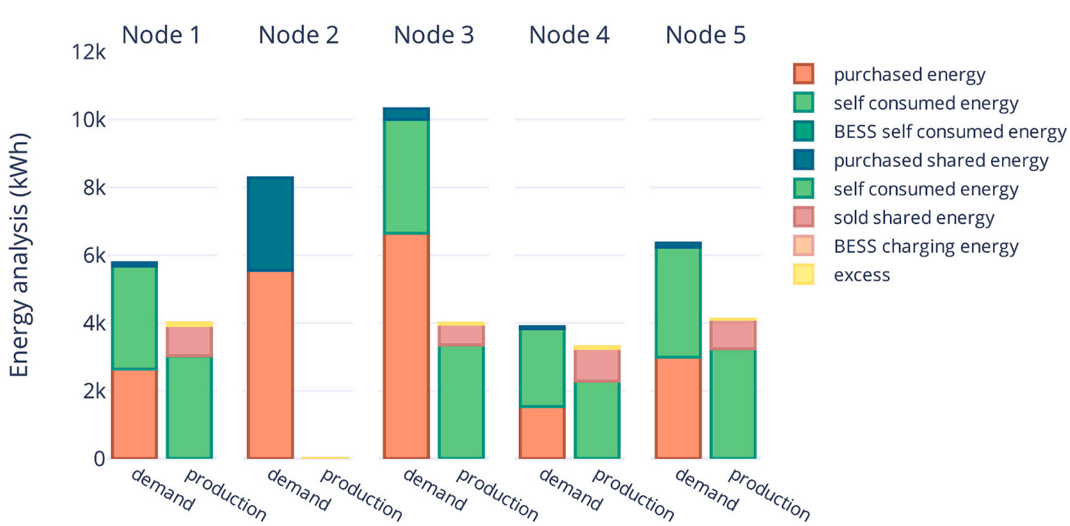

Fig. 7. Electric demand fulfilment and photovoltaic production utilization among users – case 2.

Table 9
Case 3 settings.

	Node 1	Node 2	Node 3	Node 4	Node 5
Optimized PV kW	0	0	8	0	3
Self-consumption	–	–	40 %	–	80 %
Self sufficiency	–	–	42 %	–	52 %
Shared energy consumption kWh	2370	2890	18	1734	123
Base bill €	991	1426	1779	668	1096
Self-consumption savings €	0	0	−744	0	−566
Sharing incentives €	−139	−170	−372	−102	−55
Grid feed-in revenue €	0	0	−322	0	−41
Net total €	852	1256	341	558	434

indicating a 40 % increase compared to case 2.

The optimization results (Table 9) highlight the advantages of leveraging economies of scale. Despite the greater savings from self-consumption compared to incentives for shared energy, the analysis suggests that installing a single, larger PV system and sharing the energy is more advantageous than opting for multiple smaller systems for self-consumption.

While savings appear to be lower than the previous scenario by about €100 per year, the overall investment costs, factoring in economies of scale, are approximately 33 % lower, enabling a return approximately 5 years earlier.

4.5. Discussion

Fig. 9 graphically summarizes the optimization results for the expansion capacity across the four case studies, illustrating member loads (circular elements) and PV capacity (square elements), with arrows representing admissible flows of virtually shared energy. The size of each element is proportional to the load or system capacity.

The 100 % stacked column graph in Fig. 10 offers a clear visual representation, aiding in the comparison of data categories and trend identification: initially, PV systems may not seem financially viable (base case), but as we consider diverse energy demands, their appeal grows due to increased electrical demand (case 1). Participating in energy communities enhances resource optimization and self-sufficiency (case 2). Additionally, larger, shared PV systems, leveraging economies of scale, prove superior to individual installations (case 3).

5. Limitations of the study

It is essential to emphasize that the study does not aim to provide definitive or universally applicable results. Instead, its primary value lies in its innovative methodology and its adaptability to various configurations when integrated with real-world data, which inherently carries uncertainties. Consequently, the conclusions drawn from this study are contingent on the hypothetical scenario considered and should not be

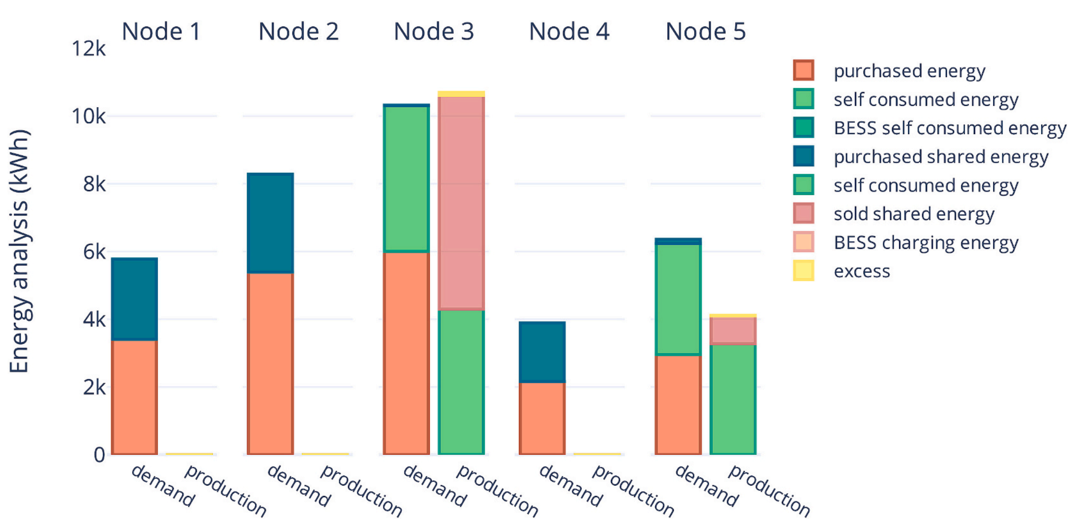

Fig. 8. Electric demand fulfilment and photovoltaic production utilization among users – case 3.

