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Scenario analysis for renewable energy communities through advanced co-simulation infrastructure

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HIGHLIGHTS

- Novel co-simulation framework for Renewable Energy Communities.
- Supports scalable simulations with over 200 buildings and year-long periods.
- Combines real scenario data with high-fidelity physical energy models.
- Integrates energy and economic analyses for REC optimization.
- Leverages open GIS and cadastral data for broad accessibility and reproducibility.

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ABSTRACT

This paper presents a comprehensive scenario analysis for a Renewable Energy Community (REC) located in a mountain area, with the aim to emphasize the interplay between building envelope performance, heating system technologies, and the penetration of PV systems. Motivated by the urgent need to transition towards sustainable energy systems, the study explores and validates the efficacy of a co-simulation infrastructure in assessing the performance of RECs by means of grid and building-level KPIs. The methodology integrates an advanced co-simulation tool to model and assess the impacts of various REC scenarios on the energy shared by the community, effectively capturing the patterns of energy production and consumption. The tool leverages a heterogeneous but limited set of input data to obtain a realistic representation of the specific REC. The major findings reveal significant insights into how the synergy between building envelope design, heating system options, and PV system penetration can enhance RECs' sustainability and energy efficiency. Conclusions drawn from the study underscore the crucial role of advanced simulation approaches in guiding decision-making processes for the development and optimization of RECs, thanks to the deeper understanding of the complex factors that drive community performance.

1. Introduction

The rapid penetration and management of Renewable Energy Sources (RESs) is crucial to the global strategy for reducing greenhouse gas emissions and transitioning towards more sustainable energy systems. Traditional energy models, dominated by centralized fossil fuel power plants, are gradually being replaced by decentralized systems that prioritize local renewable resources. This shift is underscored by policies such as the EU Renewable Energy Directive (RED II) [1], which introduces the concept of Renewable Energy Communities (RECs) to foster distributed renewable generation and enhance citizen involvement in the energy transition.

First and foremost, energy communities can be a powerful tool to face energy poverty, aligning with the United Nations' Sustainable Development Goal 11: "*Ensure access for all to affordable, reliable, sustainable, and modern energy systems*" [2]. Energy communities offer a versatile framework that accommodates various participants, including consumers and prosumers, and enables each member to play a unique

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List of acronyms

AI	Artificial Intelligence
API	Application Programming Interface
COE	Co-simulation Orchestrator Engine
COP	Coefficient of Performance
CR	Capacity Ratio
DEM	Digital Elevation Model
DER	Distributed Energy Resource
DHW	Domestic Hot Water
DSM	Digital Surface Model
DSO	Distribution System Operator
DSPL	Domain-Specific Programming Language
EU	European Union
EV	Electric Vehicle
FiT	Feed-in Tariff
FMI	Functional Mock-up Interface
FMU	Functional Mock-up Unit
GB	Gas-fired Boiler
GIS	Geographic Information System
GPPL	General-Purpose Programming Language
HELICS	Hierarchical Engine for Large-scale Infrastructure Co-Simulation
HP	Heat Pump
HVAC	Heating Ventilation and Air Conditioning
IRR	Internal Rate of Return
KPI	Key Performance Indicator
NPV	Net Present Value
P2P	Peer-to-peer
PV	Photovoltaic
PVGIS	Photovoltaic Geographical Information System
REC	Renewable Energy Community
RED	Renewable Energy Directive
RES	Renewable Energy Source
UEM	Urban Energy Model

role in the community's objectives. By facilitating the sharing of the energy produced, an energy community allows those who can afford access to the technology to support economically disadvantaged members who might otherwise be dependent on fossil fuel contracts. This approach promotes a more inclusive society, fosters a sense of belonging and delivers social benefits. Energy communities are a key tool in the transition to a decentralized energy production system, as they effectively enable both the management of prosumers' renewable energy surpluses and the provision of services to the grid [3]. The concept of local energy sharing at the community level aims to reduce the need for grid upgrades, which could lead to increased tariffs due to the potential costs associated with grid reinforcement to deal with problems such as over-voltage or overloads caused by local RES production [4]. Moreover, given that the price of locally generated energy typically falls between the Feed-in Tariff (FiT) and the retail electricity price, energy communities encourage both local load-shifting and load-balancing practices. They also promote the equitable distribution of generated electricity and private investment in local generation and storage infrastructure [5].

The design of an energy community significantly depends on the unique geographic, environmental, demographic, and infrastructural factors, together with community goals, making each case distinct with specific challenges and solutions [6]. Nevertheless, as mandated by Renewable Energy Directive (RED) II, RECs are primarily established to benefit their members or shareholders through environmental, economic, or social initiatives rather than generating financial profits [1]. The configuration of energy communities therefore affects energy and financial flows and requires detailed studies to optimize energy production, distribution and demand, and to assess economic and social viability [7]. Such analyses support stakeholders in tailoring the design to specific community needs, ensuring efficient renewable energy use and maximizing benefits.

Energy community design involves critical considerations, including ownership models that define asset distribution among members, compensation rates that incentivize developers, and subscriber enrollment methods that govern participation processes and benefits [8]. Furthermore, factors such as community size, the ratio of prosumers to consumers, Photovoltaic (PV) system capacities, and local grid constraints significantly influence feasibility and operational success. Addressing these aspects effectively requires the application of ad-hoc decision-support modeling tools tailored to the unique complexities of energy communities.

In Italy, the RED II Directive was implemented through Legislative Decree No. 199 of 2021 [9], followed by the implementing Legislative Decree No. 414 of 2023 [10]. This entered into force on January 24, 2024, and focuses on defining the methods of granting incentives to promote renewable energy projects within RECs. Italian authorities have defined incentive tariffs for shared energy within RECs boundaries to comply with European regulations. This enhances the attractiveness of RECs for local territories. The Italian transposition of RED II mandates that the same primary substation must supply all RECs members and that the capacity of any generation plant under RECs control must not exceed 1 MW.

The research effort to effectively tackle such an ambitious goal requires comprehensive simulation tools that can depict the impact of RECs scenarios, including different combinations of renewable technologies, building typologies, energy systems, and management strategies [11].

Numerous frameworks have been developed for modeling and simulating urban energy systems using a bottom-up approach. Examples include City Energy Analyst [12], SimStadt [13], and UrbanOpt [14], which are commonly used tools for this purpose. City Energy Analyst is a bottom-up simulation tool specifically designed to model building-level energy consumption and generation. In contrast, SimStadt and UrbanOpt provide capabilities for simulating energy flows at a larger scale, such as districts or entire cities. Additionally, the TEASER tool [15], developed by RWTH Aachen University, offers a versatile framework for urban-scale energy system modeling and optimization. TEASER facilitates the integration of various energy technologies, such as renewable energy sources, storage systems, and demand response strategies, enabling a comprehensive evaluation of their impact on the performance of urban energy systems. On top of TEASER, researchers from the same group also developed pyCity, a Python-based framework that aims to overcome some of the limitations of RECs modeling through a simpler handling of input data, including geometric data retrieval from OpenStreetMap [16,17].

A limitation observed in several existing RECs modeling tools is their primary reliance on highly customized and application-specific frameworks, often requiring high-level skills in energy and coding. This design choice can restrict the ease with which new modules are integrated and limit adaptability to evolving requirements or diverse energy contexts. Moreover, many of these tools have been predominantly applied to energy planning scenarios, sometimes overlooking the complex, bidirectional interactions that occur among consumers, producers, and prosumers within energy networks.

In contrast, co-simulation offers an opportunity to integrate multiple specialized tools, thereby enabling the modeling of interactions across various systems—ranging from energy and transportation to water—at district or urban scales. A plug-and-play co-simulation approach has the potential to address these limitations by offering a more flexible, comprehensive, and realistic understanding of urban energy dynamics. Such an approach could enhance support for informed decision-making tailored to a range of specific and diverse case studies.

The following section reviews recent advancements and the efforts made by the scientific community to develop co-simulation methodologies that specifically address the unique challenges and requirements of energy community applications.

1.1. Literature review on co-simulation platforms for energy communities

Co-simulation is a key approach for representing the physical complexity of energy systems, enabling detailed analysis of multiple scenarios and supporting the integration of diverse models, such as management, operational, and economic models, into a unified framework. This modularity allows researchers to effectively capture the interplay among various energy system components, including renewable energy sources, energy storage, building systems, and grid infrastructure. By leveraging co-simulation, it is possible to optimize energy management, enhance grid stability, reduce carbon emissions, and support the integration of distributed energy resources (DERs). Furthermore, co-simulation tools are instrumental in testing and validating innovative control algorithms, evaluating emerging technologies, and informing the design of effective energy policies. To explore recent advancements in this field, the most relevant findings from the scientific literature were analyzed, with the review conducted using the Scopus database and the following query:

```
TITLE-ABS-KEY ((cosimulation OR co-simulation) AND
(energy AND communities OR energy AND community)) AND
(LIMIT-TO (DOCTYPE,"ar") OR LIMIT-TO (DOCTYPE,
    "re")) AND
PUBYEAR > 2014
```

Although the research was limited to the last 10 years, it is possible to notice a rather recent interest in the topic, as shown in Fig. 1, which represents the annual distribution of the 33 publications resulting from the search. After reviewing the abstracts of all 33 papers, only 22 were included in the subsequent analysis due to their alignment with the objectives of this study.

The literature on co-simulation architectures for energy community studies can be categorized based on its primary objectives. While many frameworks are designed to accommodate various goals, three main objectives emerge:

1. **Design (Optimal)**: This objective focuses on supporting the design of energy communities, often by identifying an optimal configuration or solution. The goal is to establish the most efficient or effective setup for the community based on specific criteria.
2. **Control**: In this case, the primary objective is to manage the behavior of specific agents within the community. The goal is to fine-tune their actions or interactions in order to enhance certain community metrics, such as energy efficiency or economic performance.
3. **Optimization**: In this case, the aim is to optimize the energy flows or production and consumption parameters within an existing community or scenario. The focus is on adjusting these factors to either maximize a positive outcome or minimize an adverse effect, such as energy storage, power outages or costs.

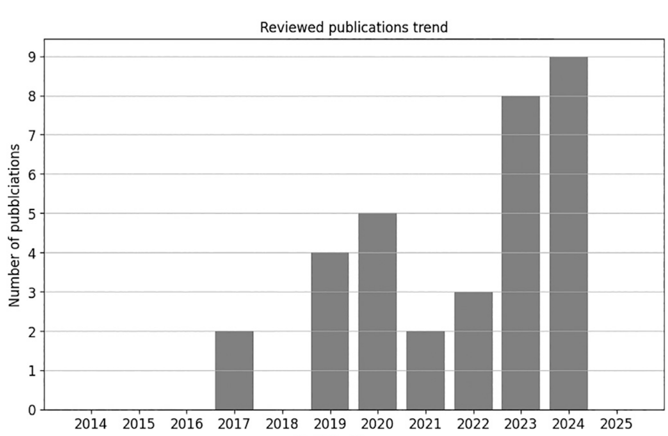

Fig. 1. Literature review query results.

Among the works that refer to the design of a community is a recent study by Mazza et al. [18]. This work demonstrates the role of geographically distributed real-time co-simulations (GD-RTDS) by analyzing different RECs case studies. This work utilized a distributed setup with components simulated in different labs across Italy and Germany, using both simulated and hardware-in-the-loop (HIL) elements to show the flexibility of an architecture developed within the VILLAS framework tool. A different approach was used by Belloni et al. [19] that propose a co-simulation approach for analyzing energy exchanges within Italian RECs combining EnergyPlus with Photovoltaic Geographical Information System (PVGIS) into the EnergyCommunity.jl co-simulation platform. With this setup, the authors evaluate the market aspects and investment and operational costs in different regions, using a mathematical optimization model to size the RECs. Another relevant study was conducted by Earle et al. [20]. In their work, the authors describe a complete co-simulation platform developed within the Hierarchical Engine for Large-scale Infrastructure Co-Simulation (HELICS) framework to study beneficial community-scale electrification, evaluating grid flexibility, and incorporating advanced Distributed Energy Resource (DER) technologies. Instead, Park et al. [21], who studied RES design options for community facilities in high-density urban areas, focused on achieving zero-energy solutions with detailed hourly energy simulations while considering hourly loads and operation schedules. The authors in this case propose a MATLAB-based co-simulation environment coupled with TRNSYS. A different approach was adopted in [22] by Cucca et al. Here, the authors detail the implementation of a co-simulation tool for evaluating complex hybrid energy systems, where an Functional Mock-up Unit (FMU) block provides a two-way interaction between a Building Performance Simulation tool (EnergyPlus) and specialized software (Dymola/Modelica), focusing on the evaluation of control strategies to achieve the best energy savings design scenario. A specific design problem was also solved by Alzahrani et al. [23] by exploring the development of smart energy communities around fishery ports. In their work, the authors used calibrated energy simulation models to manage electrical storage within a district environment to promote the formation of energy communities. Finally, an additional approach was adopted by Schiera et al. [24], by presenting an agent-based modeling (ABM) framework to assess the spatial and temporal diffusion of rooftop PV systems, integrating social, technical, economic and environmental aspects. In this architecture, the authors used the ABM approach to quantify the impact of regulatory schemes on PV adoption in urban settings to support a potential RECs development. An interesting co-simulation approach for the design of district thermal networks has been proposed by Arnaudo et al. [25]. In this paper, the authors present an approach for techno-economic analysis by introducing co-simulation using the zerOBNL toolkit, able to handle FMI from EnergyPlus and TRNSYS. The study explored demand management strategies, such as the use of building thermal mass, using co-simulation to capture indoor temperature feedback to establish operational priorities among heat supply technologies. However, the main limitation of this work remains its difficult scalability to other contexts, as the simulation infrastructure was built ad hoc for the case study.

