UNIVERSITÀ DEGLI STUDI FIRENZE

PhD in
Energetica e Tecnologie Industriali ed Ambientali Innovative

CYCLE XXXVII

Energy storage systems management in Renewable Energy Communities

Academic Discipline (SSD) ING-IND/09

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Years 2022/2024

“Voglio creare un mondo in cui l’energia si diffonda gratuitamente ovunque”

Vegapunk

“People are illogical, unreasonable, and self-centered.
Love them anyway.

If you do good, people will accuse you of selfish ulterior motives.
Do good anyway.

If you are successful, you will win false friends and true enemies.
Succeed anyway.

The good you do today will be forgotten tomorrow.
Do good anyway.

Honesty and frankness make you vulnerable.
Be honest and frank anyway.

The biggest men and women with the biggest ideas can be shot down by the smallest men and women with the smallest minds.
Think big anyway.

People favour underdogs but follow only top dogs.
Fight for a few underdogs anyway.

What you spend years building may be destroyed overnight.
Build anyway.

People really need help but may attack you if you do help them.
Help people anyway.

Give the world the best you have and you'll get kicked in the teeth.
Give the world the best you have anyway.”

Dott. Kent M. Keith

DECLARATION

I hereby declare that this submission is my own work and, to the best of my knowledge and belief, it contains no material previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any other degree or diploma at University of Florence or any other educational institution, except where due references are provided in the thesis itself.
Any contribution made to the research by others, with whom I have been working at the University of Florence or elsewhere, is explicitly acknowledged in the thesis.

Mattia Pasqui
31/10/2024

ACKNOWLEDGEMENTS

Thanks to DIEF, CONVOI and DESL, for believing in me and accompanying me during these three years of professional and personal growth. I have learnt a lot, and I will always be grateful.

Thanks to my mum for passing on to me the determination to do things and thanks to my dad for teaching me that they have to be done right.

Thanks to my brother for being stronger than me.

ABSTRACT

Across Europe, Renewable Energy Communities (RECs) are emerging as non-profit organizations composed of citizens, businesses, and public and private entities, participating as energy producers and consumers. These communities aim to generate environmental, social, and economic benefits for their members and the local territory, while actively contributing to the energy transition and addressing the challenges posed by climate change. European Union (EU) directives and national regulations underline the significant social role RECs are expected to play, while encouraging their involvement as key players in energy markets. REC members can produce, consume, store, and share energy, while also acting as aggregators, allowing them to buy and sell energy and energy services, thereby participating in energy and flexibility markets. In this evolving landscape, energy storage systems, particularly lithium-ion batteries and thermal storage coupled with heat pumps (HPs), are crucial for enhancing flexibility and efficiency.

This thesis, structured as a collection of four articles, addresses the central question of how energy storage systems should be managed within RECs to maximize their potential. Through the Italian regulatory framework and several case studies, it explores new methodologies for managing batteries and HPs in RECs from both a technical and economic perspective.

Crucially, the entire research adopts a paradigm shift from the individual prosumer viewpoint to a community perspective. In this context, the first article addresses the limitations of standard Battery Management Systems (BMS), which are designed solely for individual Self-Consumption (SC). To overcome this, it introduces a novel rule-based strategy for the centralized management of a fleet of batteries, designed to maximize Collective Self-Consumption (CSC) without penalizing individual SC, thereby aligning individual interests with the shared value of the REC. The second article applies the same logic to thermal energy storage systems coupled with HPs, focusing on load shifting to increase CSC.

However, these initial studies highlighted two critical barriers: first, individual residential batteries currently suffer from high capital costs; second, simple rule-based strategies lead to suboptimal results and are unable to handle the complexity of multi-service stacking, limiting potential revenues. Driven by these challenges, the third article executes a strategic shift towards a shared asset model managed via optimization. Adopting a Linear Programming (LP) approach to assess a Community Battery, it demonstrates that aggregating capacity allows for economies of scale, while optimization unlocks the full economic potential of multi-service provision. Consequently, enabling Energy Arbitrage (EA) alongside CSC is proven to be crucial for economic viability, potentially halving the payback period.

Yet, realizing these revenues requires the REC to operate in the market as a Balance Responsible Party (BRP), a role that entails managing forecast risks and grid imbalances. Addressing this challenge, the fourth article bridges the gap between simulation and reality by proposing and experimentally validating a robust two-layer control framework. This system enables the REC to manage forecast uncertainty and grid constraints, minimizing real-time dispatch errors. By proving the technical ability to act as a reliable BRP, this final study validates the feasibility of the economic scenarios analysed previously, ultimately providing a tool ready for real-world implementation.

Keywords: Renewable energy communities, energy storage system, collective self-consumption, multi services, optimization.

PROPOSITIONS

Motivation

- Lack of realistic techno-economic tools to assess the investment in storage system under complex regulatory constraints.
- Inadequacy of standard individual control strategies for RECs, necessitating community-centric logic to align private and collective goals.
- Financial unsustainability of individual battery investments, requiring a strategic shift to shared assets and multi-service optimization.
- Necessity for RECs to evolve into active Balance Responsible Parties (BRPs) using robust control frameworks to manage forecast uncertainty.

Original contribution

- [P1] Development of the "LoBi" profile generation method and a new centralized rule-based strategy increasing Collective Self-Consumption.
- [P2] Extension of centralized management to thermal storage, quantifying trade-offs between load shifting benefits and efficiency losses.
- [P3] LP optimization of a Shared Community Battery, proving that Energy Arbitrage halves payback periods, identifying optimal sizing and aging effects.
- [P4] Experimental validation of a two-layer control framework managing uncertainty and grid constraints, proving REC capability as a self-dispatching BRP providing CSC and EA.

Open questions

- How to integrate high-precision forecasting technologies (e.g., "Hawk Eye") to eliminate real-time dispatch errors?
- How to adapt optimization frameworks for the "Virtual Aggregation" of heterogeneous distributed fleets?
- What architectures are required to transition RECs from simple BRPs to active Balancing Service Providers (BSPs)?
- How to implement Hybrid Multi-Energy Optimization coupling electrochemical and thermal storage?

INDEX

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

Acronyms

AC	Alternating Current
ACT	BESS activation penalty
ARERA	Autorità di Regolazione per Energia Reti e Ambiente
AS	Ancillary Services
BC	Battery Cost
BESS	Battery Energy Storage System
BMS	Battery Management System
BRP	Balance Responsible Party
BSP	Balancing Service Provider
CF	Cash Flow
CN	Customer Number
CoDistFlow	Corrected DistFlow
COP	Coefficient of Performance
CSC	Collective Self-Consumption
CSS	Collective Self-Sufficiency
DER	Distributed Energy Resources
DH	Distributed Heating
DIS	Dispatchability
DoC	Depth of Charge
DoD	Depth of Discharge
DP	Dispatch Plan
DSO	Distribution System Operator
EA	Energy Arbitrage
EnCo	Energia Collettiva
EP	Energy Price
EU	European Union
GME	Gestore dei Mercati Energetici
GSE	Gestore dei Servizi Energetici
HP	Heat Pump
iDistFlow	Improved DistFlow
inc	incentive
LF	Load Flow
LP	Linear Programming
LV	Low Voltage
MESS	Multi-Energy System Simulator
MILP	Mixed-Integer Linear Programming
MV	Medium Voltage
NPV	Net Present Value
O&M	Operation and Maintenance
OPF	Optimal Power Flow

P1	Paper 1
P2	Paper 2
P3	Paper 3
P4	Paper 4
PV	Photovoltaic
RAMP	Rural Area Multi-energy Profile Generator
RD	Ritiro Dedicato
REC	Renewable Energy Community
SC	Self-Consumption
SS	Self-Sufficiency
SmBMS	Smart Battery Management System
StBMS	Standard Battery Management System
OpBMS	Optimal Battery Management System
PVrec	PV installed in a REC without batteries
RES	Renewable Energy Resources
SoE	State of Energy
SoC	State of Charge
TES	Thermal Energy Storage
TIAD	Testo Integrato Autoconsumo Diffuso
TIDE	Testo Integrato Dispacciamento Elettrico
TSO	Transmission System Operator