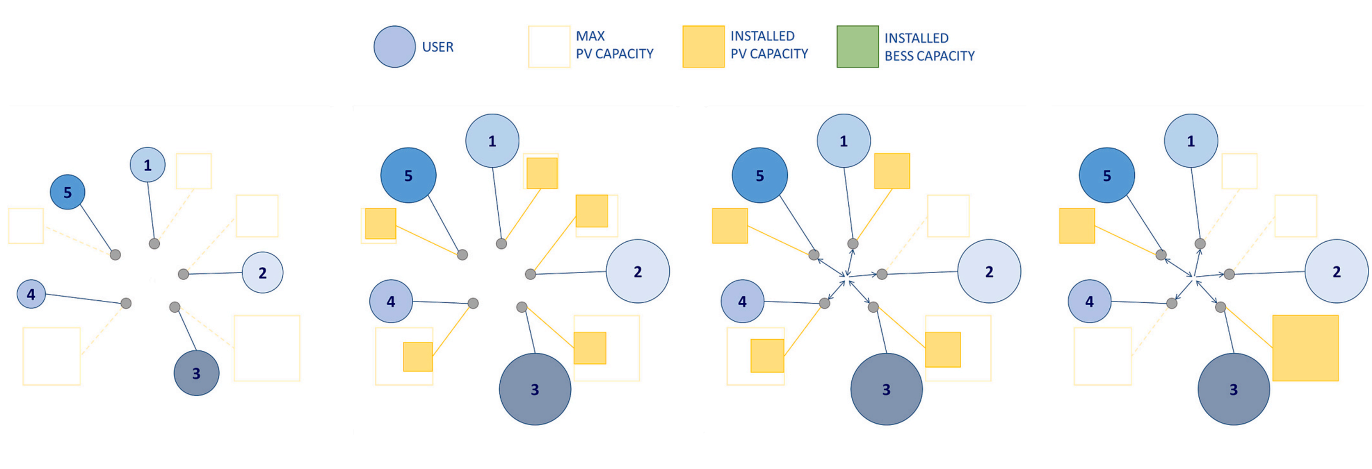

Fig. 9. Expansion capacity optimization across cases. Node sizes are proportional to electricity demand and PV/BESS capacities.

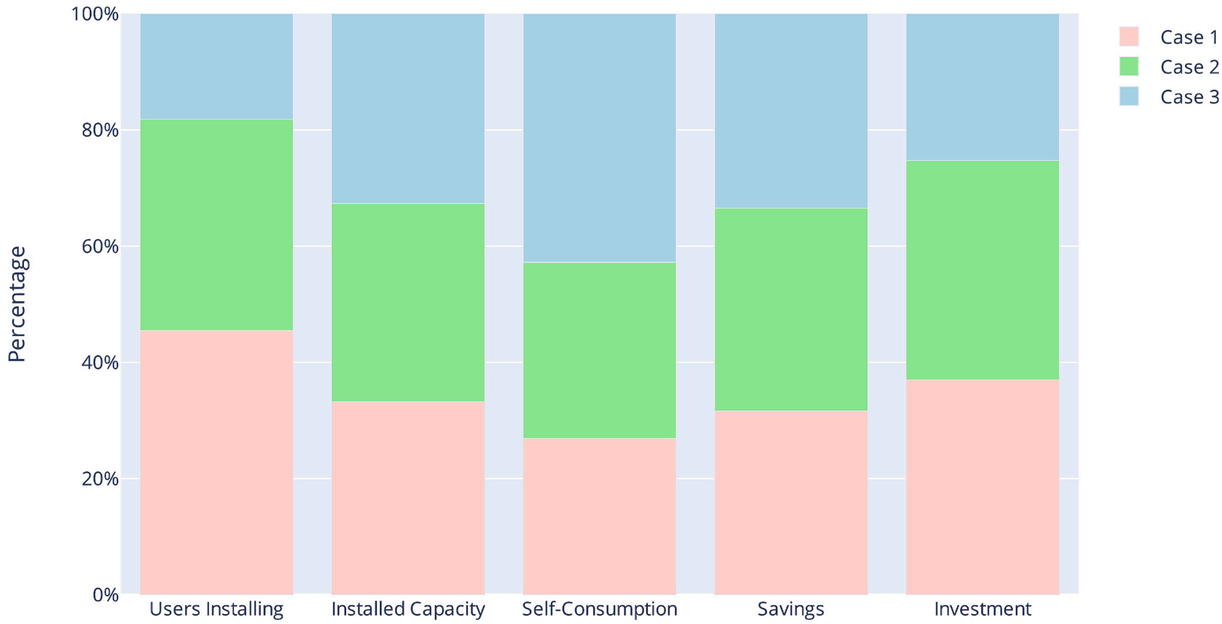

Fig. 10. Comparative analysis of photovoltaic system viability and community energy benefits across cases.

interpreted as absolute.

Specifically, synthetic demand profiles for electricity, heating, and transportation were utilized, and assumptions were applied. As a result, the data does not fully represent the actual consumption patterns of a real community. Additionally, the community analyzed is hypothetical, and its size was determined based on assumptions designed to simplify the model's presentation, while ensuring compliance with regulatory frameworks on energy community configurations.

It is also important to acknowledge that other critical data used in this analysis—such as investment costs (CAPEX), operational expenditures (OPEX), electricity prices, and other economic variables—were sourced from references without conducting a sensitivity analysis, as this was beyond the scope of the paper. Despite these limitations, the study remains an innovative tool for evaluating the feasibility of shared self-consumption configurations and assessing the benefits of sector integration and the implemented features.

6. Conclusions

This study provides valuable insights into the effectiveness of Renewable Energy Communities in promoting energy sharing while considering economic, social, and environmental dimensions. By developing a comprehensive simulation model tailored to the research objectives, we demonstrate the potential of RECs in enhancing sustainability and cost-efficiency within communities.

Our model, informed by existing frameworks and methodologies, enables to evaluate different energy optimization strategies and their impacts on economic expenditures. Through a bottom-up approach and linear programming techniques, we integrate multiple energy sectors, including electricity, heating, cooling, DHW, and transportation, into a unified framework. This approach highlights the importance of sector coupling and collaborative energy sharing in achieving significant cost savings and sustainability benefits.

Our study, set in a hypothetical small Italian community, sheds light on the economic advantages of integrating various energy demands – thermal, transportation, and electrical – within RECs. We observe noteworthy economic savings for participating households, with an average annual reduction exceeding €500 compared to base case scenarios. Moreover, by leveraging economies of scale through shared installations, households within the energy community framework achieved additional average annual savings of approximately €240, totaling over €2600 per year.

Optimizing energy communities to fully exploit economies of scale emerges as a crucial strategy for achieving even greater savings and faster returns on investment. By demonstrating the economic viability of renewable energy installations, particularly PV systems, within RECs, our study underscores the significance of collaborative energy-sharing models in advancing both energy efficiency and sustainability objectives.

Our conclusions highlight the pivotal role of integrating diverse energy sectors, leading to enhanced economic feasibility, especially concerning PV system installations. Furthermore, our analysis underscores the substantial advantages of energy communities, with significant reductions in household expenses compared to scenarios of independent operation. Lastly, the implications of economies of scale are evident, with our study demonstrating lower overall investment costs and expedited returns on investment through optimized energy community projects.