Turning to the study of architecture for controlling and managing RECs through co-simulation, the recent literature is quite extensive. Giuzio et al. [26] describe a framework for evaluating energy flexibility strategies in building clusters, using detailed building energy models with a district grid model in co-simulation to assess economic and non-economic costs, such as thermal comfort. The study shows the implementation of a Functional Mock-up Interface (FMI)-based MATLAB/Simulink platform to manage a co-simulation process between EnergyPlus and MATLAB. The same platform was also used by Reddy et al. [27], which coupled MATLAB with a Richardson model on a real-time digital simulator (RTDS). They introduced a decentralized control algorithm for a community energy storage integrated into a low-voltage network, aiming to enhance voltage profiles and maximize battery capacity utilization through the co-simulation platform. Important results on different algorithms and control strategies comparison have been achieved by the studies of Nweye et al. [28,29], which presented the open-source CityLearn project, a co-simulation platform to enable large-scale simulations of energy flexibility, focusing on control algorithm benchmarking in grid-interactive communities. Important results on controlling also thermal network are also achieved by Zabala et al. [30]. This work implements a Python test bed based on the Pymoo library, coupling meta-models of buildings with a district heating infrastructure model in Modelica, utilizing advanced control for demand flexibility optimization and energy community predictions. Python based co-simulation platforms have also been adopted by Jones et al. [31], Dominguez-Jimenez et al. [32], and Mazzarino et al. [33]. Jones et al. [31] presents a novel co-simulation framework using OpenDSS and Python for modeling and control of building and Heating Ventilation and Air Conditioning (HVAC) loads, as well as PV generation, emphasizing the benefits of sequential controls and incremental temperature adjustments in Virtual Power Plant (VPP) simulations. On the other hand, Dominguez-Jimenez et al. [32] describes a stochastic strategy for integrating electrical thermal storage in demand response for Nordic communities with wind power, utilizing distributed co-simulation and stochastic programming to show that the coordination of Electric Thermal Storage (ETS) can reduce diesel consumption, maximize renewable production, and reduce grid stress. The authors in [33] incorporate agent-based modeling (ABM) into co-simulation to evaluate control strategies for indoor temperature regulation in buildings. Their approach assumes heating systems based on heat pumps and models the thermal behavior of buildings. The results show that optimal setpoint control, without compromising indoor comfort, can provide significant flexibility to the power grid operator, especially when scaled to thousands of buildings. An important achievement in the co-simulation field is brought by Blonsky et al. [34]. In their studies, the authors introduce the OCHRE model, which is a high-resolution, controllable residential energy model designed for use in dynamic integration studies. The model integrates features of building models and grid load models, including a validated building envelope model, controllable DER models, a voltage-dependency model and a co-simulation framework. This architecture allows for optimal controls to achieve power reductions during critical peak periods for HVAC and energy storage systems.

Finally, a considerable proportion of co-simulation studies applied to energy communities have investigated optimization purposes, using multiple architectures. Xu et al. [35] create a co-simulation environment using microchip-like computers and IoT to simulate multi-agent interaction in local energy management, showing improvements in economic benefits and decision-making efficiency through hardware-level Artificial Intelligence (AI) algorithms. Optimization often involves large-scale scenarios to facilitate Distribution System Operator (DSO) operations. This is the case in the study by Mukherjee et al. [36], which introduced a multi-settlement architecture for transactive community-based markets, using a HELICS-based co-simulation framework with physics-driven load behavior and a distribution network simulator to optimize the role of the energy market operators in the coordination and arbitrage. Similarly, Saif et al. [37] present a co-simulation framework developed in MATLAB plus YALMIP that couples a local electricity market model with a distribution network simulator, exploring the potential of local electricity trading with residential energy storage under different retail pricing schemes, showing the benefits of Peer-to-peer (P2P) transactions and the impact of storage on network performance. Finally, also in this category Python-based framework has been developed in several studies. For instance, Elhefny et al. [38] present a co-simulation platform for analyzing voltage regulation in PV-rich distribution grids, using EnergyPlus models wrapped as FMUs and a Python master algorithm to simulate residential dwellings and optimize flexible loads. Python has also been coupled with Modelica in the work by Zhou et al. [39], where the authors present a predictive energy management strategy for smart communities with district cooling and Electric Vehicle (EV) charging stations, using a scenario-based stochastic model predictive control framework. Srithapon et al. [40] focused on optimal control strategies for homes with integrated EV charging, Heat Pump (HP), thermal energy storage, and solar PV, proposing a two-stage optimization framework to enhance energy flexibility and maintain grid security. Even in this case a Python-based co-simulation platform was developed integrating Reduced order models for the estimation of demand profiles and the tool PowerFactory-DigSILENT for the grid simulation.

The literature review highlights significant advancements in recent studies related to the development of co-simulation platforms. To better contextualize the literature analysis, Table 1 aims to summarize the key information from the reviewed publications. Specifically, the table identifies critical characteristics for each reference, including:

- The country in which the use case was developed.
- The tools adopted for modeling energy demand, generation, and distribution systems.
- The co-simulation platform or orchestrator employed.
- The primary application focus of the study.
- The input data requirements for each reference, categorized into three levels:
    1. *High Level*: Data collection requires extensive efforts, such as detailed site visits or significant expertise from scenario specialists.
    2. *Medium Level*: Data acquisition is moderately complex, necessitating authorization or intervention from relevant bodies but not involving highly technical efforts.
    3. *Low Level*: Data is easily accessible, freely available, and requires minimal effort to obtain.
- The main energy carrier addressed.
- The dimensions analyzed (ENE: Energy, ECO: Economics, ENV: Environmental).

The literature analysis highlights several critical challenges that must be addressed to advance co-simulation architectures that can support RECs development.

One of the key issues is the need for greater standardization and interoperability. While standards like FMI, Python libraries and HELICS have been widely adopted, there is still a significant gap in streamlining integration across diverse models and platforms. This lack of uniformity complicates the smooth interaction of different system components and limits the potential for large-scale deployment.

Another challenge is scalability, both in terms of the size of the scenarios and the time interval of the simulation. Most existing studies focus on small-scale energy communities, often using ad hoc scenarios limited to a small number of buildings. In addition, the analysis period is often limited to a few days or weeks. This limitation is partially addressed by co-simulation platforms that use meta-models or statistical regressions to describe the community, but at the expense of the accuracy of the final output.

Table 1
Studies considered in literature review.

Author(s)	Year	Use case country	Objective	Load modeling tools	Generation and distribution modeling tool	Orchestrator co-simulation tool	Num buildings	Application	Input data required	Main energy carrier	Dimensions analysed	Ref
Mazza et al.	2024	ITA	Desing	Real-time Banshee benchmark model (Load profile) [42]	Real-time monitoring (PV) + Speedgoat emulation (Wind farm) + Simulink (EV)	VILLASframework	Around 200 load profile	Decarbonization grid planning	High level (accurate single component modeling)	Electricity	ENE	[18]
Giuzio et al.	2024	ITA	Control	EnergyPlus (Buildings)	MATLAB (PV, BESS, Grid)	FMI based MATLAB/Simulink environment	3 buildings	Flexibility strategies on demand side management	Medium level (standardized building from PNLL libraries)	Electricity	ENE, ECO	[26]
Belloni et al.	2024	ITA	Design (optimal)	EnergyPlus (Buildings)	PVGIS (PV)	EnergyCommunity.jl [43]	10 members	PV and BESS sizing	High level (the buildings were modeled specifically for the case study)	Electricity	ENE, ECO	[19]
Reddy et al.	2024	IND	Control	Richardson model on RTDS (Load profile)	Richardson model on RTDS (PV) [44]	MATLAB R2020b	N/A	BESS exploitation	High level (electrical load profiles were generated ad hoc for the study)	Electricity	ENE	[27]
Nweye et al.	2023	USA	Control	EnergyPlus from NREL EULP (Buildings)	User specified (PV, EV)	CityLearn [45]	3 neighbourhoods	Control strategies benchmarking	High level	Electricity	ENE	[28]
Nweye et al.	2024	USA	Control	Integrated with NREL EULP (Buildings)	User specified (PV, EV)	CityLearn v2	10 single-family buildings	Control strategies benchmarking	Medium level	Electricity	ENE, ENV	[29]
Sanchez-Zabala	2024	SRB	Control	Metamodel (Buildings)	Modelica (DH)	Python test bed based on Pymoo library [46]	52 residential buildings	Energy community prediction	Medium level (buildings require special meta-models to be pre-generated)	Thermal	ENE	[30]
Xu et al.	2023	CHN	Optimization	Reduced order models (AC, EWH)	Reduced order models (PV, EV)	Raspberry Pi Hardware-in-the-loop environment	N/A	Economic savings	High level (specific control algorithms need to be implemented)	Electricity	ECO	[35]
Saif et al.	2023	IRL	Optimization	In-field meters (Load Profile)	In-field meters (PV)	MATLAB coupled with YALMIP [47] and MOSEK [48] optimization environment	55 residential buildings	Local electricity trading	Medium level (need for extensive monitoring through smart meters)	Electricity	ECO	[37]
Srithapon et al.	2023	SWE	Optimization	Reduced order models (Building thermal load, HP)	Reduced order models (PV, EV)	Python + PowerFactory-DigSILENT [49]	55 households	Economic savings	Medium level (need for basic thermo-physical parameters to determine thermal load of the building)	Electricity	ECO	[40]
Jones el al.	2023	USA	Control	Synthetic energy signature model based on EnergyPlus simulations (Buildings)	Python physical model (PV) + OpenDSS (Grid) [50]	Python	351 buildings	Peak power reduction	High level (an accurate datasets of buildings should be implemented in the machine learning pre simulation step)	Electricity	ENE	[31]
Domínguez-jiménez et al.	2023	CAN	Control	OpenStudio + EnergyPlus (Buildings) and Modelica (ETS)	N/A	Python (FMI + cvxpy library)	10 residential buildings	Demand response flexibility using ETS	High level (detailed households and HVAC models)	Electricity	ENE, ECO	[32]

(*continued on next page*)

Table 1 *(continued)*

Author(s)	Year	Use case country	Objective	Load modeling tools	Generation and distribution modeling tool	Orchestrator co-simulation tool	Num buildings	Application	Input data required	Main energy carrier	Dimensions analysed	Ref
Earle et al.	2023	USA	Design	OCHRE [51] (Buildings) + foresee (Control) [52]	OCHRE (PV, EV) + OpenDSS (Grid) [50]	Hierarchical Engine for Large-scale Infrastructure CoSimulation (HELICS) [53]	30 single-family buildings	Understand the impact of community electrification processes	Low level (ResTock tool helps the scenario generation [54])	Electricity	ENE, ENV, ECO	[20]
Rando Mazzarino et al.	2023	ITA	Control	Reduced order models (Building, thermal load, HVAC)	Python (Grid with static generators)	Mosaik + AIOMAS	1000 Apartment block buildings	Strategies to provide flexibility to the power grid	Low level (Building footprints, power grid network)	Electricity	ENE	[33]
Zhou et al.	2022	USA	Optimization	Modelica (Buildings) + Python-GEKKO 2.0 (Control)	Modelica (EV, Chiller)	FMI based Dymola-Python environment	3 buildings	Economic savings	High level (Detailed model of chillers and limited to three single buildings)	Electricity, Thermal	ENE, ECO	[39]
Mukherjee et al.	2022	USA	Optimization	GridLAB-D (HVAC, EWH, BESS)	GridLAB-D (Grid)	Hierarchical Engine for Large-scale Infrastructure CoSimulation (HELICS) [53]	1159 households	Energy marker coordination and arbitrage	High level (intensive market specific information are needed)	Electricity	ECO	[36]
Elhefny et al.	2022	USA	Optimization	EnergyPlus (Buildings −DOE Prototypes)	Python (PV, Grid)	FMI based Python environment	100 buildings	Building thermal load flexibility	Medium level (building prototypes are used)	Electricity	ENE	[38]
Park et al.	2021	KPR	Desing (Optimal)	Statistical data (Load profile)	TRNSYS (PV, ESS, GHHP)	GA-based MATLAB Environment	1 residential apartment complex	Supporting design decisions	High level (Detailed HVAC models)	Electricity	ENE	[21]
Blonsky et al.	2021	USA	Control	OCHRE (Buildings)	OCHRE (PV, EV, BESS) + OpenDSS (Grid) [50]	Hierarchical Engine for Large-scale Infrastructure CoSimulation (HELICS) [53]	498 households	Evaluation of peak demand reduction strategies	High level (data from home builder specifications)	Electricity	ENE	[34]
Cucca et al.	2020	UK	Desing	EnergyPlus + (Buildings)	DesignBuilder (GSHP, TES, EES)	FMI based Dymola encironment	9 households	Energy savings measures	High level (Detailed building model implementation)	Electricity	ENE	[22]
Alzahrani et al.	2020	UK	Desing	DesignBuilder (Buildings)	EnergyPlus (PV) + Simulink (BESS)	Building Control Virtual Test Bed (BCVTB) [55]	5 buildings	Energy storage management	High level (Extensive geometrical data)	Electricity	ENE	[23]
Schiera et al.	2019	ITA	Design	Statistical semi-Markov model (Buildings)	GIS-Based model (PV) [56]	ABM (MESA)	1290 building blocks	REC scenario comparison	Low level (Public data source)	Electricity	ENE, ECO, SOC	[24]
Arnaudo et al.	2019	SWE	Design	EnergyPlus + Monitored data	TRNSYS (Co-generation) + Python (TES, Boiler)	ZeroBNL [57] with FMI	10-30 buildings	Demand Side Management for reducing heat demand peaks	High level (Not disclosed data form district heating customers	Thermal	ENE, ECO, ENV	[25]

Finally, the availability and quality of input data are a key challenge for the dissemination of these tools. In fact, high quality data are often scarce and, above all, require the intervention of expert users to manipulate and use them in co-simulation platforms. On the other hand, the use of free data available to everyone runs the risk of failing to correctly describe the complex dynamics of an energy community. Leveraging existing databases and real-world data by creating methodological processes that automate the use of these data can significantly improve the accuracy and reliability of models, making it easier to test and refine co-simulation approaches. Addressing these challenges is crucial for advancing the potential of co-simulation methodologies and realizing their full benefits in the development of RECs.