Symbols

A_b	complex power entering the generic branch b of the power grid	[VA]
a_b	complex power injected/absorbed on the downstream bus of the generic branch b of the power grid	[VA]
act^{cost}	BESS activation penalty weight parameter inside the objective function	[-]
b	branch/bus index	[-]
C	Capacity	[kWh]
csc^{inc}	incentive associated to collective self-consumption	[€]
csc^{value}	value of collective self-consumption	[kWh]
dis^{cost}	dispatch ability weight parameter inside the objective function	[-]
f_b	square of the current in the generic branch b of the power grid	[A^2]
G	power grid adjacency matrix	[-]
h	hour	[-]
i	interest rate	[-]
i_b	current in the generic branch b of the power grid	[A]
$i_{b,max}$	ampacity limit of the generic branch b of the power grid	[A]
Im()	Imaginary part function	[-]
N_b	number of branches in the power grid	[-]
N_s	number of forecasted scenarios	[-]
N_t	number of timesteps	[-]
P_b	active power entering the generic branch b of the power grid	[kW]

p_b	active power injected/absorbed on downstream bus of the generic branch b of the power grid	[kW]
p_b^{bess}	active power injected/absorbed on downstream bus of the generic branch b of the power grid by BESSs	[kW]
p_b^{pv}	active power injected/absorbed on downstream bus of the generic branch b of the power grid by PVs	[kW]
p_b^{load}	active power injected/absorbed on downstream bus of the generic branch b of the power grid by loads	[kW]
$\hat{p}_b^{pv}$	active power injected/absorbed on downstream bus of the generic branch b of the power grid by PVs, forecast.	[kW]
$\hat{p}_b^{load}$	active power injected/absorbed on downstream bus of the generic branch b of the power grid by loads, forecast.	[kW]
p_b^{lco}	active power loss in the generic branch b, correction term	[kW]
p_0	active power injected/absorbed on the grid connection point (bus 0)	[kW]
$\bar{p}_0$	active power injected/absorbed on the grid connection point (bus 0) realization according to real-time data monitoring	[kW]
p_0^{DP}	active power bidded to the grid connection point (bus 0) according to the dispatch plan	[kW]
Q_b	reactive power entering the generic branch b	[kvar]
q_b	reactive power injected/absorbed on downstream bus of the generic branch b of the power grid	
q_b^{bess}	reactive power injected/absorbed on downstream bus of the generic branch b of the power grid by BESSs	[kvar]
q_b^{pv}	reactive power injected/absorbed on downstream bus of the generic branch b of the power grid by PVs	[kvar]
q_b^{load}	reactive power injected/absorbed on downstream bus of the generic branch b of the power grid by loads	[kvar]
${q_b}^{co}$	reactive power loss in the generic branch b, correction term	[kvar]
r_b	line resistance of the generic branch b of the power grid	[Ω]
r_b^{bess}	battery equivalent resistance	[Ω]
Re()	Real part function	[-]
rt	real-time control	[-]
s	scenario index	[-]
sc	scheduling	[-]
T	temperature	[°C]
t	timestep index	[-]
T^{step}	timestep interval	[s]
$T^{step,sc}$	timestep interval in the scheduling problem	[s]
$T^{step,rt}$	timestep interval in the real-time control problem	[s]
v_b	square of the voltage of the downstream bus concerning the generic branch b	[V^2]

$v_{up(b)}$	square of the voltage of the upstream bus concerning the generic branch b	[V]
v_b^{ap}	voltage on the downstream bus concerning the generic branch b, approximation term	[V^2]
v_b^{co}	square of the voltage drops between downstream and upstream buses concerning the generic branch b, correction term	[V^2]
v^{max}	square of the voltage of the downstream bus concerning the generic branch b, maximum value	[V^2]
v^{min}	square of the voltage of the downstream bus concerning the generic branch b, minimum value	[V^2]
z_b	line impedance of the generic branch b of the power grid	[Ω]
z_b^*	complex conjugate of the line impedance of the generic branch b of the power grid	[Ω]
x_b	line reactance of the generic branch b of the power grid	[Ω]
y	year	[-]

SYNOPSIS

The central goal of this PhD research is to develop innovative strategies for managing energy storage systems within REC to enhance their technical performance, economic viability, and contribution to the energy transition. This thesis addresses the challenges and opportunities related to the integration of storage technologies, both electrical and thermal, into RECs, focusing on optimizing their operation and maximizing benefits for both community members and the broader energy system.

The main research objectives are:

- Develop and test new strategies to increase the CSC of energy within RECs, thereby reducing dependency on the external grid and raising REC gains.
- Explore and evaluate the potential of different energy storage systems, such as lithium-ion batteries and thermal energy storage coupled with HPs, to support REC objectives.
- Assess the economic implications of various management strategies, identifying scenarios where storage investment is cost-effective.
- Investigate the impact of current regulatory frameworks on the feasibility and performance of RECs and propose recommendations for policy improvements to foster the development of smart energy communities.
- Propose new methods for load profile generations to be used in energy system simulations.
- Propose, simulate, and test optimization models that enable batteries to provide multiple services, specifically CSC, EA, and Self-Dispatching, while accounting for grid constraints, forecast uncertainty and battery aging.

To achieve these goals, the research follows a coherent evolutionary path, moving from simple distributed control strategies to advanced centralized optimization. This progression is visually summarized in **Figure 1**, which illustrates the logical flow connecting the four studies and highlights how the outcomes and limitations of each work motivated the subsequent one.

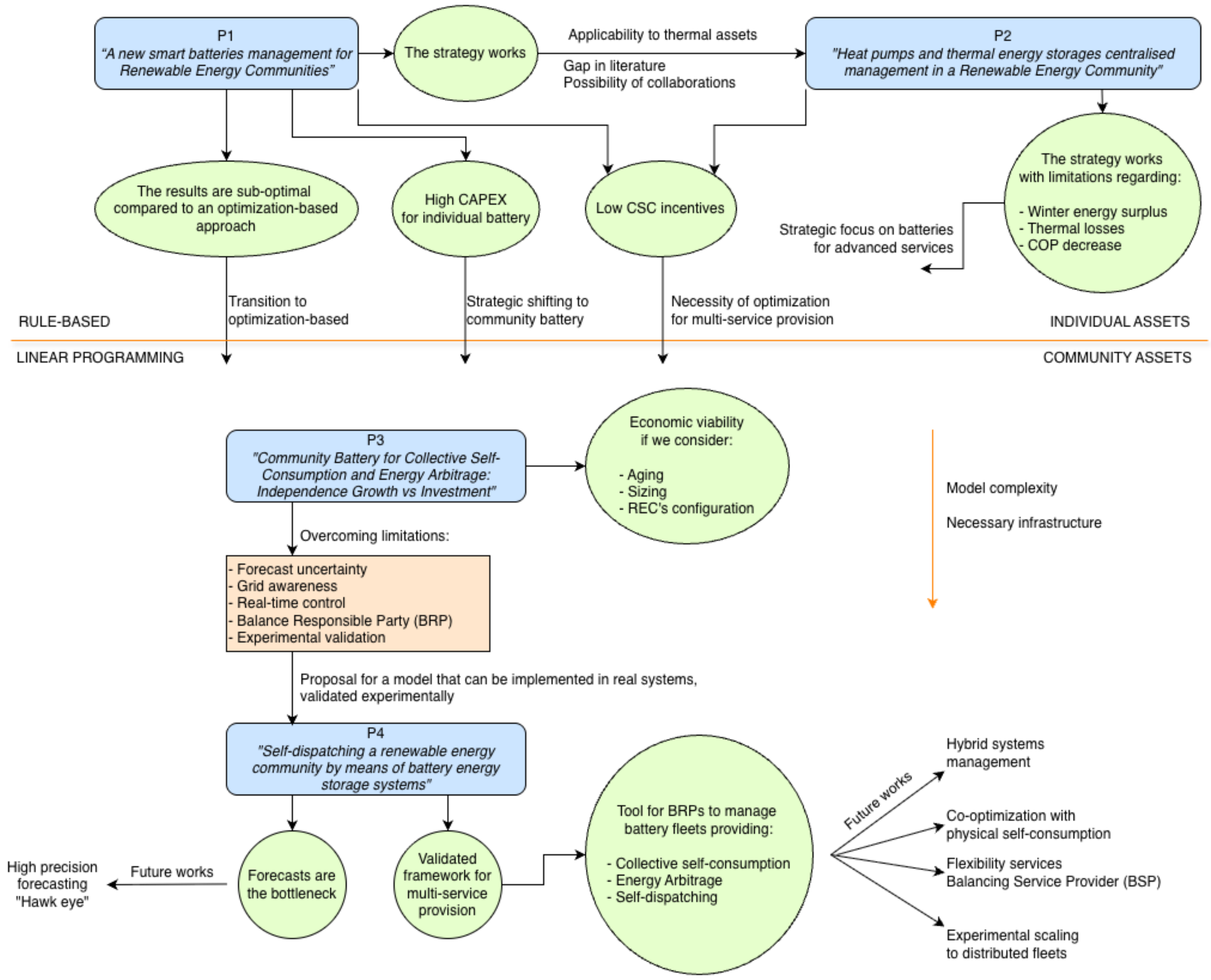


Figure 1: Logical flow and methodological evolution across the four research papers