The implications of our research extend to policymakers, industry stakeholders, and communities interested in promoting renewable energy initiatives. By incentivizing participation in RECs and facilitating investment optimization, policymakers can accelerate the transition towards a more resilient and sustainable energy future. Furthermore, our study emphasizes the importance of considering user convenience and engagement in REC design and implementation, ensuring that communities can fully realize the economic and environmental benefits of energy sharing.

Future developments may involve integrating methodologies like Multi-Criteria Decision Analysis into the model. While previous research has explored this integration, none have applied it to the analysis of RECs, where economic factors intersect with additional co-benefits and impacts. Exploring this direction presents both challenges and opportunities for advancing REC decision support systems.

CRediT authorship contribution statement

Valeria Casalicchio: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Grazia Barchi:** Writing – review & editing. **Francesca Calabria:** Writing – original draft, Software, Investigation, Data curation. **Giampaolo Manzolini:** Writing – review & editing, Supervision, Conceptualization. **Matteo Giacomo Prina:** Writing – review & editing, Supervision, Conceptualization. **David Moser:** Supervision, Conceptualization.

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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Appendix A. Appendix

This appendix presents the annual demand profiles for each sector (electricity, heating, cooling, domestic hot water, and electric vehicles) by season, using box plots to illustrate their trends.

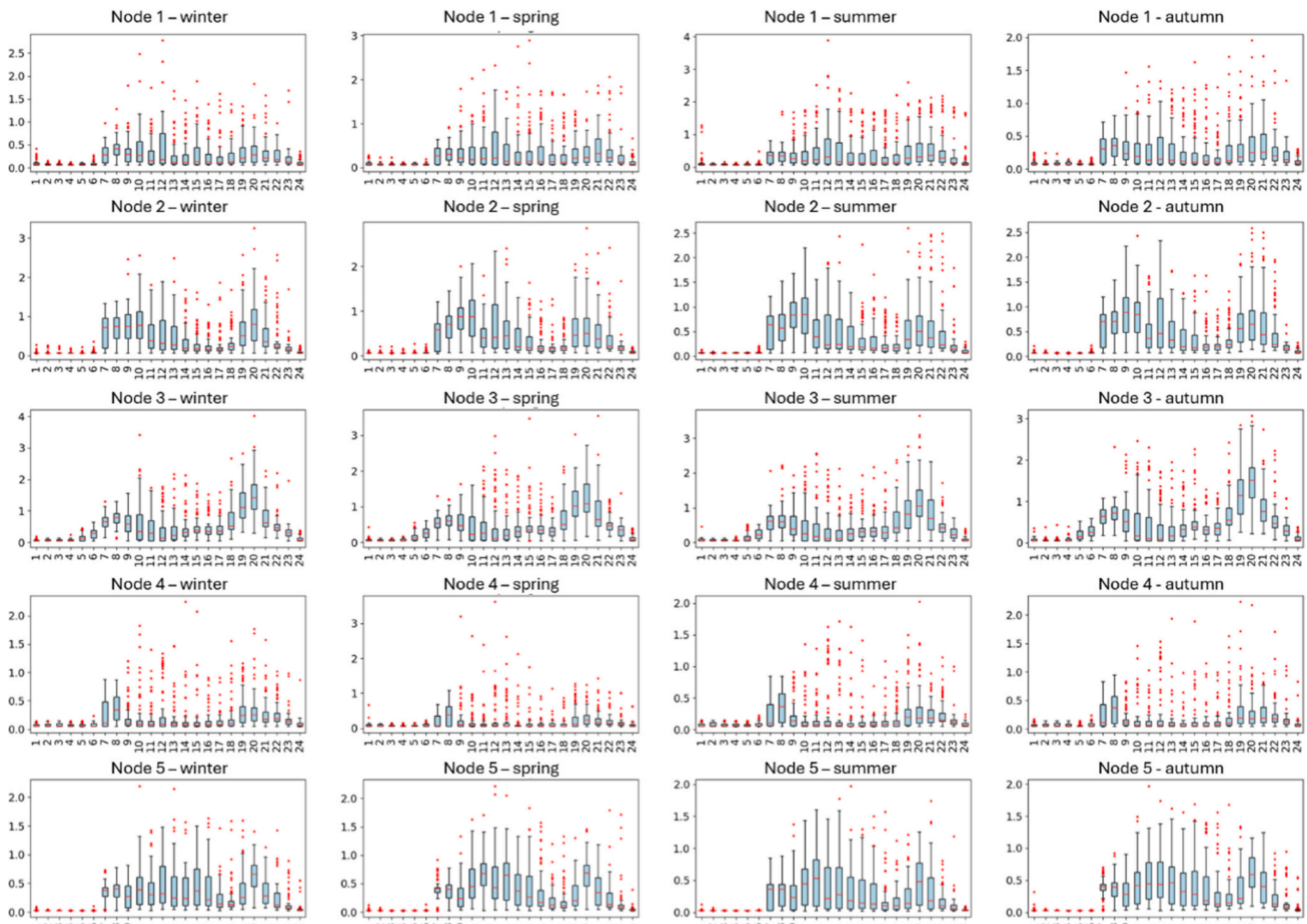

Fig. 11. Electric load profiles for season.