A first attempt to address these problems was made by Schefelbein et al. [17], who developed pyCity, an innovative modular Python framework for district modeling and data management that simplifies the creation and management of Urban Energy Models (UEMs) through automated Geographic Information System (GIS) data access, data management, data enrichment, and automated building modeling and simulation. Specifically, pyCity manages data at the district level and uses TEASER to create the detailed building models needed for energy simulations. However, this approach has two major limitations. The first is the sensitivity of the data enrichment process to the degree of heterogeneity of a district. As the enrichment is based on statistics, it may work well for neighbourhoods that are comparable to the reference neighbourhood used for the statistics, but could be problematic for very different neighbourhoods. The second is that the model does not take into account radiation or shading between buildings. This means that the mutual influence of buildings in terms of solar gain or shading is not currently modeled.

Another clear example of addressing interoperability and scalability is the Dragonfly plugin, an integral part of the Ladybug Tools suite, which offers a promising partial solution to some of the key issues in co-simulation for RECs modeling by using its Python-based framework to interface with different simulation engines and facilitate standardized data exchange. This interoperability allows users to integrate heterogeneous models, promoting modularity and adaptability in complex urban energy analyses. A remarkable application on this topic is provided by Charan et al. [41], where Dragonfly was coupled with the URBANopt SDK. In terms of scalability, Dragonfly has been shown to effectively handle large-scale scenarios, benefiting from robust back-end simulation capabilities that contribute to reliable, consistent performance over extended simulation periods. However, despite these strengths, several drawbacks limit its overall applicability. In particular, its reliance on external commercial software, such as Rhino and Grasshopper, imposes licensing constraints and may limit access to users without these proprietary tools. In addition, this reliance can hinder seamless integration with other open source platforms and contribute to a steeper learning curve for practitioners unfamiliar with commercial design environments. These factors highlight the need for further advances in co-simulation architectures that can provide the same benefits while minimizing reliance on commercial software and improving user accessibility.

1.2. Novelty and paper contribution

Based on the critical challenges identified in the literature, the present paper introduces the application of a novel co-simulation architecture within a framework to effectively simulate the performance of RECs. The framework is intended not only for research purposes, such as the design, optimization, and control of complex energy communities, but also for broader applications, including energy, economic, and social development at the territorial scale. This multi-dimensional approach aligns with the European Union's strategic emphasis on the integrated development of RECs. The key contributions of this work are as follows:

- **Utilization of low-level, free, and universally available input data**: By leveraging publicly accessible GIS databases and cadastral data, the framework ensures broad applicability without requiring specialized or proprietary datasets, significantly reducing barriers to data acquisition. Additionally, the separation of the modeling and simulation phases enables an independent information modeling approach, compatible with the co-simulation framework through the use of a user-friendly and standardized output format.
- **Enhanced modeling capabilities**: Unlike co-simulation platforms that rely on meta-models or statistical approximations, the proposed framework, thanks to the adopted co-simulation architecture, can easily integrate combination of real scenario data with white-box physical models, potentially enabling a precise representation of buildings and related energy systems with high-level accuracy. This flexibility is particularly valuable in contexts where data availability is limited, allowing users to perform a step-by-step approach that can follow the natural development of RECs.
- **Integration of energy and economic analysis**: Given the yearly time range of the simulation's energy data, the proposed framework is capable of effectively integrating and combining energy and economic analysis, enabling a better representation of the performance of RECs

This work not only addresses critical issues in co-simulation architectures—such as scalability, data accessibility, and modeling accuracy—but also provides researchers, urban planners, and municipal governments with a robust and personalized decision-support tool. Beyond its immediate application, the platform has significant potential for reuse in benchmarking studies, as well as in the operational analysis of energy communities. This adaptability ensures its relevance for both planning and ongoing management phases of RECs development.

2. Methodological framework

The methodological framework leveraging the co-simulation architecture and employed to perform the energy scenario analysis for a RECs is presented in this section. It comprises five concatenated elements as illustrated in Fig. 2: (i) the Data Sources, (ii) the Scenario Design, (iii) the Co-simulation Infrastructure, (iv) the Key Performance Indicator (KPI) Analysis and (v) Economic Analysis. These elements are comprehensively described in the following sections.

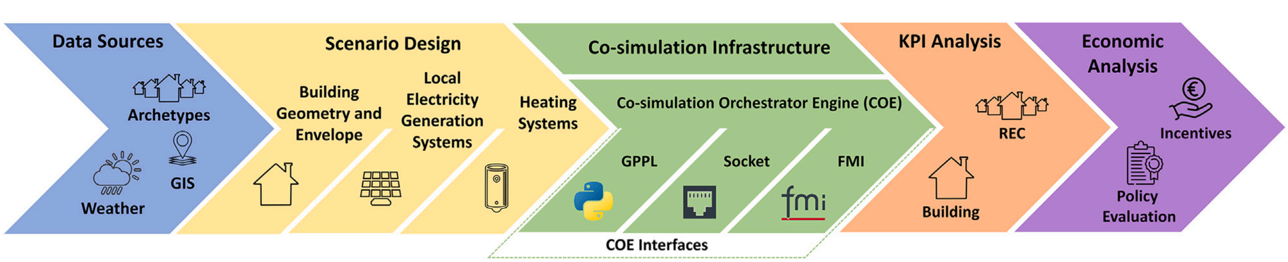

Fig. 2. The methodological framework of the present study.

2.1. Data sources

The Scenario Design phase requires specific data inputs to enable its execution. These inputs are essential for defining the parameters and constraints of the scenarios to be developed. Fig. 1 highlights three main inputs: (i) Weather data, (ii) GIS data, which is georeferenced information related to buildings and terrain, and (iii) data related to physical and technical features of building systems.

Weather data includes information on climatic conditions, such as temperature, precipitation, and wind patterns, for the specific location under analysis. This data is essential for understanding external environmental conditions impacting building thermal performance and PV system production. The data format used is a standard EnergyPlus weather file (.epw) extended to include proper radiation values. These values consider the horizon from the centroid of the chosen area to properly account for landscape shadowing. This process is carried out by downloading the correct hourly radiation data from the external web service of PVGIS [58]. By incorporating this extended weather file, the scenarios developed can accurately reflect the local climatic conditions and their impact on building thermal performance and PV production. This ensures that the scenario analysis results are relevant and realistic for the specific case study region.

GIS data provides georeferenced information related to buildings, including their spatial distribution and attributes, and the Digital Elevation Model (DEM) for the spatial representation of elevation data of the terrain and building roofs. This data allows for an accurate representation of the anthropic environment and its morphological surroundings. GIS data can then be differentiated into two distinct inputs: vectorial polygonal information about the building footprints and raster data for the elevation models. The first type of data can be either directly uploaded as a shapefile or a geoJSON file or retrieved through a simple, user-friendly process. This process, which has been automatised, consists of selecting the area of interest and downloading the building footprints from OpenStreetMap through an Application Programming Interface (API). In both cases, the georeferenced polygons representing the buildings will be accompanied by a comprehensive set of information for each building, including net and gross floor area, orientation, year of construction, height, and a list of neighbouring buildings within a configurable radius. Gross floor area is calculated directly from the polygon geometry, while net floor area is calculated by applying a configurable reducing factor to the gross floor area. The file type itself determines orientation. Without a height feature, the elevation model will be utilized to estimate the height. The list of neighbouring buildings is extracted by processing the georeferenced file containing all buildings. In addition, a list of surfaces belonging to neighbour buildings, facing the selected building and potentially casting shadows on it, is included.

Data and information regarding building physical and technical properties can be collected from different sources. Potentially, given the flexibility provided by the co-simulation architecture, each building can be modeled according to its own features regarding building envelope and energy system configuration. If detailed data about single building is not available, construction archetypes can be employed to define envelope properties. The year of construction, or at least a defined time period, is a crucial feature for assigning buildings to appropriate construction archetypes. However, obtaining this information can be challenging. To address this aspect, the implemented module offers flexible integration of multiple data sources. Specifically, for this feature, a prioritized approach is used: first, user-provided data is considered; if unavailable, OpenStreetMap (OSM) information is used; and finally, a statistical estimation method is applied. This estimation method fills in missing data by assigning random construction years to buildings while preserving the overall distribution of construction periods within the given census zone. Notably, this approach is applicable only to residential buildings, which are the primary focus of the framework. With the same statistical procedure a feature was created to express the thermal envelope performance and thanks to the information present in the census data a specific archetype was assigned to each residential building. The application of this process is detailed in Section 3 to assign archetypes for the specific case study.

A similar approach is implemented to determine technical features of building systems and especially HVAC system.

2.2. Scenario design

Once the data collection is completed, the methodological framework in Fig. 1 includes a design stage that enables the modeling of feasible RECs scenarios. A scenario is characterised by defining for each building within the RECs: (i) the building geometry and its envelope features with a specific archetype, (ii) the heating system typology and the related design parameters, (iii) the local renewable energy source (i.e., PV) and the related design features, (iv) household behavior models and (v) schedules and other inputs. The strategies and tools employed for each model are illustrated in the subsequent paragraphs.

Models of Building Geometry and Envelope. The modeling of each building and its envelope features consists of two steps. In the first step, geometric information is collected through the GIS input file, which includes the gross surface area and the number of floors. A key aspect of the modeling process involves the adaptive placement of windows on each external wall, determined by a predefined window-to-wall ratio. Moreover, internal mass is defined according to the number of floors , considering vertical and horizontal partitions. Additionally, the surrounding context of each building is carefully mapped, including assessing the impact of shadows from nearby structures, exploiting the detailed data from the GIS input file. All this spatial information is used to generate simplified geometrical models within the EnergyPlus environment using an automated workflow. The second modeling step aims to define thermal envelope features. These features can be assigned according to EnergyPlus input data file(.idf) through the definition of materials and construction stratigraphies. In case this information is not available for each building, building archetypes are employed and assigned according to construction year. To properly consider the construction technologies of the geographic area under study, archetypes derived from national standards, including the thermal performance of external walls, windows, floors, and roofs, are associated with each building. Following the same approach, infiltration rates can be defined for each building. In absence of detailed information these values can be defined according to national standards.

Models of Local Electricity Generation Systems. The area of building roofs useful for installing PV panels is obtained by processing cartographic and cadastral data. In particular, the Digital Surface Model (DSM) and the building footprints of the area of interest are used. The raster and layer data are pre-processed, exploiting the GRASS GIS software [59] to obtain the slope and orientation of raster layers. The pixels are then classified, aggregating into different slope and aspect value clusters. Finally, each surface is identified by intersecting the layers, obtaining flat surfaces with specific aspect and slope values. The surfaces are filtered to get only the surfaces suitable for PV installation, identified by selecting those that fall within specific tilt angle and orientation limits. Subsequently, the roof surfaces are used to estimate the annual producibility (kWh) by exploiting the pvlib Python library [60] to simulate the performance of PV energy systems.

Models of Heating Systems. Heating system characteristics can vary significantly due to factors such as the building's geographical location, cultural practices, and other contextual elements. The adopted co-simulation architecture supports the seamless integration of diverse models, as further detailed in the following sections. For example, it is possible to exploit the Modelica language and its open-source libraries to develop complex heating and cooling systems and use them in co-simulation. Nevertheless, the main limitations concern the connection with models of building geometry and envelope, as the input/output interfaces of the two systems must be compatible to some extent. However, this process is often case-specific and does not constrain the general applicability of the proposed framework. Section 3 describes in detail the specific heating system models and their integration within the presented application.

Household behavior models

Household behavior models are essential for simulating residential energy use and can be integrated to simulate occupant presence within the buildings. These models account for internal heat gains associated with occupant activity. Moreover, occupancy-related data provide information about electricity consumption due to plug loads, appliances, and Domestic Hot Water (DHW) usage. The co-simulation platform supports different modeling paradigms for household behavior, for example stochastic-based models use probabilistic techniques, time-use-based models rely on empirical survey data to reconstruct daily routines and link activities to corresponding energy demands, or even agent-based models represent individuals or households as autonomous agents making decisions based on predefined rules and interactions, allowing for complex and dynamic behavior modeling. These methodologies are widely used to generate occupancy schedules, appliance usage, and detailed electric load profiles, often tailored to different household types and sizes.

Schedules and other inputs

The co-simulation framework comes with some generic purpose simulators such as the Scheduler. With this simulator, it is possible to define time-based schedules for any kind of input. It has been used to set indoor temperature setpoints for the buildings. In addition, for those buildings that do not fall into the category of permanently occupied residential buildings, the Scheduler has also been used to set the values of occupancy presence, internal gains, and additional electrical loads.

2.3. Co-simulation infrastructure

As introduced in the previous section, various models are employed to simulate the energy behavior of a RECs. These models utilize various software tools and programming languages to capture and describe the multidisciplinary aspects necessary for analysing a RECs. Each tool and language addresses a specific aspect of the RECs analysis, resulting in a comprehensive and multidimensional understanding of the community's energy behavior.

To effectively manage this heterogeneity, the co-simulation infrastructure developed in our previous works [61,62] has been exploited to integrate different simulators in a coordinated manner. The co-simulation architecture leverages a pure software co-simulation framework based on Mosaik [63], a Python-based framework initially designed for Smart Grid scenarios. Its central component, the Co-simulation Orchestrator Engine (COE), handles the initialisation, time regulation and synchronisation, and data exchange management among simulators and their model instances.

During the initialisation phase, the COE retrieves the scenario from the previous design phase. It contains all parameters related to the model instances of each software tool and programming language (i.e., simulators) and their input/output relationships describing the RECs. The COE analyses the scenario and distributes to all interconnected simulators the number of model instances and their parameters, the time step duration, and the co-simulation's start and end dates. Then, the COE generates an internal graph describing the input/output relationships between the model instances. This graph is used to retrieve and exchange inputs and outputs from the interconnected simulators during each step of the co-simulation process.