The research is structured into four key studies, representing an evolution from rule-based coordination to real-time optimization:

- From Rule-Based to Optimization (Papers 1 and 2) The initial phase focused on accessible, low-complexity strategies. Paper 1 [P1] introduces a new centralized rule-based strategy for residential battery fleets. While effective for CSC, the study highlighted that rule-based methods are sub-optimal compared to an optimization approach. Paper 2 [P2] extends this logic to thermal assets, proving technical feasibility but revealing limited economic margins under current incentives, suggesting a need for high-value services like EA which requires optimization-based scheduling.
- Optimizing for Multi-Service Provision in Paper 3 [P3] To unlock economic viability and overcome the cost barriers of individual assets, [P3] transitions to a LP approach for a shared community battery, optimizing both CSC and EA. The results show that EA significantly reduces payback periods. However, the model omits a critical operational gap: to access wholesale market prices for profitable arbitrage (buying and selling at the same marginal price), the REC must act as a BRP. This role implies managing forecast errors and financial responsibility for imbalances, factors that the deterministic model in P3 did not address.
- Real-World Implementation and Validation in Paper 4 [P4] Addressing the BRP requirement, [P4] presents the culmination of this thesis: a robust, two-layer control framework validated experimentally on a microgrid. This model integrates forecast uncertainty and grid constraints, allowing the REC to minimize dispatch errors and effectively operate as a BRP.

To explicitly detail the contribution of each step, the main outcomes of each paper and their connection to the next are listed below:

[P1]: "A new smart battery management for Renewable Energy Communities"

- Development of a centralized rule-based strategy capable of increasing CSC by over 35 % compared to standard local control.
- Creation of "LoBi," a novel open-source method for generating realistic load profiles from electricity bills.
- Economic assessment proving that while PV is profitable, battery investment remains challenging.
- Comparison with an optimization-based approach used as benchmark revealed that rule-based strategies, while robust, leave untapped potential, paving the way for thermal application in [P2] and optimization methods in [P3].
- Crucially, the economic analysis proved that small-scale residential batteries are currently not cost-effective due to high specific costs. This finding motivated the strategic shift in [P3] towards a centralized Community Battery, aiming to exploit economies of scale and shared investment models to restore economic viability.

[P2]: "Heat pumps and thermal energy storages centralized management in a Renewable Energy Community"

- Successful adaptation of the rule-based strategy proposed in [P1] also to thermal assets (HPs), achieving a 5 % to 8 % increase in CSC.
- Quantification of technical trade-offs, specifically the reduction in average COP and increased thermal losses.
- Demonstration that CSC incentives alone are insufficient to justify the complexity of thermal management.
- The limited economic gain motivated the strategic shift towards EA and Optimization-based models in [P3] to stack multiple revenue streams.

[P3]: "Community Battery for Collective Self-Consumption and Energy Arbitrage"

- Formulation of a LP model for a community battery optimizing CSC and EA, considering battery aging.
- Identification of the break-even point: Arbitrage is essential for economic sustainability and can halve the payback period compared to CSC alone.
- Analysis of the trade-off between maximizing CSC (grid benefit) and Arbitrage (revenue generation).
- The study highlighted that true profitable arbitrage requires the REC to trade on the market as a BRP. Since the P3 model was deterministic and ignored imbalance penalties and grid constraints, a robust real-time control framework was necessary (P4).

[P4]: "Self-dispatching a Renewable Energy Community by means of Battery Energy Storage Systems"

- Development of a two-layer control architecture (Day-Ahead Scheduling and Real-Time Control) that manages forecast uncertainty and grid constraints.
- Experimental validation on a physical microgrid, proving the system's ability to perform Self-Dispatching (minimizing imbalance errors), Arbitrage, and CSC simultaneously.
- Establishment of a validated tool ready for scaling to distributed fleets and flexibility markets in future works.

In conclusion, this thesis offers a comprehensive set of strategies, ranging from simple coordination rules to advanced real-time optimization, providing REC managers and policymakers with validated tools to design and operate communities as active, grid-integrated market players.

1 STATE OF THE ART

1.1 Introduction to energy landscape

The energy sector is undergoing a profound transformation, driven by the need to mitigate climate change and ensure energy security for future generations. The global shift towards Renewable Energy Sources (RES) is reshaping the traditional power systems, which were once dominated by centralized fossil fuel-based plants. Today, this transformation is marked by an increased focus on decentralization, digitalization, and sustainability, setting the stage for a new energy landscape where distributed generation and energy storage systems play pivotal roles

1.1.1 Will Europe be climate-neutral by 2050?

The global shift towards a sustainable energy system is driven by major international agreements and policies, such as the Paris Agreement, the European Green Deal, and the Clean Energy for All Europeans Package. The Paris Agreement [1], adopted at COP21 in 2015, commits countries to limiting global warming to well below 2°C, aiming for 1.5°C, and has set the foundation for long-term climate goals. Following this, the European Green Deal [2] introduced in 2019, aims to make Europe the first climate-neutral continent by 2050, setting intermediate targets such as reducing greenhouse gas emissions by 55 % respect to 1990 by 2030. The Clean Energy for All Europeans Package [3], also launched in 2019, establishes specific legislative frameworks to enhance renewable energy adoption, improve energy efficiency, and reform electricity markets. These initiatives align with the recent outcomes of COP28 in Dubai (2023,[4]), where global leaders agreed to triple renewable energy capacity and double energy efficiency improvements by 2030 to stay on track for the 1.5°C target.
Despite these ambitious targets, progress towards achieving them remains mixed. According to IRENA and IEA, global renewable energy capacity needs to increase significantly to meet the tripling target by 2030. As of 2023, Europe had installed approximately 570 GW of renewable energy capacity, which must more than double to over 1,200 GW by 2030 to meet its climate goals. By 2050, the renewable energy capacity in Europe is projected to reach approximately 3,000 GW to ensure the carbon neutrality for the continent. In terms of energy storage, Europe currently has 10 GW of installed power capacity, but it needs to increase to 55 GW by 2030 and at least 160 GW by 2050 to maintain grid stability and support the integration of renewable sources. In Italy, the installed renewable energy capacity is around 60 GW, but this will need to grow to 125 GW by 2030 and to 160 GW by 2050 to align with European targets. The Italian energy storage

capacity, currently around 2.3 GW of power capacity, will need to rise to 8 GW by 2030 and further to 20 GW by 2050 to ensure flexibility in the national grid [5][6][7][8][9].
The progress made so far, when compared to the targets ahead, highlights both significant achievements and challenges. From 1990 to 2023, Europe saw its renewable energy capacity grow from 100 GW to 570 GW, a nearly sixfold increase over three decades. Italy followed a similar trend, increasing its capacity from 10 GW in 1990 to 60 GW by 2023. This historical growth underscores the strides made in the energy transition, yet it also places into context the scale of what is still needed. While Europe added 470 GW of renewable capacity in the past 30 years, it now faces the challenge of adding over 1,600 GW more in just the next 27 years to reach the 2050 target. Similarly, energy storage in Europe expanded modestly from 2 GW in 1990 to 10 GW by 2023, but the future demands call for a massive leap to 55 GW by 2030 and 160 GW by 2050. For Italy, the expansion of renewable energy from 10 GW to 60 GW over the past 30 years illustrates substantial progress, but the country now needs to double its capacity by 2030, followed by more moderate growth to 160 GW by 2050.
In summary, while the progress from 1990 to 2023 has been significant, the pace of expansion must accelerate to meet the upcoming targets. Achieving the tripling of renewable capacity and the rapid expansion required in energy storage, particularly over the next decade, will be critical to aligning with climate neutrality goals.