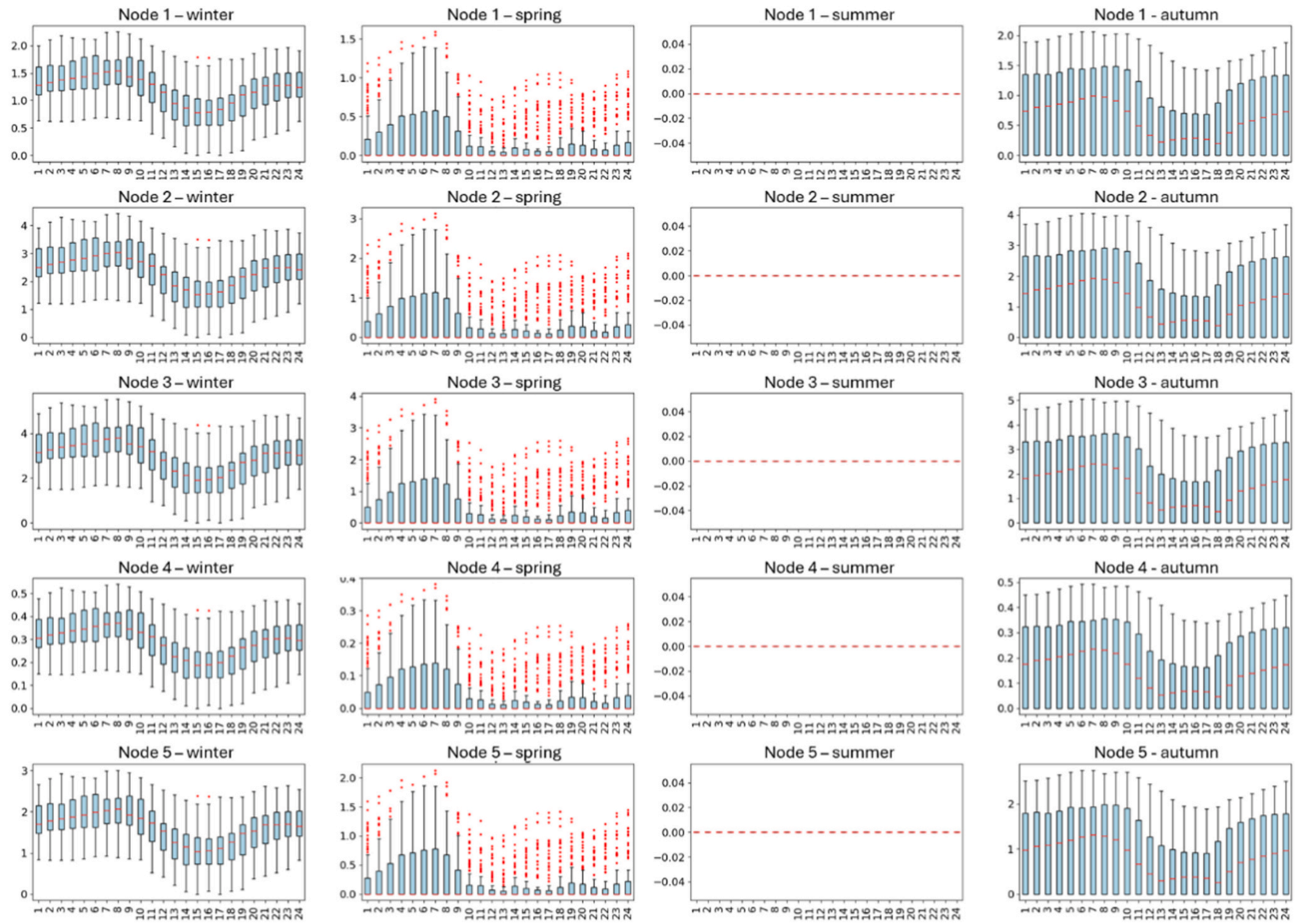

Fig. 12. Heating load profiles for season.

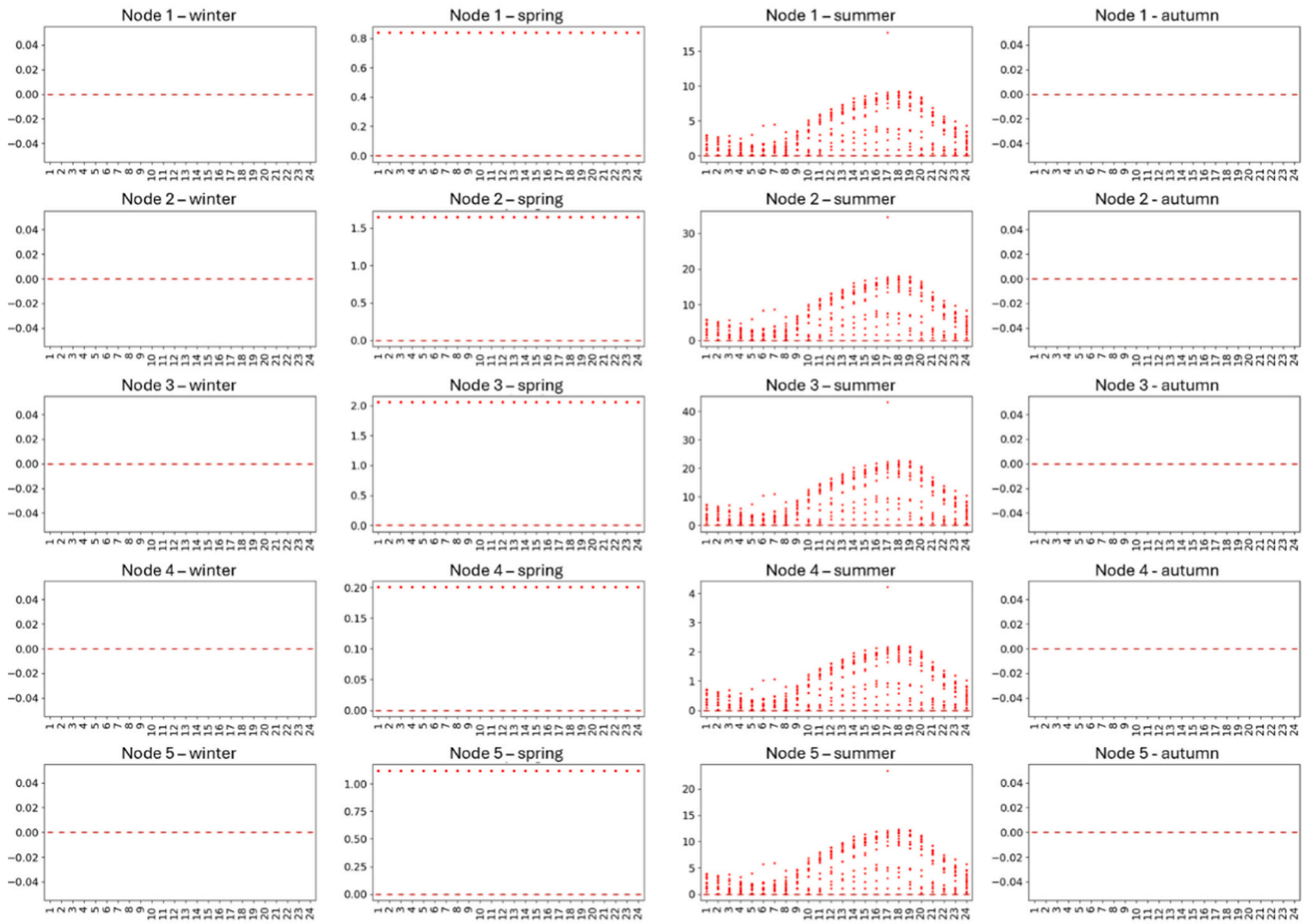

Fig. 13. Cooling load profiles for season.