During the execution of the co-simulation, the COE employs an internal Scheduler for time regulation and synchronisation purposes that starts and runs all simulators considering a common time evolution of the wall clock. Since each simulator and its model instances may have different time step durations, the Scheduler employs a time adjustment strategy to order data exchange between the simulators at different synchronised time steps. Therefore, the resulting co-simulation architecture handles time scalability for analysing different RECs scenarios.

Data exchange management is facilitated through the COE Interfaces, which allow the forwarding of initialisation information, time regulation and synchronisation commands, and the inputs/outputs of model instances to each interconnected simulator. Furthermore, the COE Interfaces enable the distribution of simulators and their model instances across different computer clusters, enhancing their vertical and horizontal scalability. Therefore, the resulting co-simulation architecture effectively addresses the need for spatial scalability, enabling the representation of flexible scenarios within the RECs. This expands capabilities in accurately capturing and analysing various RECs configurations and their spatial implications. The COE provides two main types of Interfaces: (i) the General-Purpose Programming Language (GPPL) Interfaces, which enable the interconnection of models designed with common programming languages (e.g., Python, C++, Java) to utilize their simulation libraries (e.g., pandapower, pandapipes), and (ii) the Socket Interfaces, which allow for the interconnection of distributed simulators via TCP or UDP protocols. Additionally, the COE has been enhanced by integrating an FMI standard, facilitating the coupling of models even when they are based on different Domain-Specific Programming Language (DSPL) and their simulation software (e.g., Modelica, EnergyPlus).

2.4. Energy-related KPI analysis

As shown in Fig. 2, once the co-simulation is performed, a scenario is analysed to determine the effectiveness and performance of a RECs defined by a set of characteristics. The energy-related KPI reported in Fig. 3 are evaluated hourly for each scenario, considering metrics at RECs

$$SC^i = \frac{\max(|E^i_{prod}| - E^i_{load}; 0)}{E^i_{prod}}$$

$$SS^i = \frac{max(|E^i_{prod}| - E^i_{load}; 0)}{E^i_{load}}$$

$$E^i_{net} = E^i_{load} + E^i_{prod}$$

$$E^{REC}_{wi} = \sum_{i=1}^{N} E^i_{load} + max(E^i_{net}; 0)$$

$$E^{REC}_{in} = \sum_{i=1}^{N} min(E^i_{net}; 0)$$

$$SE = min(E^{REC}_{wi}; |E^{REC}_{in}|)$$

$$VSC = \frac{SE}{|E^{REC}_{in}|}$$

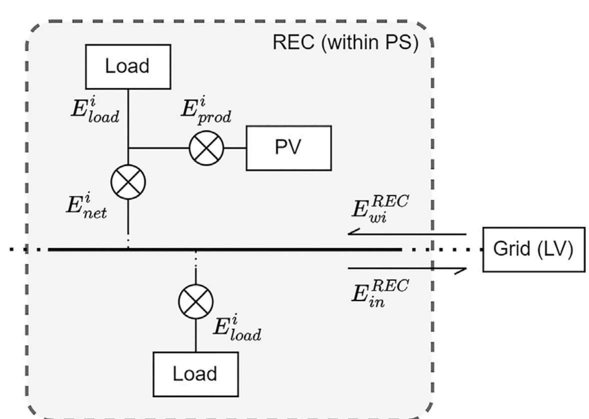

Fig. 3. Schematics of electrical energy flows within a RECs and relevant KPI.

and building level. Following the Italian regulatory framework [10], the members of the RECs must be under the Primary Substation cabin connected to the distribution grid (Low Voltage Grid).

Building Self-Consumption (SC^i): This metric refers to the proportion of locally generated electricity consumed by the prosumer itself to cover the load (E^i_{load}), without being fed into the grid, relative to the total of locally generated electricity (E^i_{prod}). It measures how effectively a prosumer can use electricity generation to meet demand. Assuming a passive sign convention, the total net energy (E^i_{net}) represents the overall energy withdrawn or injected from/to the grid. This metric is calculated for each building equipped with PV panels.

Building Self-Sufficiency (SS^i): This metric indicates how much a building can cover its electricity demand from its generation sources. Unlike self-consumption, self-sufficiency is evaluated as a ratio of the total energy demand and the generated energy that meets it over a given period, highlighting the building's ability to rely less on external energy supplies. This metric is also evaluated for buildings equipped with PV panels, similar to self-consumption.

RECs Energy Withdrawn from the Grid ($E^{\text{REC}}_{\text{wi}}$): This metric represents the total electrical energy drawn from the grid by the members of the RECs. For buildings classified as consumers, it is determined by the sum of electrical demand from plug loads and energy conversion systems. For prosumers, it is calculated as the net electrical demand after accounting for local electricity generation.

RECs Energy Injected to the Grid ($E^{\text{REC}}_{\text{in}}$): This metric represents the total electrical energy injected into the grid by members of the RECs, generated by the surplus from local electricity generation systems of the prosumers.

RECs Shared Energy (SE): Following the Italian standard for a RECs, shared energy is calculated on an hourly basis as the minimum between the power injected into the grid ($E^{\text{REC}}_{\text{in}}$) and the energy drawn from the grid ($E^{\text{REC}}_{\text{wi}}$). This quantity is evaluated at the community level and represents a "virtual" quantity, as the sharing is not performed physically.

RECs Virtual Self-Consumption (VSC): This metric refers to the proportion of energy injected into the grid that effectively contributes to shared energy. It serves as a measure of the efficiency of the RECs in utilizing surplus generation for shared energy purposes, calculated as $VSC = \frac{SE}{E^{\text{REC}}_{\text{in}}}$.

2.5. Economic analysis

The final stage of the methodological framework involves the economic assessment of the Energy Community project that aligns with the EU RED II. This analysis evaluates the profitability and sustainability of RECs across various EU member states, considering each country's specific regulatory policies and incentives. The regulatory policies can be defined flexibly to fit the country's regulatory framework under analysis. In particular, thanks to the adoption of incentives based on the shared energy between the members, the energy communities are helping the diffusion of DERs. Generally, the policy framework emphasizes valuing energy exchanged locally among members, bypassing the transmission grid and contributing to the capital with non-repayable grants. Therefore, this policy seeks to facilitate investments in renewable energy installations and enhance the economic viability of energy efficiency projects.

The economic analysis consists of evaluating the economic and financial plan of the Energy Community project through investments in renewables and renovations. Relevant economic data will be gathered, including the costs of PV technologies, operating expenditures, and the prices for purchasing and selling electricity, as well as the incentive schemes, rules and constraints from the energy policy regarding the energy community. This data will be obtained from governmental reports, market studies, and academic research.

The outcomes of the economic analysis are the financial metrics Net Present Value (NPV), Internal Rate of Return (IRR), Annualized Return On Investment (ROI), Payback Time (PBT) and simple PBT (dividing the initial investment by the mean yearly revenue) to evaluate the investment potential of the RECs. These metrics provide insights into the long-term viability of the project. Finally, based on the findings, tailored recommendations for policy adjustments or new initiatives can be provided, enhancing the economic feasibility of RECs in the respective EU countries.

3. Case study

The proposed methodology was implemented and evaluated in Frassinetto, a mountain village in the North-West of Italy. The degree days for this specific area are 3826. According to ISTAT data, the population stands at 272 persons. Utilizing a GIS cadastral map of the region, whose representation is reported in Fig. 4, 211 buildings were identified within Frassinetto. The buildings are divided as follows according to census data:

- 5 buildings are public facilities, including a school, a church, and public administration offices.
- 60 buildings are residential and are occupied year-round by local residents.
- 146 buildings are residential, primarily serving as vacation homes or short-term accommodations for tourists.

These buildings exhibit an average net surface area of 140 m^2.

Since detailed information about envelope features is not available for each building within the community, three archetypes of building envelope elements were developed to represent three different performance classes (low, medium, and high). Using the national technical standard UNI/TR 11552:2014, specific constructions consistent with the geographical location of the Frassinetto scenario were modeled within the EnergyPlus environment. Table 2 details the thermophysical properties of the main construction elements that characterise each archetype.

Considering the features of the proposed case study (i.e., a RECs in a mountain area of northern Italy), water-based heating systems have been taken into account. To assess the different energy scenarios which also consider the electrification trend of the heating-related services, heat generation system is modeled based on two energy conversion technologies: Gas-fired Boiler (GB) and air-to-water HP. The heating emission system is assumed to have aluminium radiators for both HP and GB systems, as these water terminals also work well at relatively low water temperatures.

The HP has been modeled using the open-source OpenModelica simulation environment [64], which exploits Modelica's standard components. The HP model was exported as an FMU for co-simulation interfacing, embedding the numerical solver supplied by OpenModelica. The HP model is parametric and uses the datasheets of commercial HP to reconstruct the performance curves, i.e., lookup tables of the Coefficient of Performance (COP) and the output thermal power as a function of the outdoor dry-bulb temperature and the outlet water temperature of the heating distribution system [65]. The HP supply water temperature is calculated through a climatic curve, which sets the temperature based on the outdoor temperature through a piecewise linear function, considering the inertia of the distribution system and the water buffer tank. The HP Capacity Ratio (CR) describes the ratio between the heating demand and the maximum capacity of the HP at a given outdoor and outlet flow temperatures. If the building's thermal demand does not exceed the calculated thermal power, then the HP works in part-load conditions, resulting in a CR less than one. Consequently, the COP is corrected based on the CR through a part-load performance curve. Auxiliary heating equipment is modeled to cover the part of heating demand that the HP cannot meet when it is at full load conditions, and CR is higher than one. Consequently, in those cases, the model considers supply heating energy as the sum of the thermal energy provided by the HP and the auxiliary system.

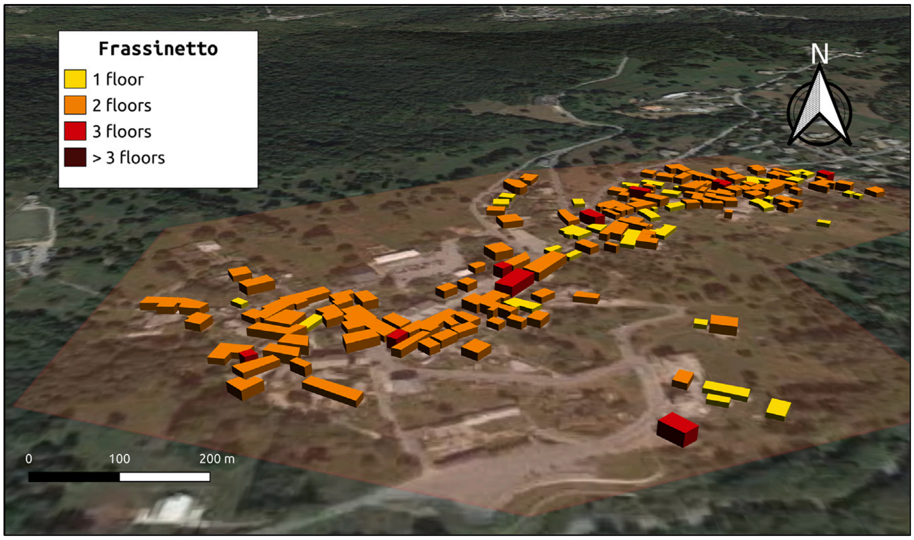

Fig. 4. GIS representation of the buildings included in the present case study.

Table 2
Thermophysical properties of the main construction elements characterising the building envelope models adopted in this study.

Archetype class	External wall *U* [W/m^{2}K]	Roof *U* [W/m^{2}K]	Floor *U* [W/m^{2}K]	Window *U* [W/m^{2}K]
Low	1.95	2.50	2.68	4.30
Medium	0.90	1.18	1.97	2.10
High	0.61	0.45	0.73	1.67

The GB is modeled in Python through a parametric logarithmic relationship to calculate the efficiency at nominal and part-load conditions from the nominal capacity. It is worth noting that the HP and GB sizing and the setup of the climatic curve are performed based on the building energy signature performance during the initialisation phase.

The HP and GB systems were sized during the initialisation phase, and nominal capacities were calculated based on the specific energy performances of the buildings. The models were parametrised, exploiting the datasheet information of the most common HP and GB technologies, and finally sized at a project temperature of 0 °C, considering the thermal inertia of the buildings and their annual heating consumptions retrieved from the energy performance certificates. However, the HPs are equipped with auxiliary heating coils to meet the heating needs during short periods of high energy demand on very cold days without oversizing the HPs

Concerning renewable generation, the DSM and the building footprints of Frassinetto were used to extract the rooftop surfaces of the buildings. All surfaces with an orientation between North-West and North-East and an inclination greater than 60° were excluded as they have few equivalent hours and, therefore, low annual productivity. The suitable surfaces were fully exploited, assuming that the maximum peak power is installed. The most common PV technology on the market was considered, particularly a panel c-Si type with an area of 1.63 m^2 and a peak power of 330 W. Total PV system losses are assumed to be 14 %. As a result, the average peak power identified for the 211 buildings is 6 kWp, with a maximum of 40.2 kWp and a minimum of 1.5 kWp.

According to these definitions, six different building categories were identified:

1. Buildings with high-performing envelopes equipped with an HP.
2. Buildings with high-performing envelopes equipped with a gas-fired boiler.
3. Buildings with medium-performing envelopes equipped with an HP.
4. Buildings with medium-performing envelopes equipped with a gas-fired boiler.
5. Buildings with low-performing envelopes equipped with an HP.
6. Buildings with low-performing envelopes equipped with a gas-fired boiler.