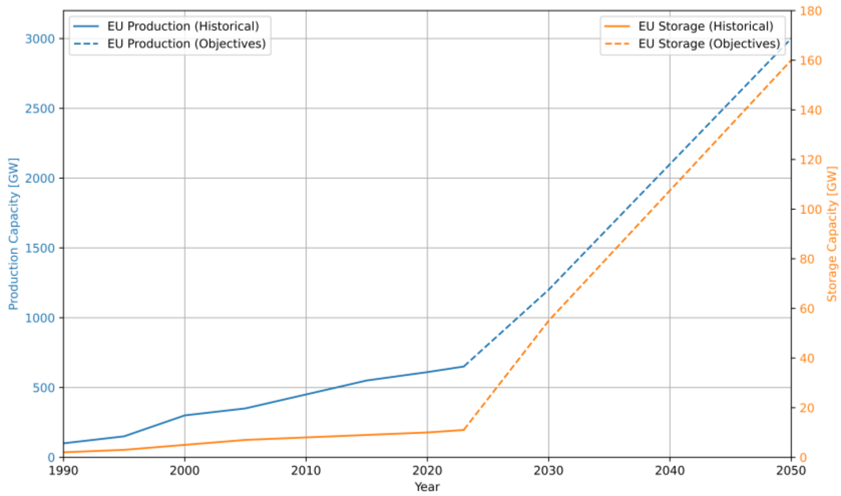


Figure 1.1: Renewable energy production and storage capacity in Europe.

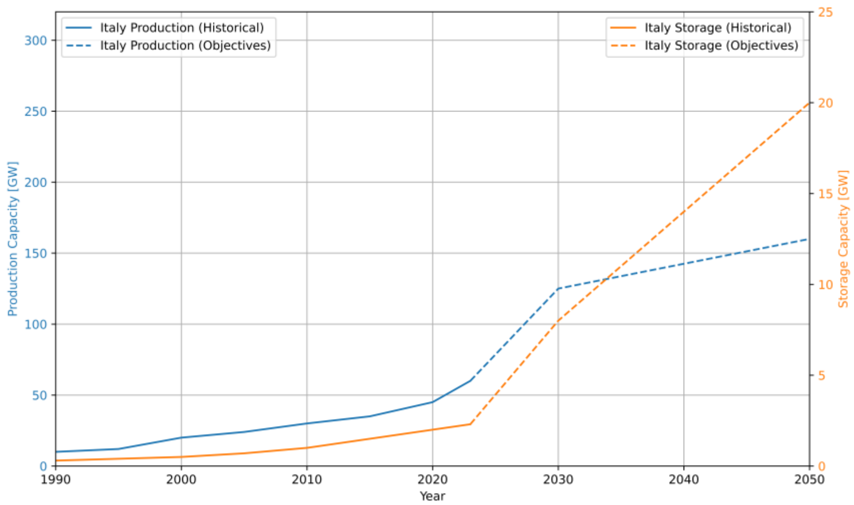


Figure 1.2: Renewable energy production and storage capacity in Italy.

1.1.2 Distributed energy systems

A key aspect of the ongoing energy transition is the move towards distributed generation (DG), where energy is produced closer to the point of consumption. This shift is exemplified in **Figure 1.3** and **Figure 1.4**, where the traditional centralized power grid reliant on large fossil-fuel-based plants is being replaced by a decentralized grid, driven by RES such as rooftop solar panels, wind turbines, and small-scale hydroelectric systems. This decentralized system introduces several advantages, including reduced greenhouse gas emissions, enhanced energy security through diversified sources of supply, and increased efficiency by minimizing transmission losses.

However, as depicted in the **Figure 1.4**, the move towards a decentralized system comes with its own set of challenges. One of the primary issues is the need for advanced grid management to integrate many small-scale generators and handle the variability inherent in RES such as solar and wind. Unlike traditional power plants, these decentralized generators produce energy intermittently, depending on weather conditions, requiring dynamic solutions for balancing supply and demand. Furthermore, distributed generation necessitates a transformation in electricity markets, allowing decentralized assets not only to participate in energy markets but also in flexibility markets, where they can provide grid services that are essential for maintaining stability. In the future, the grid must allow prosumers, households and small businesses that produce their own energy, to actively contribute to both markets, which historically were dominated by large utility companies.

In this evolving context, RECs and energy storage systems emerge as crucial components of the energy transition. RECs, supported by European directives, enable citizens, businesses, and public institutions to collaborate in generating, sharing, and managing renewable energy locally. These communities play a pivotal role in aggregating distributed energy assets, such as solar panels and wind turbines, and enabling them to participate in energy and flexibility markets. Energy storage systems, particularly lithium-ion batteries and thermal storage systems are essential for ensuring the smooth operation of these distributed energy systems. Storage allows RECs to store excess energy generated during periods of high renewable output and use it during times of lower production or high demand, providing vital services like grid balancing and EA. This capability enhances local energy Self-Sufficiency (SS) and reduces reliance on centralized grids, as shown in **Figure 1.4**, where fewer large power plants are needed.

The figure illustrates how decentralized systems aggregate multiple assets such as small renewable plants, batteries, and other storage systems, which together will play a more prominent role in the future energy markets. These aggregated assets will eventually replace large fossil fuel plants in the grid energy and flexibility markets. For this transition to be successful, it is crucial to develop market mechanisms that allow these smaller, aggregated assets to participate competitively alongside traditional large-scale producers.

However, the successful integration of distributed generation and the realization of the full potential of RECs depends on addressing several pressing challenges. A key challenge is the effective management of energy storage systems, which will play a central role in balancing the intermittency of renewable generation and providing essential grid services. The complexity of managing storage within a decentralized system is heightened by the need to coordinate the actions of numerous small-scale assets. Therefore, learning how to optimize the management of storage systems within RECs is critical for ensuring that these communities can contribute to grid stability and accelerate the energy transition.

In conclusion, as we move towards a decentralized energy future, energy storage and RECs will be at the forefront of this transformation. To fully unlock their potential and drive the transition, we must rapidly develop strategies to manage these assets efficiently, particularly in the context of RECs, which are poised to become key players in both energy and flexibility markets. By doing so, we can significantly accelerate the energy transition and move closer to achieving climate neutrality.

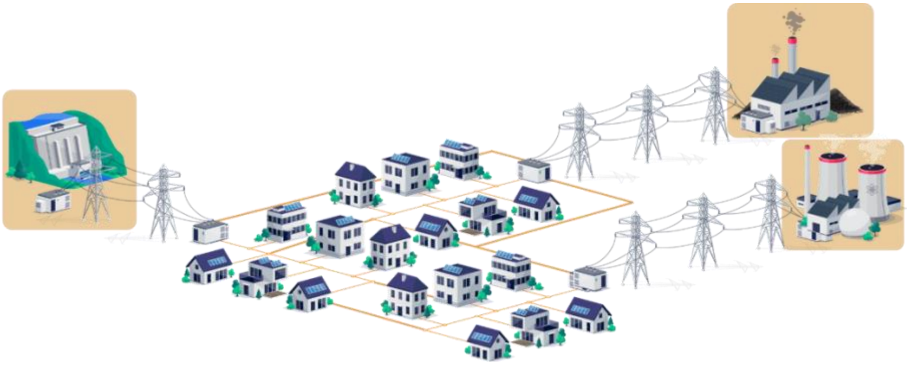


Figure 1.3: Centralised energy system

Figure 1.4: Distributed energy system

1.2 Renewable energy communities

This chapter explores the key regulatory, organizational, and technical frameworks that enable RECs in Europe and Italy. It begins with 1.2.1, outlining European policies like the European Green Deal and Clean Energy for All Europeans Package, followed by 1.2.2, which focuses on the Italian evolving regulations, from the Milleproroghe Decree to the CACER Decree. In 1.2.3, we examine the organizational structures RECs can adopt, including associations and cooperatives. 1.2.4 explains CSC and virtual energy sharing, while 1.2.5 discusses the economic incentives available to RECs. 1.2.6 presents case studies of flourishing RECs in Italy and Europe, and 1.2.7 introduces simulation method used to optimize REC performance. Together, these sections provide a comprehensive understanding of the frameworks that govern RECs.