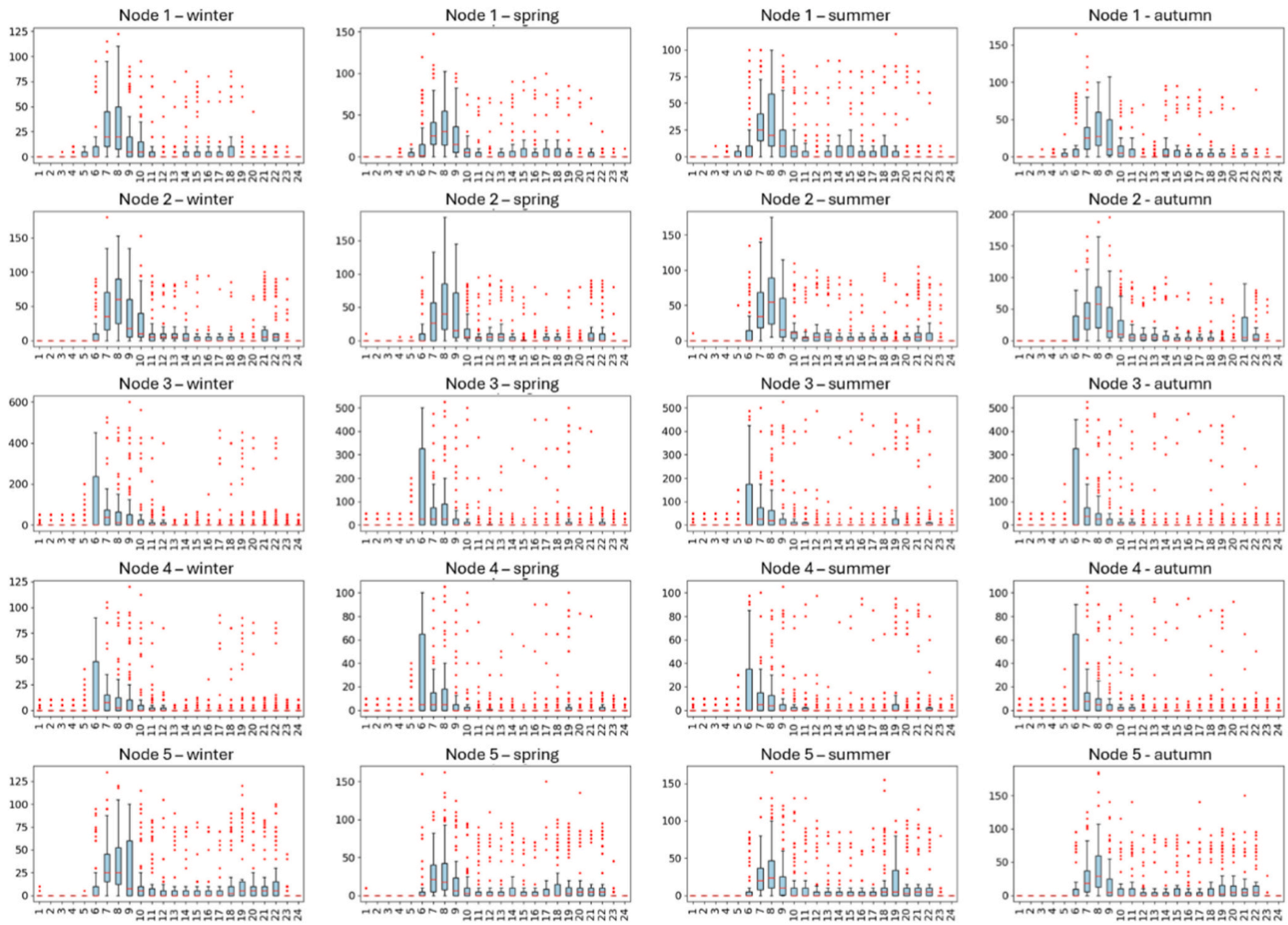

Fig. 14. DHW load (liters) profiles for season.

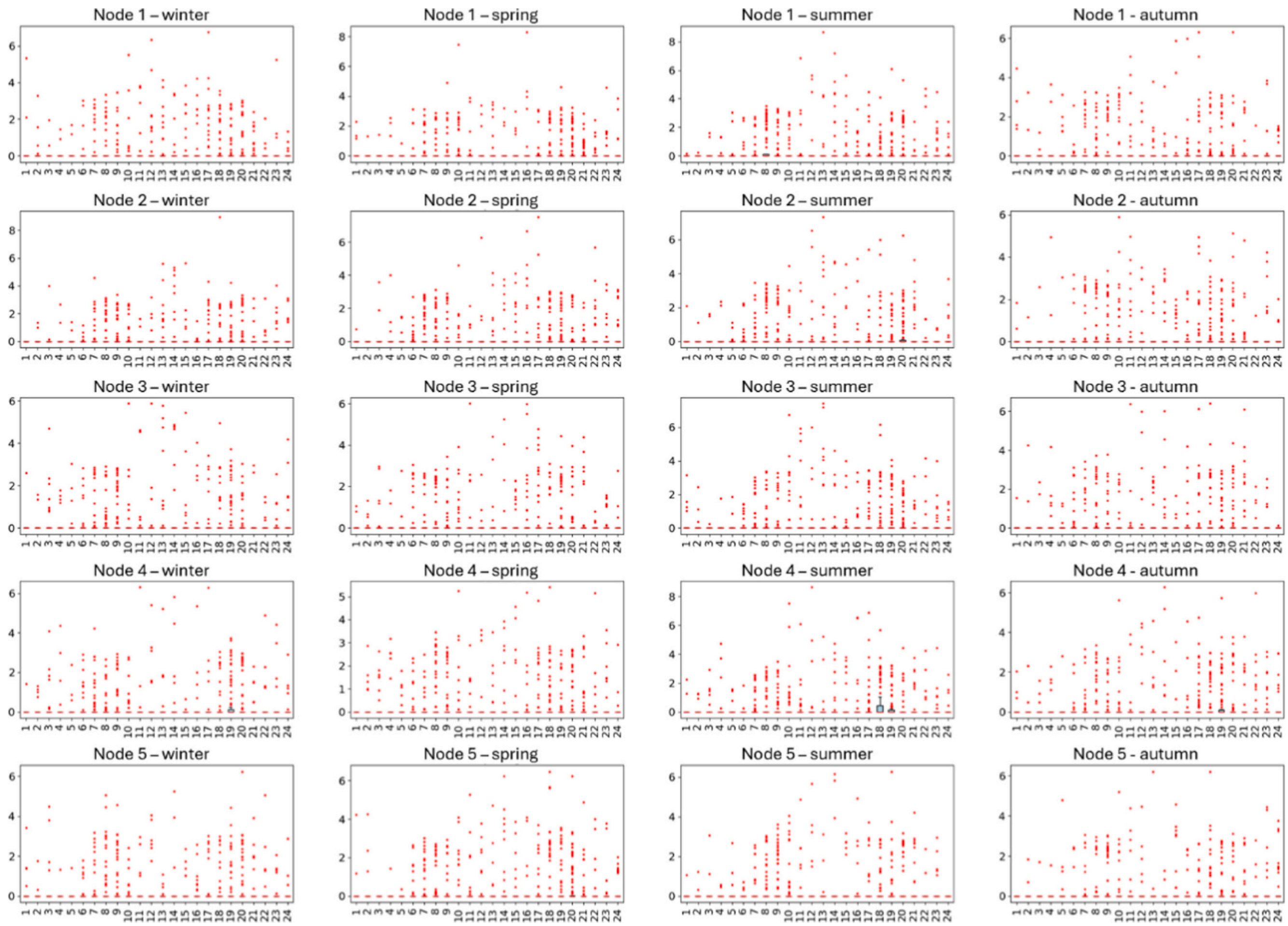

Fig. 15. Electric vehicle load profiles for season.