For the building models, a fixed window-to-wall ratio was imposed on each surface, equal to 0.2. Within the proposed case study, the household behavior was modeled by adapting the open-source tool *richardsonpy* [66]. Its workflows were modified for co-simulation stepped generation of the occupancy-related variables, instead of one-shot profile generation. This tool implements the household behavior model from [67], which generates stochastic occupancy, internal gain, appliance loads and domestic hot water demand. The residential buildings occupied year-round have been connected to the modified Richardsonpy model. The model outputs data for 5 types of families that are categorized by the number of members. Each building receives the values multiplied based on the type of families living inside and their number. For the other typologies of buildings, precompiled schedules were employed to cover these attributes. The vacation buildings were connected to a schedule reading a plausible time series of occupancy for a family of four people that covers holiday seasons and weekends. From this baseline, 9 other schedules have been generated, applying some slight noise to obtain more heterogeneity. These schedules have been connected to vacation buildings with a multiplication factor proportional to the number of floors. The administrative offices have been connected to a schedule that was considering a classic office with ten people at its complete. The schedule has been generated considering work hours and work days. Finally, the church has been considered occupied by one-third of Frassinetto residents during the most frequented celebration periods (e.g., Sundays or specific festivities) for the average time of the ceremony of around 2 h. The definition of these last schedules has been done through authors-expertise and common sense but being highly configurable any possible configuration could be tested understanding for example the impact of a high/low visitors flow. For all buildings, the indoor temperature set-point is scheduled to 20 °C during the activity period and to 16 °C during nights for non-vacation residential buildings and to 0 °C (HVAC off) for all the others when no one is present.

All the buildings were assumed to be naturally ventilated. The number of air changes per hour was set to 0.5 ACH in accordance with

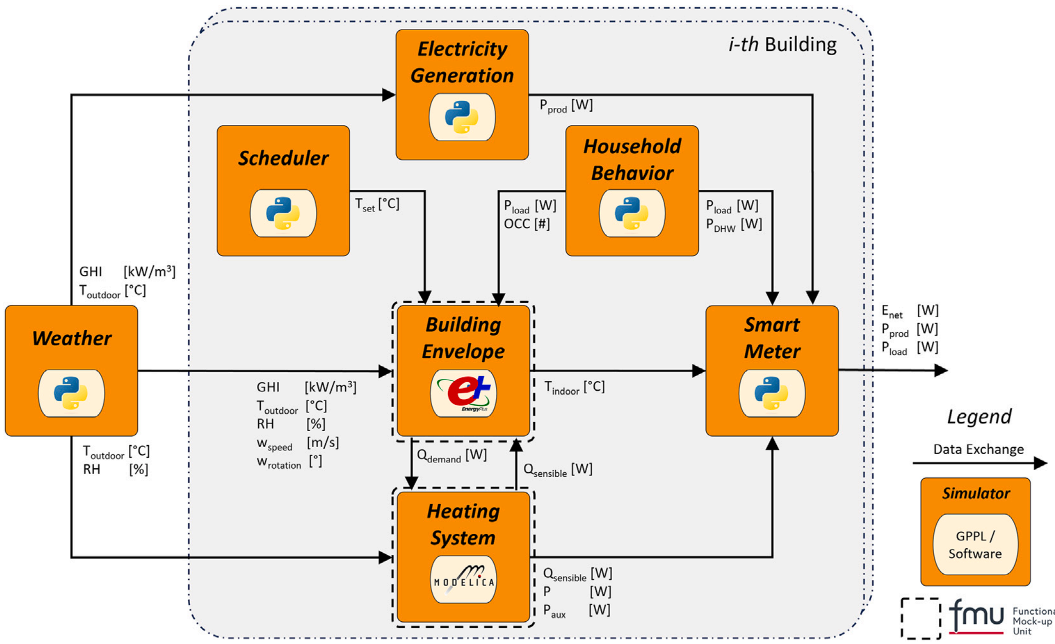

Fig. 5. Interconnections among the simulators with related exchanged variables.

UNI/TR 11552. This value can potentially be set dynamically throughout the simulation using models or schedules. However, in the present case study, it was considered constant and fixed.

Each building in the RECs is simulated through the proposed model's interconnection via the co-simulation infrastructure. Fig. 5 shows the interconnection among the simulators and their model instances for the RECs under analysis.

The simulators include seven distinct elements:

- **Weather:** This element loads the specified weather input dataset and passes the required variables to each model. It is based on Python.
- **Scheduler:** This element loads schedules related to indoor air temperature set-points (T_{set}), provided to the building model in EnergyPlus to determine the target heat demand (Q_{demand}). It is also based on Python.
- **Electricity Generation:** Employed to simulate PV systems, it receives weather information on Global Horizontal Irradiance (GHI) and outdoor air temperature ($T_{outdoor}$) and calculates PV power production (P_{prod}). This element is Python-based.
- **Household Behavior:** This module provides information on electrical demand related to plug loads (P_{load}), electrical demand for DHW production (P_{DHW}), and occupant presence to other models. Electrical demand for DHW production was considered only when an HP system was installed. In the case of gas boilers, DHW was assumed to be generated using these non-electrical systems. In case of public facilities and vacation buildings this simulator is replaced by a Scheduler as previously described.
- **Building:** Developed in EnergyPlus, this module simulates the thermal dynamics of a building, determining the evolution of indoor air temperature values given the sensible heating power (Q_{sensible}) provided by the heating system, weather data, behavior data and the defined indoor temperature set-point schedule.
- **Heating System:** This module, developed in Modelica, simulates the energy conversion system that provides the building's heat energy to meet the heating energy needs (Q_{demand}). The output of this module is the sensible heating energy (Q_{sensible}) to the building, constrained by the system size. Additionally, the module calculates the electrical load (P) required by the HP (according to the calculated COP) or the thermal power related to the source used by the GB (according to the efficiency) at each time step. Moreover, the module evaluates the electrical energy required by the backup systems (P_{aux}).
- **Smart Meter:** It collects the total load (E_{load}), the net electricity consumption (E_{net}) and the locally generated electricity (E_{prod}) to perform KPI analysis on different scenarios.

Simulations were conducted over a one-year period with a 10-minute time step. The Typical Meteorological Year (TMY) file provided by PVGIS based on the SARAH3 database for the location of Frassinetto was employed. The heating system was set to operate between the 1 st of October and the 16th of April. Considering the geographical location of Frassinetto, it was assumed that no cooling system was present.

Eventually, a scenario is defined by selecting the number of buildings falling into one of the six categories previously introduced and the number of prosumers, determining the amount of electrical energy locally generated.

Two scenarios were defined to characterise the building envelope performance and heat generation system conditions.

Scenario 0 – Baseline: This scenario represents the existing conditions within the REC. Building envelope performance was assigned based on Italian census data, which classifies buildings into four categories of preservation: *ottimo (excellent)*, *buono (good)*, *mediocre (fair)*, and *pessimo (poor)*. Due to the absence of detailed, building-level data, it was ensured that the total number of buildings matched the census-reported distribution for each category. To streamline the analysis, these categories were mapped to three envelope performance archetypes: high-performance (*excellent*), medium-performance (*good*), and low-performance (combining *fair* and *poor*). The decision to merge *poor* with *fair* was made due to the limited representation of the *poor* category in the census data. The resulting distribution included 9 high-performance buildings, 139 medium-performance buildings, and 63 low-performance buildings. For all buildings, a gas boiler was assumed as the heat generator.

Scenario 1 – Refurbishment: This scenario represents the case of envelope and heating system refurbishment within the REC. Starting from the baseline scenario, the envelope performance was improved considering only buildings occupied by local residents, assuming an upgrade to high-performance envelope. Additionally, an HP heating system was

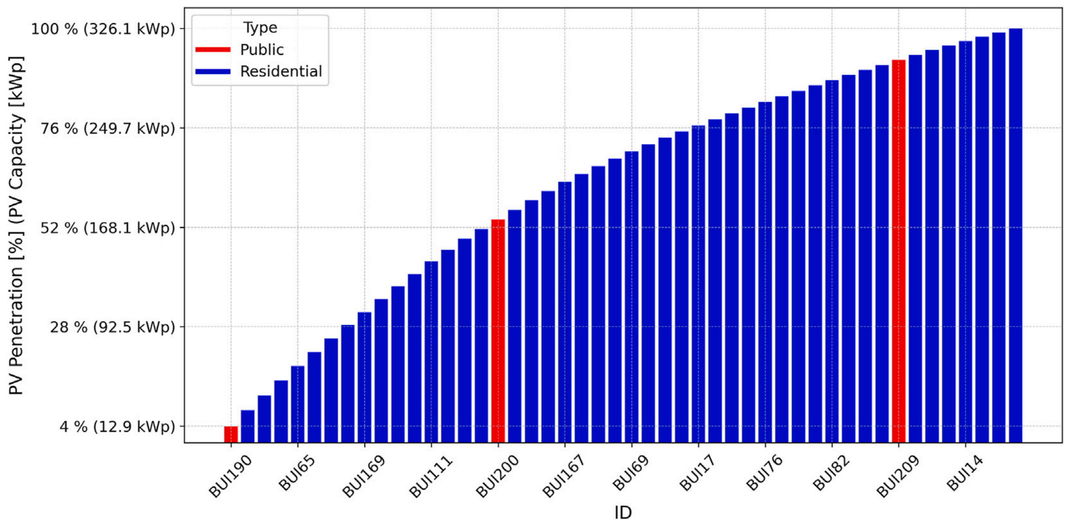

Fig. 6. PV penetration percentage and total PV capacity as a function of the progressive number of buildings.

installed in these buildings. Renovation measures were not applied to public or vacation buildings.

A parametric analysis of PV installations was performed for both scenarios. PV systems were assumed to be installed on public buildings and residential buildings occupied by local residents. These buildings were ranked in descending order based on their rooftop PV installation capacity (expressed in kWp). Buildings with an available PV installation capacity of less than 3 kWp were excluded from this process. Fig. 6 illustrates the PV penetration percentage—defined as the ratio between the installed PV capacity and the total potential rooftop PV capacity—and total PV capacity as a function of the progressive number of buildings, with PV installations prioritized in descending order of rooftop installation capacity.

For each scenario, the evolution of various REC KPIs was evaluated as PV systems were incrementally installed, beginning with buildings offering the highest installation capacities. In Scenario 1, PV installation was additionally tied to the refurbishment of the building envelope and the heating system for residential buildings.

The economic analysis was conducted at level of REC, considering the Italian Legislative Decree on the promotion of REC [68], which defines the incentive scheme for shared energy, and subsequent operating rules [69], which define the technical constraints and details of the realization of REC. The shared energy is valued through a two-part tariff: a fixed base rate determined by the size of the PV system, and a variable rate linked to the zonal market price. The total value cannot exceed a maximum of 120 €/MWh, with an additional bonus of up to 10 €/MWh depending on the geographical area. The costs of PV systems were estimated by exploiting the last Italian market report from IEA-PVPS [70] which reports the turn-key price of the PV systems based on size and typology, while the hourly-based electricity prices were taken from the Italian Electricity Market Authority (GME) in order to estimate the electricity bill and sell prices (equal to zonal prices), and the fuel prices from the Regulatory Authority for Energy, Networks and Environment (ARERA). For 2024, the weighted-average of the PV system turnkey price was 768.1 €/kW, the average electricity bill price was 204 €/MWh, the average zonal price was 127 €/MWh, while the average fuel price was 0.455 €/Sm^3. Regarding the fuel switching to HP system, it was assumed a weighted-average plant cost of about 1889 €/kW_{el}, while for renovation project it was assumed a weighted-average cost based on the different renovation scenarios of 115 €/m^2. For all scenarios, a 40 % non-repayable grant covering the capital expenditure for PV installation was assumed, along with a 50 % reduction in capital expenditure for fuel switching and renovation projects, enabled by Italian tax incentives., alongside a 60 % debt covered by a 10-year loan at an interest rate of 7 %. Ultimately, an 8 % interest rate was considered based on the weighted cost of capital. For a detailed explanation of the economic and financial model, including all underlying assumptions and data, please refer to Appendix A.

Detailed scenarios were defined by combining Scenario 0 and Scenario 1 with specific levels of PV penetration, expressed as a percentage of the total installation capacity. These scenarios were further evaluated to assess the capabilities of the proposed co-simulation infrastructure.

4. Experimental results from the co-simulation framework

This section presents the results of simulating the previously introduced scenarios. Fig. 7 illustrates the relationship between PV penetration, shared energy (in MWh), and virtual self-consumption (in %) for the Baseline and Refurbishment scenarios. The PV penetration is plotted on a logarithmic scale to emphasize the effects of incremental PV installations.

Shared energy increases with PV penetration in both scenarios, with the Baseline scenario consistently showing higher values than the Refurbishment scenario. This can be attributed to the fact that, in the Baseline scenario, the energy injected into the grid by the REC (E_{in}^{REC}) is higher due to the absence of HP heating systems.

Virtual self-consumption decreases as PV penetration increases, primarily due to surplus PV generation exceeding local energy demand at higher capacities. In the Refurbishment scenario, VSC values are slightly higher compared to the Baseline scenario at intermediate and high penetration levels. This indicates that in the Refurbishment Scenario shared energy is better utilized, thanks to the partial electrification of the heating systems.