1.2.1 European directives

The EU's legal and regulatory framework places a strong emphasis on fostering RECs as key enablers of the energy transition. Through a set of directives, the EU has established mechanisms that not only promote the uptake of RES but also encourage active citizen participation in energy production and market integration. This new decentralized approach empowers local communities to play an integral role in achieving the EU's ambitious climate goals.
A cornerstone of this framework is Directive (EU) 2019/944 [10] on common rules for the internal market for electricity. This directive, which reshapes the electricity market across Europe, directly supports the development and integration of distributed generation (DG) systems, primarily driven

by renewable energy. Under this directive, Member States are required to ensure that the electricity markets are open and accessible to energy aggregators, prosumers, and especially RECs.
RECs are viewed as essential participants in the decentralized energy landscape. The directive encourages their formation by providing the legal framework that enables communities to generate, consume, store, and sell renewable energy at the local level. In doing so, RECs not only reduce their carbon footprint but also contribute to grid stability by providing flexibility services such as balancing supply and demand within local grids. This is critical for supporting the shift from large-scale centralized power plants to a more flexible, decentralized system.
Directive 2019/944 also establishes the concept of active consumers, recognizing that individuals and local entities should be able to take full advantage of market opportunities, not only as consumers but also as producers. In this context, RECs are seen as aggregators of Distributed Energy Resources (DER), enabling citizens and small businesses to pool their renewable energy production, engage in energy trading, and collectively participate in both the energy markets and the flexibility markets. This aggregation is vital for smaller players to gain access to markets that were traditionally dominated by large utilities.
Equally important is Directive (EU) 2018/2001 [11] on the promotion of renewable energy, which explicitly highlights the role of RECs in achieving the EU's renewable energy targets. This directive sets binding targets for the share of renewable energy in the EU's overall energy mix aiming for at least 32 % by 2030 and provides a strong legal basis for supporting citizen-driven energy projects. RECs are empowered by this directive to operate as key local actors, capable of generating, storing, and sharing energy at the community level.
Directive 2018/2001 further ensures that RECs receive non-discriminatory access to energy markets, and it obliges Member States to remove barriers that prevent communities from fully participating in energy production and trading. The directive encourages the development of local energy projects by simplifying administrative procedures and providing financial incentives, such as feed-in tariffs, that enable RECs to compete with larger energy producers. Additionally, it promotes peer-to-peer energy sharing within RECs, allowing members to trade surplus energy among themselves or with the grid, enhancing energy independence and local SS.
The flexibility markets enabled by both directives are critical for the role of RECs, particularly as they begin to integrate more energy storage systems such as batteries. These systems allow communities to balance intermittent renewable generation, store excess energy, and release it when needed, ensuring a steady energy supply and enhancing the stability of local grids. By offering services such as demand response and grid balancing, RECs contribute to overall grid resilience and help reduce the reliance on fossil fuel-based backup generation.
In summary, the EU's legal framework, particularly through Directives 2019/944 and 2018/2001, positions RECs as central actors in the energy transition. By facilitating local ownership of renewable energy projects and promoting active participation in both the energy and flexibility markets, these directives empower communities to contribute directly to Europe's decarbonization goals. RECs are thus not only crucial for achieving the EU's 2030 and 2050 climate targets but also for transforming the energy market into a more democratic, inclusive, and resilient system.

1.2.2 Italian regulation

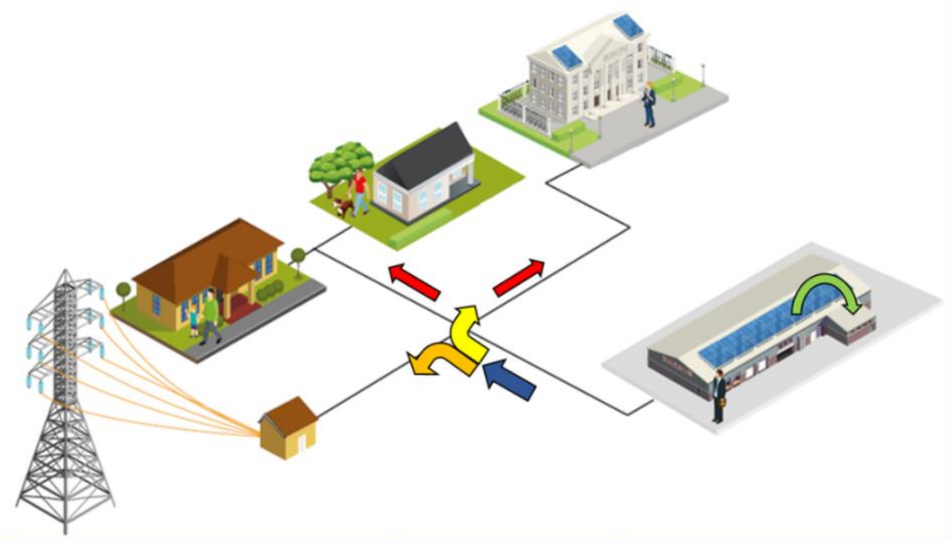
This thesis takes as its primary case study the regulatory framework governing RECs in Italy, a system that has evolved significantly over the past years. As discussed in the previous chapter, while the EU has provided general directives and guidelines for the development of RECs, each member state, including Italy, has implemented these frameworks in different ways, adapting to national needs and specific energy market conditions. The methodologies and strategies proposed in this thesis are designed with flexibility, allowing them to be applied in other EU states with only minor modifications regarding the economic context, as the core principles of battery management and energy optimization are consistent across Europe. This is because RECs across Europe are built on the same EU directives, making their fundamental structures highly similar.

In this chapter, we will outline the history of Italian regulations related to RECs, focusing on key legislative developments, and then provide an in-depth analysis of the most recent regulatory instruments that define the operational aspects of RECs in Italy, specifically the CACER Decree and the TIAD [12]. The RECs in Italy were introduced in 2020 in an experimental phase and only became fully operational in January 2024 with the implementation of the latest regulations. Below is a chronological summary of the major legislative milestones that have shaped the Italian approach to RECs:

- Milleproroghe Decree-Law 162/2019 [13]: This decree introduced the first provisions for CSC and energy sharing. It allowed prosumers (individuals or entities producing their own energy) to aggregate and share energy within a defined geographical area, typically under the same secondary electrical substation (medium to low voltage). This marked the first step toward creating the legal foundation for RECs in Italy. In subsequent regulations, the perimeter for CSC was expanded to include the primary electrical substation (high to medium voltage), broadening the geographical scope and allowing more flexibility for REC configurations.
- Legislative Decree 199/2021 [14]: It provided the legal basis for the formation of RECs and introduced the concept of CSC. CSC, as defined by this decree, occurs in a virtual manner, meaning that energy produced and consumed by the community members is shared and accounted for through the grid, without the need for a direct physical connection. This virtual model allows prosumers and consumers within the defined geographical area to participate in energy sharing, maximizing the local use of renewable energy and enhancing the economic viability of the community. The decree set the groundwork for this virtual model, enabling both energy sharing and incentivizing the consumption of renewable energy produced within the community.
- Legislative Decree 210/2021 [15]: This law transposed the provisions of Directive (EU) 2019/944, focusing on consumer empowerment, flexibility markets, and energy communities. It allowed broader participation in energy markets by smaller, DER, including RECs, thereby enabling energy aggregation and the provision of grid flexibility services.
- ARERA Deliberation 318/2020 [16] and ARERA Deliberation 727/2022 [17]: Issued by the Italian Regulatory Authority for Energy, Networks, and Environment (ARERA), these regulations laid out the technical and economic frameworks for CSC and RECs. The deliberations provided mechanisms for energy sharing and outlined the incentives available for energy communities. They also defined the operational rules for calculating shared energy based on the minimum hourly energy injected and withdrawn by all members of the REC [18] [19]. The first version of these operational rules defined the mechanisms that supported the experimental phase, which led to the creation of the first small RECs in Italy. This phase lasted for two years and provided valuable insights into the technical and economic viability of energy sharing models.
- CACER Decree (2024) [12]: The most recent and comprehensive regulatory instrument, it defines the operational rules and financial incentives for RECs, providing detailed guidelines on how to access government incentives. It specifies the technical requirements for CSC, as well as how RECs can valorise the energy they produce and share. Having established the regulatory foundation for RECs, we now turn to the technical mechanics of how energy is shared and consumed within these communities.