Data availability

Data will be made available on request.

References

[1] European Commission. Transport and the green deal' [Online]. Available: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal/transport-and-green-deal_en; 2025.

[2] European Environment Agency. Greenhouse gas emissions from energy use in buildings in Europe [Online]. Available, https://www.eea.europa.eu/en/analysis/indicators/greenhouse-gas-emissions-from-energy; 2025.

[3] European Commission. EU strategy on energy system integration [Online]. Available: https://energy.ec.europa.eu/topics/energy-systems-integration/eu-strategy-energy-system-integration_en?etransnolive=1; 2025.

[4] European Commission. Energy communities repository [Online]. Available: https://energy.ec.europa.eu/topics/markets-and-consumers/energy-consumers-and-prosumers/energy-communities/energy-communities-repository-products_en; 2022.

[5] European Commission. In focus: energy communities to transform the EU's energy system - European Commission [Online]. Available: https://energy.ec.europa.eu/news/focus-energy-communities-transform-eus-energy-system-2022-12-13_en; 2022.

[6] Prina MG, Manzolini G, Moser D, Nastasi B, Sparber W. Classification and challenges of bottom-up energy system models - a review. Renew Sust Energ Rev Sep. 2020;vol. 129:109917. https://doi.org/10.1016/j.rser.2020.109917.

[7] Cielo A, Margiaria P, Lazzeroni P, Mariuzzo I, Repetto M. Renewable energy communities business models under the 2020 Italian regulation. J Clean Prod Sep. 2021;vol. 316:128217. https://doi.org/10.1016/j.jclepro.2021.128217.

[8] Minuto FD, Lazzeroni P, Borchiellini R, Olivero S, Bottaccioli L, Lanzini A. Modeling technology retrofit scenarios for the conversion of condominium into an energy community: an Italian case study. J Clean Prod 2021;282:124536. https://doi.org/10.1016/j.jclepro.2020.124536.

[9] Coletta G, Pellegrino L. Optimal design of energy communities in the Italian regulatory framework. In: In *2021 AEIT international annual conference (AEIT)*. Milan, Italy: IEEE; Oct. 2021. p. 1–6. https://doi.org/10.23919/AEIT53387.2021.9626852.

[10] Cutore E, Volpe R, Sgroi R, Fichera A. Energy management and sustainability assessment of renewable energy communities: the Italian context. Energy Convers Manag Feb. 2023;vol. 278:116713. https://doi.org/10.1016/j.enconman.2023.116713.

[11] Pontes Luz G, Amaro R, Silva E. Modeling energy communities with collective photovoltaic self-consumption: synergies between a Small City and a winery in Portugal. Energies Jan. 2021;vol. 14(2):323. https://doi.org/10.3390/en14020323.

[12] Karunathilake H, Hewage K, Prabatha T, Ruparathna R, Sadiq R. Project deployment strategies for community renewable energy: a dynamic multi-period planning approach. Renew Energy Jun. 2020;vol. 152:237–58. https://doi.org/10.1016/j.renene.2020.01.045.

[13] Cosic A, Stadler M, Mansoor M, Zellinger M. Mixed-integer linear programming based optimization strategies for renewable energy communities. Energy Dec. 2021;vol. 237:121559. https://doi.org/10.1016/j.energy.2021.121559.

[14] Alonso À, De La Hoz J, Martín H, Coronas S, Matas J. Individual vs. community: economic assessment of energy management systems under different regulatory frameworks. Energies Jan. 2021;vol. 14(3):676. https://doi.org/10.3390/en14030676.

[15] Rikkas R, Lahdelma R. Energy supply and storage optimization for mixed-type buildings. Energy Sep. 2021;vol. 231:120839. https://doi.org/10.1016/j.energy.2021.120839.

[16] Kotarela F, Kyritsis A, Papanikolaou N. On the implementation of the nearly zero energy building concept for jointly acting renewables self-consumers in Mediterranean climate conditions. Energies Feb. 2020;vol. 13(5):1032. https://doi.org/10.3390/en13051032.

[17] Gjorgievski VZ, Cundeva S, Markovska Natasa, Georghiou GE. Virtual net-billing: a fair energy sharing method for collective self-consumption. 2021. https://doi.org/10.13140/RG.2.2.21529.34406.