Fig. 8 depicts the payback time as a function of PV penetration for two scenarios: (a) Scenario 0 – Baseline and (b) Scenario 1—Refurbishment. It is worth noting that the results presented do not include the investment costs associated with envelope renovation and the adoption of HP systems in residential buildings. At the same time, the analysis does not account for the potential economic benefits that such building-level renovations may bring to individual users, such as reduced energy bills or long-term cost savings from improved efficiency. These measures, while relevant to the overall energy performance, were not considered in the economic analysis since they are not explicitly addressed within the current Italian REC regulatory framework. Moreover, such interventions are typically undertaken at the household/building

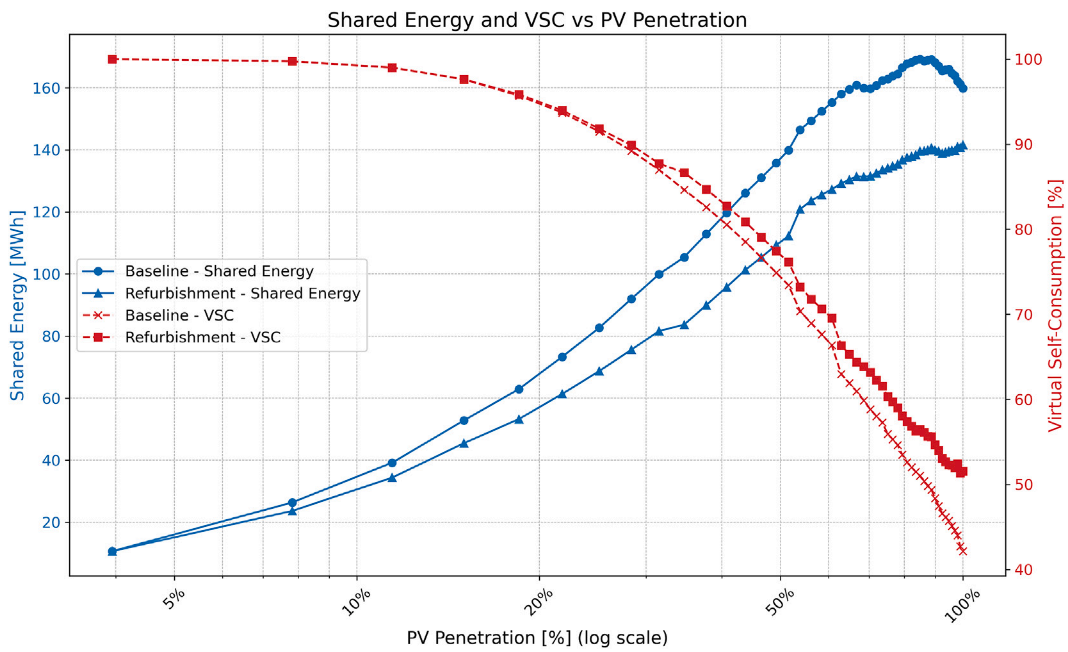

Fig. 7. Shared energy and virtual self-consumption as function of PV penetration for Scenario 0 – Baseline (a) and Scenario 1 – Refurbishment (b).

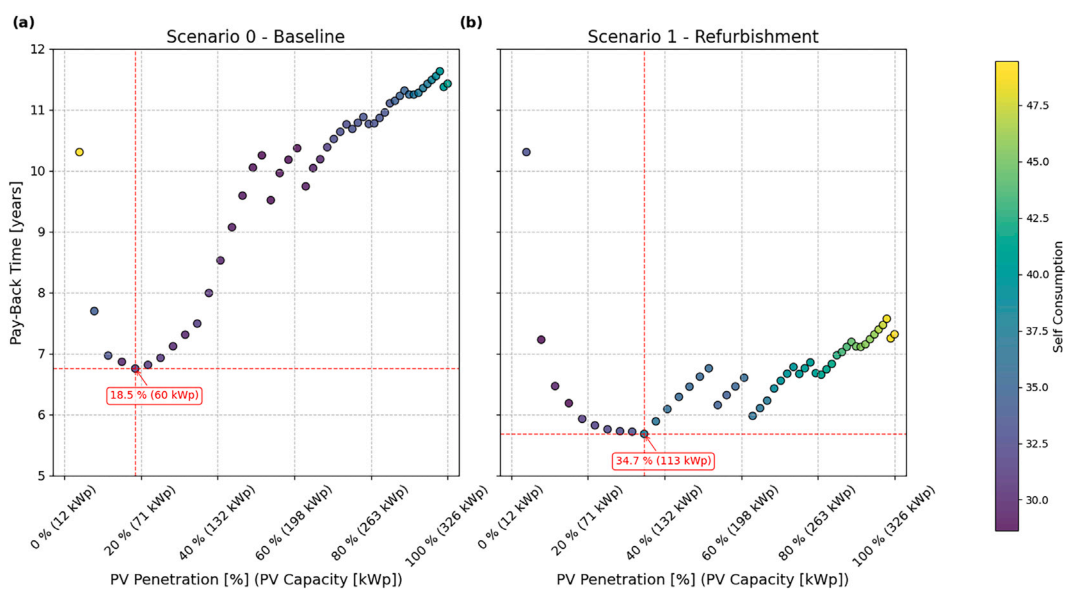

Fig. 8. Payback Time as function of PV penetration for Scenario 0 – Baseline (a) and Scenario 1 – Refurbishment (b).

level, and their inclusion would require assumptions on private investment decisions. For these reasons, the following analysis focuses exclusively on photovoltaic (PV) adoption as the shared investment evaluated within the REC framework. In the figure the x-axis represents the PV penetration percentage and the corresponding PV installed capacity (kWp), while the y-axis shows the payback time (years). The data points are color-coded to indicate the self-consumption percentage, as displayed in the color bar on the right.

The results highlight the relationship between increasing PV penetration and the payback time for each scenario. In both scenarios, the payback time initially decreases as PV penetration increases, reaching a minimum at an intermediate level of PV capacity, after which it starts to rise. This trend reflects the interplay between the benefits of increased PV generation (reduced energy costs and higher energy share potential) and the diminishing returns at higher penetration levels, where surplus energy exceeds local demand and energy injected into the grid by the REC is not fully balanced by the REC's withdrawal.

For Scenario 0 – Baseline, the minimum payback time of approximately 6.8 years occurs at a PV penetration of 18.5 %, corresponding to a total installed capacity of 60 kWp. Beyond this point, further increases in PV capacity result in a longer payback time, due to the incapacity of the REC to effectively share the additional energy injected into the grid.

In Scenario 1—Refurbishment, the minimum payback time of approximately 6.5 years is observed at a PV penetration of 34.7 %, corresponding to a total installed capacity of 113 kWp. The lower payback time at this penetration level compared to the baseline scenario is attributable to the increased self-consumption facilitated by the

Table 3
Energy-related KPIs in function of different PV penetrations for Scenario 0 – Baseline.

$PV_{\%}$	PV_{kWp}	SE [MWh]	E_{wi}^{REC} [MWh]	E_{in}^{REC} [MWh]	SC [%]	SS [%]	VSC [%]
3.9	12.9	10.7	1210.6	10.7	33.0	36.2	100.0
18.5	60.3	62.9	1200.8	65.7	18.8	40.7	95.7
34.7	113.1	105.4	1187.7	124.5	18.6	43.3	84.7
60.7	198.1	155.3	1170.0	233.9	16.3	41.9	66.4
100.0	326.1	159.8	1103.5	379.3	26.3	37.2	42.1

Table 4
Energy-related KPIs in function of different PV penetrations for Scenario 1—refurbishment.

$PV_{\%}$	PV_{kWp}	SE [MWh]	E_{wi}^{REC} [MWh]	E_{in}^{REC} [MWh]	SC [%]	SS [%]	VSC [%]
3.9	12.9	10.7	1210.6	10.7	33.0	36.2	100.0
18.5	60.3	53.3	1229.0	55.6	31.4	33.2	95.9
34.7	113.1	83.7	1264.1	96.5	37.3	33.6	86.6
60.7	198.1	127.3	1306.0	183.0	35.6	33.0	69.5
100.0	326.1	141.6	1509.6	274.8	49.5	27.4	51.6

electrification of heating systems and enhanced energy efficiency due to building envelope upgrades.

The color-coded self-consumption percentage demonstrates the differences between the two scenarios. Scenario 1 achieves higher self-consumption levels, particularly at intermediate PV penetrations, underscoring the impact of refurbishment measures on enhancing local energy use.

Tables 3 and 4 present energy-related KPIs for different levels of PV penetration under the two defined scenarios: Scenario 0 – Baseline and Scenario 1 – Refurbishment. The KPIs include shared energy (SE), REC energy withdrawn from the grid (E_{wi}^{REC}), REC energy injected to the grid (E_{in}^{REC}), Average self-consumption of prosumers (SC), Average self-sufficiency of prosumers (SS), and REC virtual self-consumption (VSC), with PV penetration expressed as a percentage of the total installed capacity.

In Scenario 0 – Baseline (Table 3), SE increases as PV penetration rises, reaching a maximum of 159.8 MWh at 100 % penetration. However, self-consumption and self-sufficiency decline at higher penetration levels, with SC decreasing from 18.3 % at 21.8 % penetration to 16.3 % at 60.7 %, before increasing to 26.3 % at 100 % penetration. This behavior reflects the increase in PV generation, leading to higher grid injections (E_{in}^{REC}), which rise significantly from 78.2 MWh at 21.8 % penetration to 379.3 MWh at 100 %.

In Scenario 1 – Refurbishment (Table 4), SE is consistently lower than in the Baseline scenario at each level of PV penetration. However, self-consumption is markedly higher due to the improved energy efficiency and electrification of heating systems by prosumers. At 21.8 % penetration, self-consumption is 31.8 %, nearly double that of the Baseline scenario. Similarly, SS follows a similar trend, starting at 33.7 % for low penetration and decreasing to 27.4 % at full penetration. Notably, the total energy withdrawn (E_{wi}^{REC}) is higher in the Refurbishment scenario, reflecting increased electrification demand. However, energy injected into the grid (E_{in}^{REC}) is significantly lower compared to Baseline scenario.

Tables 5 and 6 present economic KPIs for different levels of PV penetration under the two defined scenarios: Scenario 0 – Baseline and Scenario 1 – Refurbishment. The reported KPIs include capital expenditure (CAPEX), net present value over 25 years (NPV25), payback time (PBT), simple payback time, internal rate of return (IRR), and annual return on investment (ROI).

As shown in Table 5, CAPEX increases with PV penetration, reflecting the additional costs associated with the larger installed PV capacities. At 3.9 % PV penetration (12.9 kWp), the CAPEX is 9.4 k€, while at full penetration (100 %, 326.1 kWp), it reaches 259.5 k€. The NPV25 also grows with higher PV penetration, peaking at 278.9 k€ for 100 % penetration. However, the PBT demonstrates a non-linear trend as shown in Fig. 8, with the minimum value of 6.8 years occurring at 18.5 % PV penetration (60.3 kWp). Beyond this point, the payback time progressively increases, reaching 11.4 years at full penetration. Similar trend can be observed for Simple PBT. The IRR and annual ROI both decline as PV penetration increases. The IRR peaks at 22.2 % at 18.5 % penetration and decreases to 15.9 % at full penetration. Similarly, the annual ROI

Table 5
Economic KPIs in function of different PV penetrations for Scenario 0 – Baseline.

$PV_{\%}$	PV_{kWp}	CAPEX [k€]	NPV25 [k€]	PBT [years]	Simple PBT [years]	IRR [%]	Ann. ROI [%]
3.9	12.9	9.4	12.2	10.3	4.0	17.7	7.6
18.5	60.3	44.2	80.8	6.8	3.4	22.2	8.3
34.7	113.1	82.8	139.4	7.5	3.5	20.9	8.2
60.7	198.1	153.3	193.2	10.4	4.0	17.5	7.6
100.0	326.1	259.5	278.9	11.4	4.2	15.9	7.4

Table 6
Economic KPIs in function of different PV penetrations for Scenario 1 – Refurbishment.

$PV_{\%}$	PV_{kWp}	CAPEX [k€]	NPV25 [k€]	PBT [years]	Simple PBT [years]	IRR [%]	Ann. ROI [%]
3.9	12.9	9.4	12.2	10.3	4.0	17.7	7.6
18.5	60.3	44.2	92.5	5.9	3.1	24.1	8.7
34.7	113.1	82.8	181.4	5.7	3.0	24.7	8.9
60.7	198.1	153.3	296.8	6.6	3.2	22.6	8.6
100.0	326.1	259.5	471.9	7.3	3.2	21.4	8.5

Table 7
Economic KPIs in function of different PV penetrations for Scenario 1—refurbishment—considering costs for envelope renovation and HP adoption

$PV_{\%}$	PV_{kW_p}	CAPEX [k€]	NPV25 [k€]	PBT [years]	Simple PBT [years]	IRR [%]	Ann. ROI [%]
3.9	12.9	9.4	12.2	10.3	4.0	17.7	7.6
18.5	60.3	188.2	−49.9	>50	13.6	4.96	2.46
34.7	113.1	480.3	−66.5	>50	11.8	6.4	3.03
60.7	198.1	826.4	466.7	11.07	6.6	13.8	5.45
100.0	326.1	2091.1	3676.9	4.96	3.81	25.2	7.8

decreases slightly from 8.3 % at 18.5 % penetration to 7.4 % at 100 %. These results indicate that while larger PV installations generate higher NPVs, the financial performance metrics such as IRR and PBT diminish due to the decreasing marginal returns associated with higher PV penetration.

Table 6 presents the results for Scenario 1 – Refurbishment. Compared to Scenario 0, this scenario achieves better economic performance at all levels of PV penetration. At 3.9 % penetration, the CAPEX is identical to the Baseline scenario (9.4 k€), but the NPV25 is higher, reaching 12.2 k€. As PV penetration increases, the NPV25 grows significantly, peaking at 471.9 k€for 100 % penetration, substantially higher than the corresponding value in the Baseline scenario.

The PBT in Scenario 1 is shorter than in Scenario 0 across all penetration levels, indicating improved economic viability. The minimum PBT of 5.7 years is observed at 34.7 % penetration (113.1 kWp). Even at full penetration, the PBT remains reasonable at 7.3 years, shorter than the 11.4 years observed in Scenario 0. The simple payback time remains consistent, ranging between 3.0 and 3.2 years. The IRR and annual ROI are also consistently higher in Scenario 1 compared to Scenario 0. The IRR peaks at 24.7 % at 34.7 % penetration and remains above 21.0 % even at full penetration. Similarly, the annual ROI peaks at 8.9 % at 34.7 % penetration, with only a slight decline to 8.5 % at 100 %.

To provide further insight, Table 7 reports the economic KPIs for Scenario 1, including the costs associated with envelope renovation and HP adoption considered at the community level. The analysis also accounts for the change in energy vectors, specifically the reduction in gas consumption and the corresponding increase in electricity purchased from the grid due to the use of HPs. Investment costs were discounted based on the Italian tax incentives, as detailed in the appendix. This extended analysis offers a more comprehensive perspective by assuming that, even for interventions at the single-building level, the community could operate as a unified entity.