1.2.3 Collective self-consumption and energy flows

Understanding the flow of energy within a REC is crucial to optimizing both technical performance and economic benefits. The following sections detail the various ways energy is injected, consumed, and shared within the REC. The main principles of operation are defined below thanks in part to the use of Figure 1.7.



Self-consumption	+ 30 c€/kWh	Bill savings
Feed	+ 10 c€/kWh	Sale to GSE
Withdrawal	- 30 c€/kWh	Purchase from supplier
Collective self-consumption	+ 12 c€/kWh	Incentives

Figure 1.5: Collective self-consumption scheme

In Italy, a core principle of RECs is the concept of CSC, which allows members of a community to share renewable energy generated within the geographical area defined under the same primary substation. However, before understanding CSC, it is essential to first explain the related concepts of physical self-consumption (SC), injected energy, and withdrawn energy, as these are critical to grasping how energy and financial flows function within RECs, using as reference **Figure 1.5**.

- SC refers to the direct consumption of energy produced by a member’s own renewable energy system, such as solar panels or a wind turbine, without injecting the energy into the grid. This form of energy usage is immediate and local energy produced on-site is used on-site. It represents the most efficient use of renewable energy since no energy losses occur during transportation, and the energy producer directly benefits from reduced electricity bills, as they avoid paying for grid energy or transmission fees. Members who self-consume energy physically thus experience direct financial savings through reduced electricity costs, as they are not relying on energy supplied through the grid.
- SS is defined as the percentage of a single user total energy demand that is met directly by their own on-site generation (SC). This metric applies only to prosumers and indicates their individual independence from the grid.
- Fed energy refers to the energy that is not consumed physically on-site by the producer and is instead fed into the grid. This can happen regardless of whether the producer is part of a REC or not. Once injected, this excess energy is made available to other grid users, including members of the REC or consumers outside of the community. In the Italian regulatory framework, energy that is injected into the grid is typically sold to the GSE (Gestore dei Servizi Energetici), which pays a variable price for the energy, generally around 0.10 €/kWh, although

this value can fluctuate depending on market conditions. This injected energy is considered part of the broader national grid and, technically, could be consumed by anyone connected to the grid, not just members of the REC. However, if the injected energy is consumed by other members of the REC, it qualifies as part of the community CSC, and this shared energy becomes eligible for the incentive tariff. In this case, the producer benefits both from selling the energy to the GSE and, through the REC redistribution, from the additional incentive for promoting local consumption of renewable energy.

- Withdrawn energy refers to the energy that REC members pull from the grid when their own renewable energy production is insufficient to meet their consumption needs. This energy can either come from renewable sources injected by other REC members or, if necessary, from the national grid. Regardless of whether a member is part of a REC or not, any energy withdrawn from the grid is purchased from an energy provider through a standard contract.
  The cost of withdrawn energy is determined by the terms of the purchase agreement with the energy supplier, typically reflecting the current market price of electricity, and is subject to standard grid energy costs. For REC members, if the withdrawn energy comes from other members of the REC, it counts as part of the CSC, and this qualifies the community for the incentive tariff. This financial mechanism encourages REC members to consume energy that has been produced and injected by other members of the community, promoting local energy use and reducing reliance on external grid sources. However, if the energy is withdrawn from the national grid, no incentive is applied, and members are subject to standard electricity rates.
- CSC is calculated on an hourly basis by taking the minimum amount of energy injected into the grid and withdrawn by the members of the REC during that period. In other words, it represents the self-consumption on an hourly basis of all aggregated community members. This virtual model of energy sharing means that no physical infrastructure, such as additional meters or private lines, needs to be installed; instead, the energy is virtually shared through the existing public grid and measured by the standard meters already installed. This virtual nature of CSC eliminates the need for installing new physical infrastructure, thereby reducing costs and making it simpler for new members to join the REC.
  The financial benefit of CSC comes through two main components. The first component is an actual incentive of approximately 0.10 €/kWh, which serves to encourage renewable energy use within the community. The second component is a valorisation of around 0.02 €/kWh, which is related to the reduction of distribution and transformation costs, as the energy remains local. This means that the shared energy avoids additional costs and losses that would typically occur during long-distance transmission and transformation processes.
- Collective self-sufficiency (CSS) is defined as the percentage of the aggregate energy demand of all REC members that is covered by the energy produced within the community. This includes both the energy physically self-consumed by prosumers and the energy shared among members (CSC). A high CSS indicates that the community as a whole relies minimally on external grid withdrawals.

The financial benefit aims to encourage REC members to align their consumption with periods of high renewable energy generation within the REC, promoting load shifting to maximize the use of locally produced renewable energy. By ensuring that the energy remains within the community, this mechanism reduces transmission losses and enhances grid stability. The primary electrical substation acts as the geographical limit for determining eligibility for CSC incentives, ensuring that energy stays within a defined area. This not only helps optimize grid efficiency by reducing losses from long-distance transmission, but it also incentivizes REC members to consume energy produced within the community rather than relying on external sources from the national grid.

It is important to highlight that a REC can still extend and have members across more than one primary substation; however, CSC is calculated separately for each group belonging to the same substation. The true limit to the expansion of a REC is the electricity market zone, which can span

multiple regions. For example, the Centro-Nord zone in Italy includes both Tuscany and Marche, meaning a REC could have members across this entire zone. These members could be aggregated for participation in energy and flexibility markets, while being kept separate only for the purposes of calculating the incentive for CSC.
The incentive is granted to the REC, based on the CSC. The community is then free to decide how to use this incentive according to its statutes and internal regulations. For example, some RECs may choose to redistribute the financial benefits among their members, providing direct economic benefits. Other communities may choose to reinvest the funds in environmental or social projects that benefit the broader community. This flexibility in how incentives are used is a key feature of the Italian REC model, allowing each community to tailor its economic strategy to meet local needs and priorities.

1.2.4 The possible organizational structures

RECs in Italy adopt various organizational forms to align with national regulations and optimize community management and participation. These structures are crucial for ensuring that the community can operate efficiently, while meeting the objectives of environmental, social, and economic sustainability. According to [20], the most common structures include:

- Associations
  Associations represent a non-profit form of organization that allows communities to be flexible and efficient in managing their activities. Associations, both recognized and unrecognized, are favoured due to their low setup and maintenance costs, particularly in the case of unrecognized associations, which are simpler to manage. Associations also offer the advantage of requiring only two members to be established, making them ideal for smaller RECs starting with minimal resources.
  Despite these benefits, associations are not without limitations. The regulatory framework for associations was not designed with entrepreneurial activities in mind, which can present challenges, particularly when it comes to the distribution of public contributions.
- Cooperatives
  Cooperatives are another popular organizational form for RECs and are especially suited for communities that emphasize mutualistic principles. Cooperatives can adopt a range of structures, including the social enterprise model or even a benefit company, provided they meet the corresponding legal requirements.
  Cooperatives offer significant financial and organizational flexibility, as they can raise funds through member contributions and external investments. Additionally, cooperatives can reinvest profits into the community or redistribute them among members. Importantly, cooperatives also enable the REC to operate as both a producer and consumer, creating a well-rounded approach to energy sharing.
  A key requirement for REC cooperatives is that they must have at least nine members to ensure economic sustainability and adhere to the principles of mutualism. The cooperative structure is also particularly advantageous for RECs that need to access financial tools provided under Italian law for cooperatives, making them an ideal form for communities looking to expand their energy projects.
- Foundations
  Foundations, while less common, may be chosen when a REC has a long-term focus on environmental or educational projects. The foundation structure ensures a democratic and open governance model, although this form is best suited for communities prioritizing non-profit objectives without direct financial returns to members. Foundations typically reinvest any

financial surplus into projects that benefit the broader community, aligning with the REC sustainability goals.