[18] Perger T, Wachter L, Fleischhacker A, Auer H. PV sharing in local communities: peer-to-peer trading under consideration of the prosumers' willingness-to-pay. Sustain Cities Soc Mar. 2021;vol. 66:102634. https://doi.org/10.1016/j.scs.2020.102634.
[19] Zatti M, Moncecchi M, Gabba M, Chiesa A, Bovera F, Merlo M. Energy communities design optimization in the Italian framework. Appl Sci Jun. 2021;vol. 11(11):5218. https://doi.org/10.3390/app11115218.
[20] Fioriti D, Frangioni A, Poli D. Optimal sizing of energy communities with fair revenue sharing and exit clauses: value, role and business model of aggregators and users. Appl Energy Oct. 2021;vol. 299:117328. https://doi.org/10.1016/j.apenergy.2021.117328.
[21] Fleischhacker A, Lettner G, Schwabeneder D, Auer H. Portfolio optimization of energy communities to meet reductions in costs and emissions. Energy Apr. 2019;vol. 173:1092–105. https://doi.org/10.1016/j.energy.2019.02.104.
[22] Radl J, Fleischhacker A, Revheim FH, Lettner G, Auer H. Comparison of profitability of PV electricity sharing in renewable energy communities in selected European countries. Energies Sep. 2020;vol. 13(19):5007. https://doi.org/10.3390/en13195007.
[23] Wang Y, et al. Modelling and analysis of a two-level incentive mechanism based peer-to-peer energy sharing community. Int J Electr Power Energy Syst Dec. 2021;vol. 133:107202. https://doi.org/10.1016/j.ijepes.2021.107202.
[24] Bashir AA, Lund A, Pourakbari-Kasmaei M, Lehtonen M. Optimizing power and heat sector coupling for the implementation of carbon-free communities. Energies Mar. 2021;vol. 14(7):1911. https://doi.org/10.3390/en14071911.
[25] Celik B, Roche R, Bouquain D, Miraoui A. Coordinated neighborhood energy sharing using game theory and multi-agent systems. In: in *2017 IEEE Manchester PowerTech*. Manchester, United Kingdom: IEEE; Jun. 2017. p. 1–6. https://doi.org/10.1109/PTC.2017.7980820.
[26] Chronis A-G, Palaiogiannis F, Kouveliotis-Lysikatos I, Kotsampopoulos P, Hatziargyriou N. Photovoltaics enabling sustainable energy communities: technological drivers and emerging markets. Energies Mar. 2021;vol. 14(7):1862. https://doi.org/10.3390/en14071862.
[27] Secchi M, Barchi G, Macii D, Moser D, Petri D. Multi-objective battery sizing optimisation for renewable energy communities with distribution-level constraints: a prosumer-driven perspective. Appl Energy Sep. 2021;vol. 297:117171. https://doi.org/10.1016/j.apenergy.2021.117171.
[28] Alnaser SW, Althaher SZ, Long C, Zhou Y, Wu J. Residential community with PV and batteries: reserve provision under grid constraints. Int J Electr Power Energy Syst Jul. 2020;vol. 119:105856. https://doi.org/10.1016/j.ijepes.2020.105856.
[29] Reis IFG, Gonçalves I, Lopes MAR, Antunes CH. A multi-agent system approach to exploit demand-side flexibility in an energy community. Util Policy Dec. 2020;vol. 67:101114. https://doi.org/10.1016/j.jup.2020.101114.
[30] Di Lorenzo G, Martirano L, Araneo R, Petrone G. Modeling and Design of a Residential Energy Community with PV sharing. In: In *2020 IEEE international conference on environment and electrical engineering and 2020 IEEE industrial and commercial power systems Europe (EEEIC / I&CPS Europe)*. Madrid, Spain: IEEE; Jun. 2020. p. 1–5. https://doi.org/10.1109/EEEIC/ICPSEurope49358.2020.9160650.
[31] Volpato G, Carraro G, Cont M, Danieli P, Rech S, Lazzaretto A. General guidelines for the optimal economic aggregation of prosumers in energy communities. Energy Nov. 2022;vol. 258:124800. https://doi.org/10.1016/j.energy.2022.124800.
[32] Silvestre MLD, Montana F, Sanseverino ER, Sciumè G, Zizzo G. An algorithm for renewable energy communities designing by maximizing shared energy. In: In *2023 AEIT international annual conference (AEIT)*. Rome, Italy: IEEE; Oct. 2023. p. 1–6. https://doi.org/10.23919/AEIT60520.2023.10330365.
[33] Elomari Y, Mateu C, Marín-Genescà M, Boer D. A data-driven framework for designing a renewable energy community based on the integration of machine learning model with life cycle assessment and life cycle cost parameters. Appl Energy Mar. 2024;vol. 358:122619. https://doi.org/10.1016/j.apenergy.2024.122619.
[34] Minelli F, Ciriello I, Minichiello F, D'Agostino D. From net zero energy buildings to an energy sharing model - the role of NZEBs in renewable energy communities. Renew Energy Mar. 2024;vol. 223:120110. https://doi.org/10.1016/j.renene.2024.120110.
[35] Casalicchio V, Manzolini G, Prina MG, Moser D. Optimal allocation method for a fair distribution of the benefits in an energy community. Sol RRL May 2022;vol. 6(5):2100473. https://doi.org/10.1002/solr.202100473.
[36] Casalicchio V, Manzolini G, Prina MG, Moser D. From investment optimization to fair benefit distribution in renewable energy community modelling. Appl Energy Mar. 2022;vol. 310:118447. https://doi.org/10.1016/j.apenergy.2021.118447.
[37] Krien U, Schönfeldt P, Launer J, Hilpert S, Kaldemeyer C, Pleßmann G. Oemof. Solph—a model generator for linear and mixed-integer linear optimisation of energy systems. Soft Impacts Nov. 2020;vol. 6:100028. https://doi.org/10.1016/j.simpa.2020.100028.
[38] Pflugradt N, Stenzel P, Kotzur L, Stolten D. LoadProfileGenerator: an agent-based BehaviorSimulation for generating residential load profiles. JOSS Mar. 2022;vol. 7(71):3574. https://doi.org/10.21105/joss.03574.
[39] Gils HC. Balancing of intermittent renewable power generation by demand response and thermal energy storage. 2015. https://doi.org/10.18419/OPUS-6888.
[40] Bloess A, Schill W-P, Zerrahn A. Power-to-heat for renewable energy integration: a review of technologies, modeling approaches, and flexibility potentials. Appl Energy Feb. 2018;vol. 212:1611–26. https://doi.org/10.1016/j.apenergy.2017.12.073.
[41] UNI Ente Nazionale Italiano di Unificazione. UNI EN ISO 7730 Ergonomia degli ambienti termici - determinazione analitica e interpretazione del benessere termico mediante il calcolo degli indici PMV e PPD e dei criteri di benessere termico locale. 2006.
[42] Karakoyun Y, Acikgoz O, Yumurtacı Z, Dalkilic AS. An experimental investigation on heat transfer characteristics arising over an underfloor cooling system exposed to different radiant heating loads through walls. Appl Therm Eng Jan. 2020;vol. 164:114517. https://doi.org/10.1016/j.applthermaleng.2019.114517.
[43] UNI Ente Nazionale Italiano di Unificazione. UNI EN 15316–4-2:2018 Prestazione energetica degli edifici - Metodo per il calcolo delle richieste di energia e delle efficienze del sistema - Parte 4–2: Sistemi di generazione per il riscaldamento degli ambienti, pompe di calore Moduli M3–8-2, M8–8-2. 2018.
[44] Caleffi. Produzione di acqua calda ad accumulo. Idraulica; 1999.
[45] Raccanello J, Rech S, Lazzaretto A. Simplified dynamic modeling of single-tank thermal energy storage systems. Energy Sep. 2019;vol. 182:1154–72. https://doi.org/10.1016/j.energy.2019.06.088.
[46] Secchi M, Barchi G, Macii D, Petri D. Smart electric vehicles charging with centralised vehicle-to-grid capability for net-load variance minimisation under increasing EV and PV penetration levels. Sustain Energy Grids Net Sep. 2023;vol. 35:101120. https://doi.org/10.1016/j.segan.2023.101120.
[47] Jadoun VK, Sharma N, Jha P, Malik JNSH, Márquez FP Garcia. Optimal scheduling of dynamic pricing based V2G and G2V operation in microgrid using improved elephant herding optimization. Sustainability Jul. 2021;vol. 13(14):7551. https://doi.org/10.3390/su13147551.
[48] Shi S, et al. Two-step intelligent control for a green flexible EV energy supply station oriented to dual carbon targets. Processes Oct. 2021;vol. 9(11):1918. https://doi.org/10.3390/pr9111918.
[49] García-Villalobos J, Zamora I, Knezović K, Marinelli M. Multi-objective optimization control of plug-in electric vehicles in low voltage distribution networks. Appl Energy Oct. 2016;vol. 180:155–68. https://doi.org/10.1016/j.apenergy.2016.07.110.
[50] Englberger S, Abo Gamra K, Tepe B, Schreiber M, Jossen A, Hesse H. Electric vehicle multi-use: optimizing multiple value streams using mobile storage systems in a vehicle-to-grid context. Appl Energy Dec. 2021;vol. 304:117862. https://doi.org/10.1016/j.apenergy.2021.117862.
[51] Mangipinto A, Lombardi F, Sanvito FD, Pavičević M, Quoilin S, Colombo E. Impact of mass-scale deployment of electric vehicles and benefits of smart charging across all European countries. Appl Energy Apr. 2022;vol. 312:118676. https://doi.org/10.1016/j.apenergy.2022.118676.
[52] European Commission. CM SAF solar radiation [Online]. Available: https://joint-research-centre.ec.europa.eu/photovoltaic-geographical-information-system-pvgis/pvgis-data-download/cm-saf-solar-radiation_en; 2025.
[53] Gazzetta Ufficiale Della Repubblica Italiana. Decreto legislativo 8 novembre 2021. *n. 199*. Accessed: Apr. 15. [Online]. Available, https://www.gazzettaufficiale.it/eli/id/2021/11/30/21G00214/sg; 2024.
[54] Ministero dello Sviluppo Economico. Decreto interministeriale 26 giugno 2015 - Adeguamento linee guida nazionali per la certificazione energetica degli edifici [Online]. Available, https://www.mimit.gov.it/index.php/it/normativa/decreti-interministeriali/decreto-interministeriale-26-giugno-2015-adeguamento-linee-guida-nazionali-per-la-certificazione-energetica-degli-edifici; 2015.
[55] Gazzetta Ufficiale Della Repubblica Italiana. Decreto del presidente della repubblica. 16 Aprile. *N. 74*. Accessed: Apr. 15, 2024. [Online]. Available, https://www.gazzettaufficiale.it/eli/id/2013/06/27/13G00114/sg; 2013.
[56] UNI Ente Italiano di Normazione. UNI 9182:2014 - Impianti di alimentazione e distribuzione d'acqua fredda e calda - Progettazione, installazione e collaudo. Feb. 20. [Online]. Available: https://store.uni.com/uni-9182-2014; 2014.
[57] Centi G, Iatauro D, Morigoni S, Romeo C, Signoretti P, Terrinoni L. 'Valutazione delle prestazioni energetiche (EP) negli edifici nZEB', ENEA, Report RdS/PAR2016/264. 2017.
[58] Eurostat. - Passenger mobility statistics [Online]. Available, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Passenger_mobility_statistics; 2021.
[59] De Cauwer C, Maarten M, Heyvaert S, Coosemans T, Van Mierlo J. Electric vehicle use and energy consumption based on Realworld electric vehicle Fleet trip and charge data and its impact on existing EV research models. WEVJ Sep. 2015;vol. 7(3):436–46. https://doi.org/10.3390/wevj7030436.
[60] EV Database. EV database. Accessed: Apr15; 2024 [Online]. Available: https://ev-database.org/.
[61] Fachrizal R, Ramadhani UH, Munkhammar J, Widén J. Combined PV–EV hosting capacity assessment for a residential LV distribution grid with smart EV charging and PV curtailment. Sustain Energy Grids Net Jun. 2021;vol. 26:100445. https://doi.org/10.1016/j.segan.2021.100445.
[62] Pannelli Fotovoltaici | Enel X Store Italy. Enel X store master. Accessed: Apr15; 2024 [Online]. Available: https://www.enelxstore.com/it/it/prodotti/fotovoltaico/pannelli-fotovoltaici.
[63] Batterie di Accumulo Per Fotovoltaico | Enel X Store Italy. Enel X store master. Accessed: Apr. 15. [Online]. Available, https://www.enelxstore.com/it/it/prodotti/fotovoltaico/batterie-accumulo-fotovoltaico; 2024.
[64] IRENA. Renewable power generation costs in 2020 [Online]. Available, https://www.irena.org/publications/2021/Jun/Renewable-Power-Costs-in-2020; 2021.
[65] Veronese E, Prina MG, Berizzi A, Moser D, Manzolini G. Costs of utility-scale photovoltaic systems integration in the future Italian energy scenarios. Prog Photovolt Jul. 2021;vol. 29(7):786–801. https://doi.org/10.1002/pip.3382.
[66] Jnnr, et al. Oemof/oemof-thermal: Mere maintenance. Nov. 15. 2021. https://doi.org/10.5281/ZENODO.3606384 [object Object].