Compared to the results in Table 6, which consider only PV investments, a substantial increase in total CAPEX is observed across all levels of PV penetration, reflecting the additional costs of refurbishment measures. This inclusion significantly impacts the economic performance indicators. In particular, the NPV_{25} becomes negative for intermediate levels of PV penetration (18.5 % and 34.7 %), indicating that the investments are not economically attractive over the 25-year analysis period without further incentives or reductions in upfront costs. Payback times are also considerably extended, with values exceeding 50 years at certain penetration levels. Conversely, at full PV penetration (100 %), the NPV_{25} becomes strongly positive again, suggesting that high levels of PV deployment can partially offset the economic burden of the additional refurbishment measures, leading to improved financial feasibility. IRR and annual ROI also decrease when renovation costs are included, particularly at intermediate PV sizes. These trends highlight the trade-off between enhanced energy performance and economic viability when building-level interventions are considered within the REC investment scope. Notably, the simple payback time remains within acceptable limits at low and high PV penetration levels, suggesting that bundled investments may still be appealing under specific design or policy conditions.

Fig. 9 illustrates the monthly variation of energy metrics and maximum power demand for the two scenarios: (a) Scenario 0 – Baseline and (b) Scenario 1 – Refurbishment, considering a PV penetration of 34.7 %,

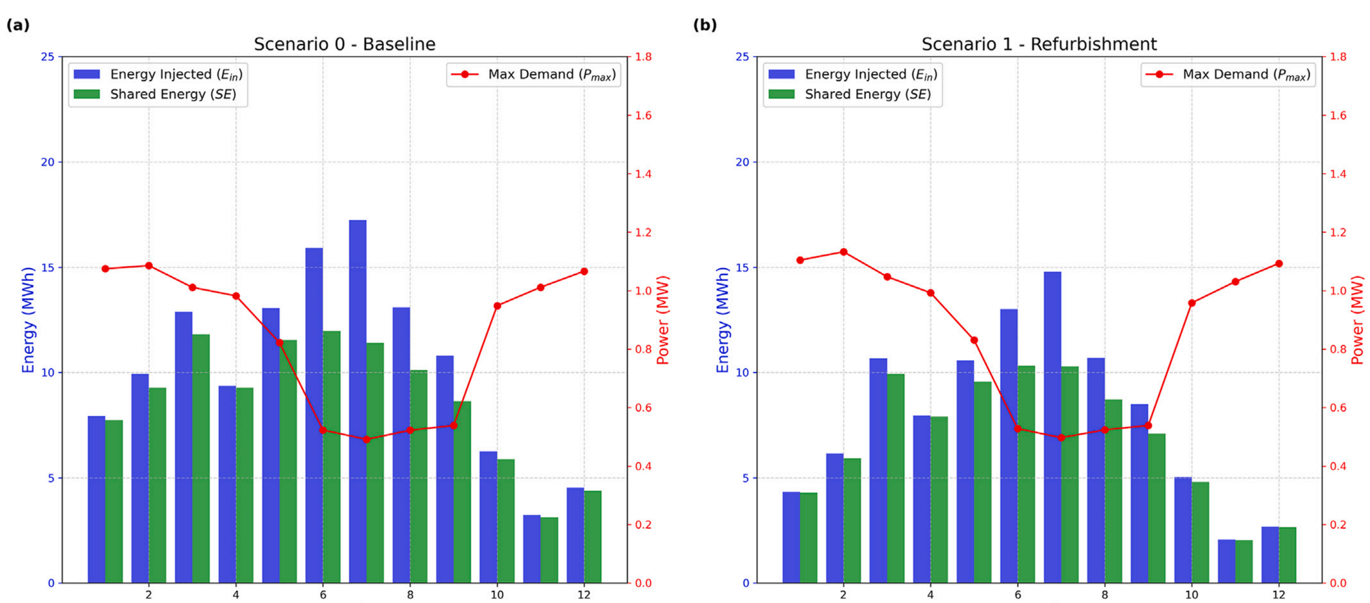

Fig. 9. Shared energy, REC energy injected to the grid and max power demand from grid by month for Scenario 0 – Baseline (a) and Scenario 1 – Refurbishment (b) with 34.7 % PV penetration

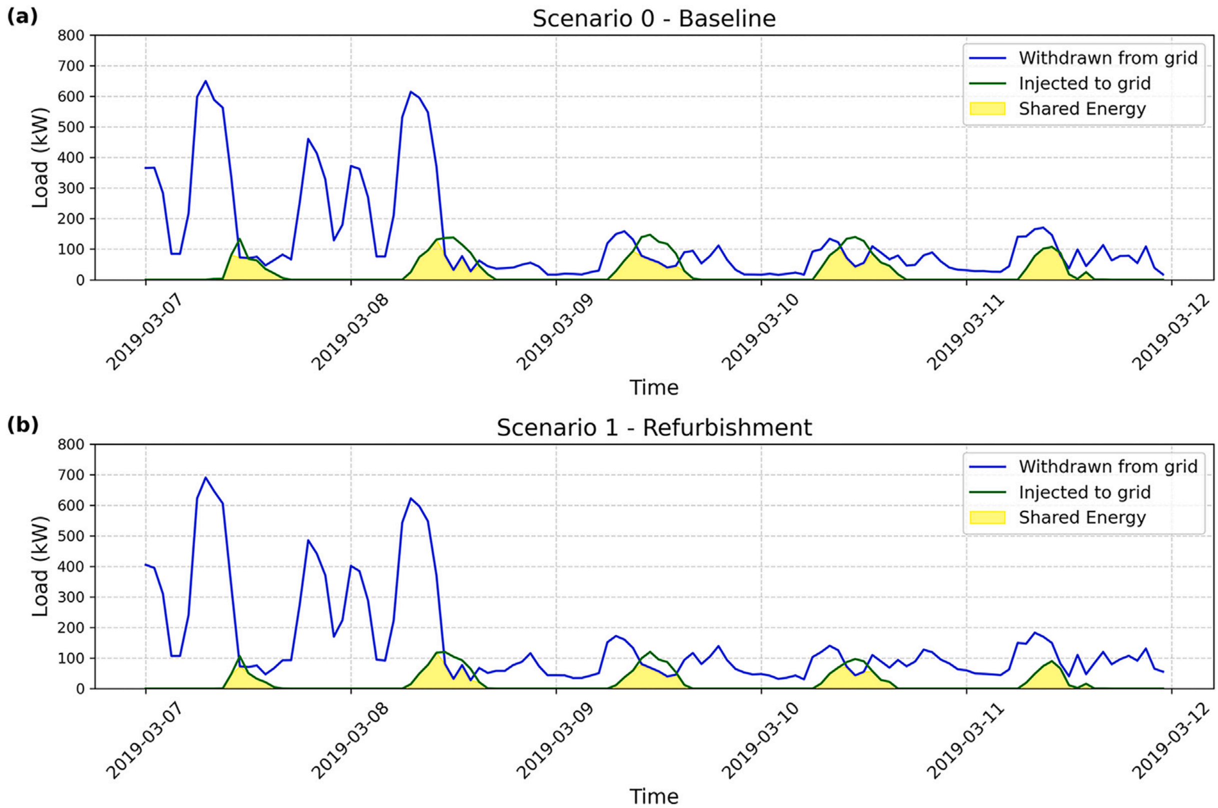

Fig. 10. Energy balance of the REC with the grid in case of Scenario 0 – Baseline (a) and Scenario 1 – Refurbishment (b)

which corresponds to the installation of 19 systems with a total capacity of 113 kWp. The energy metrics include REC energy injected into the grid (E_{in}^{REC}) and shared energy (SE), represented by blue and green bars, respectively, with values reported on the left y-axis (MWh). The red line represents the maximum power demand ($P_{wi,\max}^{REC}$), with values shown on the right y-axis (MW).

Both scenarios exhibit similar seasonal trends. The energy injected into the grid (E_{in}) peaks during the summer months (May–August), driven by increased PV generation. Shared energy remains relatively stable throughout the year, while maximum power demand (P_{max}) decreases during the summer due to lower heating requirements and rises during the colder months.

The primary differences between the scenarios are observed in the absolute values of the metrics. In Scenario 1 – Refurbishment, the REC energy injected into the grid is consistently lower than in Scenario 0 – Baseline, particularly during the summer months. This reduction highlights the improved self-consumption resulting from the partial electrification of heating systems in Scenario 1. Additionally, maximum power demand (P_{max}) is slightly higher during the winter months in Scenario 1, for the same reason. Shared energy is marginally lower in Scenario 1, aligning with the reduced overall energy demand due to enhanced building performance.

These results are derived from a detailed simulation that enables an analysis of the different scenarios with high temporal resolution, as shown in Fig. 10.

The figure presents the electrical energy balance of the REC with the grid, illustrating patterns of electrical energy supplied to the grid from the prosumers' PV surplus (labelled as 'Injected to grid' in green solid line), electrical energy withdrawn from the grid to power the REC (labelled as 'Withdrawn from grid' in blue solid line), and the shared energy (yellow area).

The resolution offered by the co-simulation architecture is both temporal and spatial. Fig. 11 displays the profiles of indoor air temperature and electrical load with details about load associated with (i) HP operation (blue area), (ii) HP auxiliaries operation (yellow area) and plug loads (red area). The figure shows a building in Scenario 1 – Refurbishments, characterised by the high performance of the envelope and HP technology.

From the bottom plot, it is interesting to observe how the backup auxiliary elements of the HP are activated in the morning, responding to a change in the thermal load. This is observed through the change in indoor set-point temperature value.

5. Discussion

The proposed manuscript presents an advanced co-simulation infrastructure and an innovative methodological framework for analyzing RECs. This framework was applied to study various scenarios of a REC in Frassinetto, a mountain village in northern Italy. The scenarios explored potential REC configurations, including retrofit interventions on building envelopes and heat generation technologies. A sensitivity analysis of PV installations was also conducted, showcasing the framework's ability to provide a detailed and realistic spatiotemporal analysis of REC energy performance.

5.1. Discussion on the proposed framework

Several frameworks and methodologies have been proposed recently for the co-simulation of RECs and, more generally, clusters of buildings. However, many of these approaches are applicable only to small-scale scenarios, involving a limited number of buildings. This limitation arises due to challenges related to the level and quality of input data required

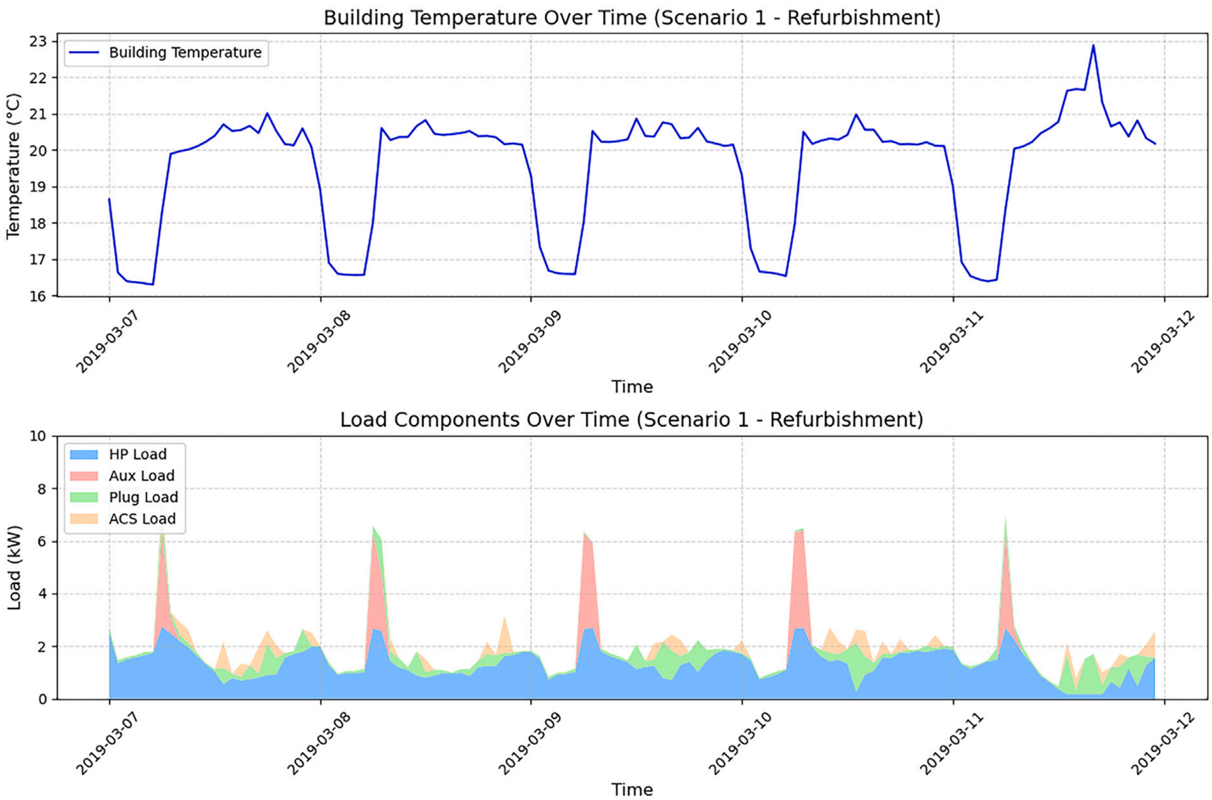

Fig. 11. Profiles of indoor air temperature and electrical load of a specific building within the REC with high performance of the envelope and HP technology.

to build the energy models, as well as the scalability of the co-simulation architecture and its ability to handle hundreds of models simultaneously.

The proposed framework integrates heterogeneous input data sources using a bottom-up approach, potentially enabling detailed modeling of each building with a high level of granularity. Moreover, only easily accessible and freely available information has been employed as input data sources in the present work. This aspect combined with tools adopted for modeling the buildings and HVAC systems, namely EnergyPlus and Modelica, enabled the definition of different REC subsystems. Thanks to this approach, over 200 building models were developed, automatically instantiated, and co-simulated multiple times over an entire year using a 10-min time resolution. The results demonstrated that the proposed framework effectively deploys detailed models of the key REC elements using widely accessible data across a broad spatio-temporal scale. Moreover, the flexibility of the co-simulation infrastructure allows integration of diverse simulation tools based on different modeling paradigms. For example, the infrastructure can handle agent-based models for simulating the behavior of the households towards the adoption or not of PV systems [24] or even simulating their activities to analyse the impact of urban electric mobility on the energy communities [71].