One limitation of the foundation structure is that it cannot pursue mutualistic activities, meaning it cannot distribute profits among its members. However, foundations are ideal for projects focused on public utility, such as community outreach, environmental restoration, or education programs related to renewable energy.

- Partnerships and Other Forms

  RECs in Italy may also be organized as consortia, partnerships, or other non-profit entities, provided they align with the overarching principle of generating social, environmental, and economic benefits for their members and the surrounding community. These forms offer flexibility, allowing RECs to tailor their legal structure to meet the specific needs of their members while ensuring compliance with national energy regulations.

The choice of organizational structure plays a significant role in shaping how a REC operates, engages with its members, and distributes its benefits. Whether structured as an association, cooperative, or foundation, RECs are required to adhere to a non-profit model that prioritizes the well-being of the community and the environment. In addition to selecting an appropriate organizational form, RECs must also determine how to allocate the financial incentives generated from energy production and CSC. The distribution and reinvestment of these incentives is a critical decision that impacts the long-term sustainability of the community. Some RECs choose to redistribute these benefits directly to their members, while others reinvest in broader environmental or social projects, thereby enhancing the collective value of the community.

The following chapter will explore the various ways in which RECs can utilize these incentives, discussing redistribution models and examples of community-focused projects that have been funded through these mechanisms. These decisions ultimately shape the social, economic, and environmental impact that RECs have on both their members and the wider territory.

1.2.5 The importance of a well-designed incentive scheme

In RECS incentives play a pivotal role in ensuring the economic viability of energy sharing models and fostering community engagement. These incentives help to offset the upfront costs of renewable energy infrastructure, provide financial returns for energy production, and encourage the efficient use of shared resources within the community. This chapter outlines the various ways incentives are used within RECs, providing examples from case studies in Europe and beyond.

The incentives provided to RECs can take several forms, ranging from feed-in tariffs, subsidies, and shared energy incentives to tax credits and reinvestment opportunities. In Italy, as already stated, RECs are eligible for an incentive of approximately 0.12 €/kWh for the energy shared within the community. This financial support encourages community members to optimize their consumption of locally produced renewable energy, aligning consumption with periods of high generation to maximize CSC.

According to Casalicchio at al. [21], one of the primary purposes of these incentives is to create a fair and equitable distribution of benefits within the community. This can be achieved through various mechanisms, including the redistribution of financial gains to community members based on their energy contribution or consumption, or reinvestment in community-wide projects. Such mechanisms ensure that the economic benefits of renewable energy production are accessible to all members, including those who may not be able to invest heavily in infrastructure.

One common approach to utilizing incentives in RECs is to redistribute the financial returns directly to community members. This method allows members to benefit financially from their participation in the community, either through reduced energy bills or direct payments based on their energy production or consumption. For instance, in Belgium, a study by Felice et al. [22]

demonstrated that RECs that implement a redistribution model see higher engagement from members, as the tangible economic benefits encourage long-term participation. This model works particularly well in residential communities, where most members are households seeking to reduce their energy costs. In such cases, members receive compensation for the energy they produce and share, which is particularly appealing to prosumers who may have invested in rooftop solar or other small-scale renewable energy systems.

Furthermore, studies like those by Gui and MacGill [23] emphasize that such incentives can serve as a tool to address energy poverty, ensuring that even low-income households can participate in and benefit from the REC.

Another approach involves using the incentives generated by the REC to fund community-wide projects, ranging from energy infrastructure upgrades to social and environmental initiatives. This reinvestment model aligns with the broader goals of RECs to foster sustainability and social cohesion. For example, the REC in a case study from Sale et al. [24] used the incentives generated from shared energy to fund the installation of additional solar panels in local schools, thereby extending the benefits of renewable energy to the broader community. This approach not only enhances the community energy SS but also strengthens its social fabric by involving members in decisions about how to best allocate the community financial resources. By investing in environmental and social projects, RECs can maximize their impact beyond mere energy savings. Grasso et al. [25] highlight that RECs can use these funds to support local job creation, educational programs, and environmental restoration efforts, which further contributes to the community resilience and sustainability.

In addition to local reinvestment, incentives also enable RECs to participate in larger energy and flexibility markets. By aggregating the energy production of their members, RECs can act as market participants, selling energy to the grid and providing grid balancing services through demand response and energy storage. The incentive structures in place help to ensure that RECs remain financially viable while engaging in these more complex market dynamics. Studies such as those by Oh [26] and Weckesser et al. [27] suggest that REC incentives can also be tied to market participation by providing financial rewards for optimizing energy storage and load shifting, which enhances grid flexibility and helps to integrate higher levels of renewable energy into the national grid. The financial returns from participating in flexibility markets can then be redistributed to members or reinvested in further energy infrastructure, creating a positive feedback loop for the REC.

While incentives are critical for the success of RECs, ensuring their fair distribution among members presents significant challenges. Casalicchio et al. [28] emphasize the importance of designing incentive schemes that ensure fairness, particularly in communities where there are disparities in financial contributions, energy production capacities, or energy consumption. For example, in communities with both large-scale prosumers (such as those with rooftop solar installations) and smaller, less financially capable consumers, there is a risk that the wealthier members will benefit disproportionately from the incentives, while the less capable members may be left with fewer direct benefits.

To address these issues, some RECs have developed models where incentives are redistributed based on both energy contribution and energy need, ensuring that all members benefit from the community activities. Gui and MacGill [23] discuss the role of inclusive governance structures within RECs, where all members have a voice in deciding how incentives should be distributed. This ensures that the needs of vulnerable members are considered and helps create a more equitable community framework.

In the long term, the use of incentives in RECs not only ensures economic sustainability but also supports the broader energy transition towards decarbonization. By encouraging the local production and consumption of renewable energy, incentives help communities reduce their reliance on fossil fuels and contribute to national and European climate goals. As discussed by

Lilliu et al. [29], RECs that effectively use their incentives to optimize local energy flows also help reduce grid congestion, lower transmission losses, and provide valuable Ancillary Services (AS) to the grid. Furthermore, the effective use of incentives can lead to increased community resilience. By investing in renewable energy infrastructure and storage, RECs can protect themselves from Energy Price (EP) volatility and ensure a stable energy supply even in times of market disruption. The incentives provided to these communities thus have a ripple effect, contributing not only to economic and environmental sustainability but also to the social cohesion and resilience of the community.

The successful deployment of incentives within RECs is key to ensuring their long-term viability and impact. Whether through direct redistribution to members or reinvestment in community projects, incentives allow RECs to maximize both economic and social benefits. By participating in energy markets, providing grid services, and addressing challenges related to equity and fairness, RECs supported by well-designed incentive schemes can play a crucial role in advancing the energy transition.

To avoid ambiguity regarding the allocation of economic value within a REC, it is essential to distinguish between benefits generated at the community level and those directly accruing to individual members.

Community Level Benefits are revenues granted to the REC as a legal entity.

- Incentives on Shared Energy: The premium tariff for CSC (approx. 110 €/MWh in Italy) and the restitution of grid charges (approx. 8 €/MWh).
- Market Revenues from Community Assets: If the REC owns shared assets (e.g., a community battery or a centralized PV plant), it can generate revenue through energy trading (selling surplus energy), EA, or participation in energy and flexibility markets as or through BRP and Balancing Service Provider (BSP).

Member Level Benefits are the direct economic gains for individual participants. It is important to note that some of these are pre-existing benefits for any prosumer, while others are exclusive to REC participation.