[67] Patteeuw D, Helsen L. Combined design and control optimization of residential heating systems in a smart-grid context. Energ Build Dec. 2016;vol. 133:640–57. https://doi.org/10.1016/j.enbuild.2016.09.030.
[68] European Association for Storage of Energy. Thermal energy storage [Online]. Available, https://ease-storage.eu/publication/thermal-energy-storage/; 2016.
[69] Cordivari. Informazioni tecniche - accumulo acqua calda sanitaria [Online]. Available, https://www.cordivari.it/prodotto/vaso-inerziale/; 2025.
[70] Cordivari. Catalogo bollitori e termoaccumulatori [Online]. Available, https://www.cordivari.it/area-download/; 2018.
[71] Arera. Condizioni economiche per i clienti del mercato tutelato [Online]. Available, https://www.arera.it/area-operatori/prezzi-e-tariffe/condizioni-economiche-per-i-clienti-del-mercato-tutelato; 2025.
[72] GME - Gestore dei Mercati Energetici SpA [Online]. Available, https://www.mercatoelettrico.org/it/; 2025.
[73] Ministry of Environment and Energy Security. Energy and mining analysis and statistics - annual fuel prices [Online]. Available, https://dgsaie.mise.gov.it/prezzi_carburanti_annuali.php?lang=en_US; 2025.
[74] Arera. Delibera 318/2020/R/eel [Online]. Available, https://www.arera.it/atti-e-provvedimenti/dettaglio/20/318-20; 2020.
[75] Ministero dello Sviluppo Economico. Decreto ministeriale 16 settembre 2020 [Online]. Available, https://www.gazzettaufficiale.it/eli/id/2020/11/16/20A06224/sg; 2020.