With a simulation period of one year achieved through the proposed framework, energy-related and economic KPIs derived from the co-simulation process can be effectively used to evaluate REC performance. These KPIs provide valuable insights to guide various stakeholders in the design and optimization of a REC.

Overall, this work advances the state of the art by integrating a novel co-simulation framework that leverages freely available data, integrates high-resolution physical modeling, and provides detailed and realistic simulation timescales. This approach not only overcomes some of the limitations of existing tools, but also provides a starting point for building a solid platform to serve local governments, energy planners, and policy makers to properly assess complex energy communities at both the city and district levels.

5.2. Discussion on the proposed case study

In the development of the proposed case study, the capabilities of the co-simulation architecture were exploited as discussed above. However, further improvements can be made to the individual models implemented. The architecture allows for detailed specification of the envelope properties of each building within the REC. This feature was not fully utilized, as the building envelopes were defined using archetypes due to the lack of detailed information for individual buildings. Additionally, the ventilation rate—an important driver of building energy consumption—was modeled using a simplified approach, rather than implementing more sophisticated schedules that the infrastructure is fully capable of handling. For these reasons, despite the potential offered by the co-simulation framework, the accuracy of the resulting models cannot be considered inherently superior to other approaches based on lower-resolution inputs. Nonetheless, it is important to emphasize that the framework supports a higher level of detail and physical fidelity, and when supported by richer input data, it can fully exploit the advantages of white-box modeling to improve simulation accuracy and transparency. The results of the analysis, provided interesting details about the impact of building envelope refurbishment and the adoption of HP technology over REC performance. Despite the reduction in shared energy resulting from increased self-consumption by prosumers, the refurbishment had a positive impact on virtual self-consumption, indicating a more effective distribution of the energy injected into the grid by the community. However, the gains in virtual-self consumption remain limited, suggesting that additional strategies are needed to enhance community-level energy performance. On the prosumer side, the integration of storage technologies such as BESS or TES allows for a more efficient use of locally generated photovoltaic (PV) energy. Batteries can store electrical surplus for later use, while TES can shift thermal loads by storing heat during PV generation peaks. Both solutions contribute to increased self-consumption and self-sufficiency. Nonetheless, this also results in a reduced quantity of excess energy being injected into the grid, potentially decreasing the amount available for shared use within the community. On the consumer side, the implementation of TES—particularly in buildings with electrified thermal energy generation—introduces additional flexibility that can be strategically exploited. By increasing thermal demand during hours of high prosumer generation, it becomes possible to consume local surplus generated by prosumers, thereby improving the shared energy indicator and reducing grid dependency. From a system perspective, this load-shifting approach may be more effective than maximizing prosumer self-consumption alone, as it enhances overall REC synergy. A limitation of the current case study is the absence of TES and BESS in the modeled scenarios. Their potential contribution to demand-side flexibility, both in individual buildings and at the community level, is worth of further investigation through integrated modeling approaches that consider temporal patterns of generation, storage behavior, and advanced control strategies. For what concerns economic KPIs, the introduction of PV on renovated buildings, proved to be a more economically viable intervention compared to the introduction of PV in the baseline scenario, when considering exclusively the investment costs and benefits provided by the PV. Additionally, the parametric analysis allowed the identification of the most advantageous level of PV penetration for the selected case study.

When the costs associated with envelope renovation and HP adoption are included in the analysis, the results show that increasing the number of buildings undergoing renovation and equipped with PV systems gradually improves overall economic viability. It is important to note that this analysis represents a simplification, as building renovation typically falls under the responsibility of individual households. Nonetheless, these results can support stakeholders in prioritizing interventions, suggesting that—even within the boundaries of current REC incentives—adopting a holistic approach to energy efficiency may lead to more economically robust outcomes.

Eventually, the proposed framework, with its bottom-up approach, provides the capability to conduct detailed building-level analyses of the energy and economic benefits of retrofit interventions.

6. Conclusion

This paper presents a novel co-simulation framework designed to analyze the energy performance of RECs with a detailed spatio-temporal approach. The proposed methodological framework serves as a modeling tool for energy communities that prioritizes accessibility for stakeholders through the use of free and readily available input data. It is designed to be highly scalable and grounded in precise, physics-based models, ensuring both usability and accuracy in diverse applications.

Applied to the Frassinetto case study, the framework effectively models the interactions between building envelope performance, heating technologies, and PV systems. It provides valuable insights into the dynamics of energy sharing and consumption within a community, along with a detailed economic analysis to assess the feasibility of a REC project across different levels of PV penetration.

The results of the case study suggest that while retrofitting building envelopes and upgrading technologies can improve energy efficiency, they alone may not fully unlock the potential for energy sharing within the REC. In this context, energy management strategies may play a key role in optimizing the integration of renewable energy into the community's energy system. Furthermore, the findings underscore the need to incorporate more flexible and adaptive approaches, such as energy storage and stochastic models for occupant behavior, to better capture the complexities of real-world energy use.

The following steps are proposed for future research and improvements:

- Integration of Stochastic Occupant Behavior Models: To improve the accuracy of energy demand predictions, future simulations should incorporate stochastic models that capture the variability in human behavior, moving beyond deterministic schedules.
- Incorporation of Energy Flexibility Technologies: Future work should explore the integration of energy storage systems, such as thermal energy storage and battery storage, to assess their impact on demand-side management, energy efficiency, and REC resilience.
- Refinement of Co-Simulation Infrastructure: The co-simulation framework can be further enhanced to accommodate larger-scale simulations, including district-level energy systems and more complex interactions between multiple energy systems (e.g., transportation and water systems).
- Exploration of Advanced Control Strategies: Future research could investigate advanced control algorithms for optimizing energy flows within RECs, particularly in relation to the integration of distributed energy resources (DERs), storage, and demand-side management.

By addressing these areas, the potentialities of the co-simulation framework presented in this study can be fully exploited to guide the design, optimization, and operation of RECs, ultimately contributing to the development of more sustainable, efficient, and resilient energy systems at the community level.

CRediT authorship contribution statement

Silvio Brandi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Pietro Rando Mazzarino:** Writing – original draft, Visualization, Software, Methodology, Investigation, Data curation, Conceptualization. **Daniele Salvatore Schiera:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Matteo Bilardo:** Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization. **Luca Barbierato:** Writing – original draft, Visualization, Software, Methodology, Conceptualization. **Lorenzo Bottaccioli:** Writing – review & editing, Supervision, Methodology, Investigation. **Edoardo Patti:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Conceptualization. **Alfonso Capozzoli:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, 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. Economic and financial analysis

This appendix reports the detailed description of the economic and financial model, assumptions and data adopted for the evaluation of the REC in all the scenarios considered in the case study.

Economic parameters

Turnkey PV system price. A turnkey PV system price, which includes design, installation, and commissioning, depends on size and category. Table A.8 reports the prices proposed by IEA-PVPS [70]. Moreover, a 10 % increase in cost was considered to take into account the cost of installation in rural areas.

It was assumed that an annual productivity degradation of PV system equal to 0.5 % per year. This accounts for the decrease in production over the system's useful life. Regarding the operating costs, the PV insurance cost was assumed as a percentage of the turnkey system cost, equal to 0.25 %, and the PV maintenance cost was assumed on average about 25 €/kW/year.

HP system and renovation project prices. The cost of the HP system is reported in Table A.9, and an extra 10 % of the cost was assumed to account for installation.

The cost of renovation projects depends on the type of surface to renovate and its starting energy performance. Table A.10 reports the unit renovation costs per surface area in different scenarios. Additionally, an extra 10 % of the cost was assumed to account for the renovation in rural areas.

Financing

Non-repayable grant. Non-repayable grant (%) relative to the PV system cost (max 40 % for municipalities with fewer than 5000 inhabitants). The grant is limited based on the PV system size as reported in Table A.11.

Debt. It was assumed a 60 % debt (relative to PV System Cost – Non-repayable grant) covered by a 10-year loan at an interest rate of 7 %. Monthly payments are assumed using the French amortization method.

Table A.8
Reference costs based on category/size, excluding VAT [70].

Category/Size	[€/W]
Residential BAPV < 10 kW	1.70
Small commercial BAPV 10–100 kW	1.50
Large commercial BAPV 100–250 kW	1.35
Industrial BAPV > 250 kW	1.15
Small centralized PV 1–20 MW	0.90
Large centralized PV 10–50 MW	0.75

Table A.9
Unit cost of HP system.

Capacity [kW_{el}]	Unit cost [€/kW]
<3	1667
3–5	1800
5–10	2000

Table A.10
Unit renovation costs per surface area in different retrofit scenarios [€/m^2]

Element	(Low → Medium)	(Low → High)	(Medium → High)
Walls	80	100	50
Roof	120	150	80
Floor	90	120	60
Windows	450	550	300

Table A.11
Maximum non-repayable grant by PV system size

Max grant [€/kW]	PV system size [kW]
1500	< 20
1200	20–200
1050	200–1000

Table A.12
Incentive TIP based on PV system size

Plant size P [kW]	TIP [€/MWh]	Min/Max TIP [€/MWh]
P ≤ 200 kW	$80 + \max(0, 180 - P_z)$	80/120
200 < P ≤ 600 kW	$70 + \max(0, 180 - P_z)$	70/110
P > 600 kW	$60 + \max(0, 180 - P_z)$	60/100

Discount on capital expenditure. For the HP system and renovation project, a 50 % discount on capital expenditure was assumed, as provided by the actual Italian tax incentives.

Taxation

The Italian taxation is basically composed by: VAT (IVA) 22 %, the Corporate income tax (IRES) 24 % calculated on EBT, and the Regional tax on productive activities (IRAP) that for Piedmont region is 8.5 %, calculated on EBIT. Moreover, it is assumed a tax depreciation equal to 2 % in the first year and 4 % in the following years, applied to the (PV System Cost – Non-repayable grant).

REC incentives and costs

In Italy, the REC is incentivised by valuing the shared energy by the community members [68]. In particular, the REC incentive on shared energy, called TIP, is associated with each PV plant installed, with an additional bonus of 10 €/MWh for the geographical area. Moreover, an additional contribution is provided for avoided system costs REF, of about 9 €/MWh. Finally, all the energy produced and injected into the grid is sold at the zonal price P_z, which is, on average, about 127 €/MWh for the Nord area of Italy.

The TIP is calculated based on the following Table A.12

However, if the PV plants are funded from a Non-repayable Grant, the TIP is corrected by the following formula: $TIP_c = TIP \cdot (1 - F)$ where F varies linearly between 0 (no grant) and 0.50 (grant covering 40 % of the investment). This reduction factor does not apply to shared electricity from consumption points owned by local authorities, religious organizations, third-sector entities, and environmental protection organizations.

Finally, the REC operating and management costs, e.g., accounting, member management, digital tools, etc., were assumed equal to 500 €/year.

Economic analysis

The Net Present Value (NPV) is calculated using the following formula:

$$NPV = -I + \sum_{t=1}^{T=25} \frac{FCF_t}{(1+i)^t}$$

$$FCF_t = \big[R_{RID} + R_{INC} + R_{REF} + R_{SC} + R_{LF} \\ -C_{ME} - C_{PV\_OPEX} - C_{MAN} - C_{T\_IRES} - C_{T\_IRAP} - C_{FIN}\big]_t$$

where:

- I: total capital expenditure for PV systems, HP systems and renovation projects.
- $R_{RID} = E_{in}^{REC} \cdot P_z$: revenue from selling injected energy.

- $R_{INC} = SE \cdot \left(\sum_{k=1}^{P} TIP_k^p \cdot X_k^p\right)$: incentive revenues where X_k^p is the rate of SE covered by the production unit k, and TIP_k^p is as folows:

$$TIP_k^p = \begin{cases} TIP_k^p & \text{if \% grant} = 0 \\ TIP_k^p \cdot X_{PA}^c + TIP_k^p \cdot (1 - F) \cdot X_{PRV}^c & \text{if \% grant ¿ 0} \end{cases}$$

With: $\sum_{k=1}^{P} X_k^p = X_{PA}^c + X_{PRV}^c = 1$, where X_{PRV}^c and X_{PA}^c are the rate of SE covered by the load from privates and public administration, respectively.
- $R_{REF} = SE \cdot REF$: Avoided System Cost Revenue
- R_{SC}: avoided cost resulting from physical self-consumption
- R_{LF}: avoided cost resulting from reduced fuel consumption by fuel switching from gas-fired boiler to HP system
- C_{ME}: additional cost incurred due to the increased electricity consumption of the HP system compared to the gas-fired boiler
- C_{MAN}: REC management and operating costs
- $C_{PV\_OPEX} = C_{PV} \cdot INS + P_{PV} \cdot PV_{O\&M}$: PV operating costs
- $C_{T\_IRES} = EBT \cdot IRES$: tax cost related to corporate income tax
- $EBT = EBIT - Q_i$: Q_i is the quota of interest
- $EBIT = EBITDA - Q_{depr}$: Q_{depr} is the quota of depreciation
- $EBITDA = R_{RID} - C_{PV\_OPEX}$
- $C_{T\_IRAP} = EBIT \cdot IRAP$
- C_{FIN}: loan payments
- i: interest rate 8 %

Key economic indicators

- Payback Time (PBT): Time at which NPV = 0

$$NPV = 0 = -I + \sum_{t=1}^{T=25} \frac{FCF_t}{(1 + WACC)^t}$$

- Internal Rate of Return (IRR): Rate at which NPV = 0

$$NPV = 0 = -I + \sum_{t=1}^{T=25} \frac{FCF_t}{(1 + IRR)^t}$$

- Annualized ROI:

$$ROI_{ann} = \left(1 + \frac{\sum_{t=1}^{T} FCF_t - I}{I}\right)^{1/T} - 1$$

Data availability

Data will be made available on request.

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