- Bill Savings (Independent Benefit): Prosumers immediately reduce their electricity bills through physical SC. This benefit is strictly linked to owning a generation plant connected to the user specific Point of Delivery (POD) where consumption occurs, and it is independent of REC membership (i.e., it would be obtained even without the participation to a REC).
- Sale of Surplus Energy (Independent Benefit): Revenue from feeding excess energy into the grid (e.g., via "Ritiro Dedicato" (RD)) is a benefit attributed to the plant owner. Like bill savings, this is independent of the REC.
- Redistributed Incentives (REC-Specific): A share of the community-level incentives is distributed to members (both consumers and prosumers) according to the REC internal regulations. This redistribution is the true economic value added by joining the community.
- Dividends from shared assets (REC-Specific): If members financed community assets (e.g., through crowdfunding campaigns), they receive returns on their investment derived from the asset market performance.

Furthermore, membership in a REC can unlock additional indirect benefits. By acting as a large, aggregated entity, a REC gains bargaining power to negotiate commercial agreements with local partners. This can lead to discounted rates for energy supply, collective purchasing groups for technology (e.g., PV panels, HPs), or other services, providing value to members beyond the regulatory incentives.

1.2.6 Examples of flourishing RECs

RECs across Europe have emerged as key players in the decentralized energy transition. These communities differ in their organizational structure, member composition, and the renewable energy assets they manage. In this chapter, we explore some of the most successful REC initiatives across Europe, beginning with examples from Belgium, Germany, and other European countries, and concluding with a focus on Italy.

One of the most successful REC examples in Belgium is REScoop Vlaanderen, a federation of renewable energy cooperatives operating across the Flanders region. REScoop is structured as a cooperative, with over 10,000 individual members who actively participate in energy production, consumption, and governance. According to Felice et al. [30], the cooperative model used by REScoop Vlaanderen has proven highly effective at engaging citizens in the energy transition. The community operates solar PV installations and onshore wind turbines, with the electricity generated being shared among members. The cooperative reinvests the financial returns into expanding renewable energy projects and community-wide social initiatives, such as energy efficiency improvements in public buildings. This REC also benefits from demand-response programs, allowing members to shift their energy consumption to match periods of high renewable energy generation. Through these initiatives, REScoop Vlaanderen not only enhances local SS but also provides valuable grid flexibility services.

In Germany, the BürgerEnergie Berlin cooperative has grown into one of the leading examples of a successful REC. Structured as a citizen-owned cooperative, it operates with the mission to democratize the energy market and empower local communities. Gährs and Knoefel [31] describe how the cooperative is composed of over 2,000 individual and institutional members who collectively own and manage renewable energy assets, including solar panels, biogas plants, and battery storage systems. BürgerEnergie Berlin also actively participates in the energy and flexibility markets, selling excess energy back to the grid and providing AS such as frequency regulation. Members benefit not only from reduced energy costs but also from annual dividends generated by the management of shared assets and the valorisation of the energy fed into the grid. The cooperative reinvests a portion of its profits into educational programs and local environmental projects, further promoting sustainability within the community.

Coopérnico, based in Portugal, is another flourishing REC that has successfully blended social, environmental, and economic goals. De São José et al. [32] highlight that Coopérnico is structured as a cooperative, with over 1,700 members spread across Portugal. The REC operates solar photovoltaic (PV) plants installed on schools, community centres, and healthcare facilities, and the energy produced is shared with local citizens. The cooperative follows a social business model, where a significant portion of the financial returns is reinvested into social projects, including energy poverty alleviation initiatives. This REC also prioritizes energy literacy and community engagement, organizing workshops and events to educate citizens about renewable energy and the importance of sustainable energy practices. Coopérnico has become a key player in promoting energy justice across Portugal, ensuring that low-income households also benefit from renewable energy and its associated economic returns.

The development of RECs in Italy has accelerated significantly in recent years, driven by both the evolving regulatory framework and financial incentives designed to promote local energy autonomy and sustainability. However, it is important to note that much of the literature discusses only the initial RECs that emerged during the experimental phase, beginning with the Decree-Law 162/2019 [13] and the operational rules for calculating shared energy of the REC [18] [19]. These early communities laid the groundwork for further development, and now, with the official implementation of the REC regulations in 2024, a growing number of RECs are emerging across Italy, ranging in size, structure, and scope. The following highlights the most notable examples of pioneering RECs established during the experimental phase, while providing insight into how they are structured, organized, and contribute to their local communities.

Magliano Alpi, located in the Piemonte region, was the first officially recognized REC in Italy [33], launched in 2020 under the experimental framework of the REC regulations. This small municipality, with a population of approximately 2,200 people, serves as a model for other Italian

RECs due to its focus on energy sharing and local SC. As outlined by Barchi et al. [34], the REC operates a combination of rooftop solar PV systems installed on municipal buildings, supported by energy storage units to optimize energy usage throughout the day. Magliano Alpi's structure is built around a democratic governance model, where all members, both producers and consumers, have equal participation in decision-making processes. The community uses its CSC incentives to lower energy costs for residents and reinvests in further renewable energy projects to enhance local energy autonomy. The project demonstrates the technical and economic feasibility of small-scale RECs in Italy, and it has been pivotal in encouraging other communities to follow suit.

Another early REC established in Northern Italy is Monticello d'Alba, a village in the same region as Magliano Alpi. This REC operates primarily through solar PV systems with integrated energy storage, installed on municipal buildings such as schools and a gymnasium. As highlighted in Cielo et al. [35], Monticello d'Alba REC has produced significant economic returns for the village, along with a notable reduction in greenhouse gas emissions, estimated at 45 %. The REC focuses on local energy autonomy and CSC, ensuring that the energy produced by the community stays within the village. The incentives received from CSC have been reinvested into further expanding renewable energy capacity, as well as promoting energy efficiency initiatives.

In the Bolzano province, several RECs have been successfully established, benefiting from the area's high levels of solar irradiation. These communities primarily rely on PV systems to generate renewable energy, which is then shared among local residential buildings. According to Casalicchio et al. [28], the Bolzano RECs have also integrated energy storage systems to increase CSC, thereby reducing the community dependence on the national grid.

The RECs in this region demonstrate how smaller-scale, localized communities can successfully use financial incentives to cover their energy needs while generating surplus energy for the broader grid. These communities are also reinvesting their economic returns in local environmental projects, further contributing to the region's sustainability goals.

The REC Caldari di Ortona, located in Abruzzo, is an example of a REC structured as a cooperative, involving a wide range of stakeholders, including households, small businesses, and local institutions. According to Minuto et al. [36], the REC has invested in rooftop solar PV installations across the municipality, along with a small-scale biomass plant to diversify its RES. The cooperative reinvests its profits into energy efficiency programs and social projects that benefit the entire community. This strategy aligns with the cooperative's mission to enhance sustainability and social welfare using renewable energy.

In Southern Italy, the Ponticelli District in Naples has developed a REC with a specific focus on energy autonomy for a low-income urban area. The community integrates solar PV panels, small-scale wind turbines, and energy-efficient appliances to optimize energy usage and reduce overall consumption. As described by Grasso et al. [25][37], the Ponticelli REC was designed with substantial community involvement to ensure that the benefits of clean energy reach the most vulnerable populations. The financial incentives generated by the REC are reinvested in social programs, including energy education initiatives aimed at helping residents optimize their energy usage. Additionally, the community profits are redistributed to support energy poverty reduction, ensuring that low-income households benefit equitably from the community renewable energy production.

In conclusion, these pioneering examples from Italy illustrate how the first RECs, established during the experimental phase, have successfully leveraged the regulatory framework and financial incentives to create resilient, energy-autonomous communities. As the official regulatory framework takes full effect, many more RECs are expected to emerge across Italy, varying in size and structure, and contributing significantly to the national and European energy transition goals. It is easy to track and catalogue these communities, using the official database developed by the GSE [38], allowing a better understanding of the impact of RECs and their potential for replication across the country.

In the next chapter, we will explore the techno-economic simulation methods used to optimize the performance of RECs, focusing on how these models can maximize both economic and environmental outcomes for energy communities.

1.2.7 REC simulation methods

Techno-economic simulations are fundamental tools in both the feasibility study phase and the operational phase of RECs. During the early stages of development, simulations help assess the financial viability of the project, forecasting expected costs, savings, and returns based on various energy generation and consumption scenarios. These simulations also play a crucial role in optimizing the day-to-day operation of RECs, helping communities maximize the use of renewable energy, reduce dependence on the grid, and optimize energy storage and consumption patterns. By incorporating economic, technical, and regulatory considerations, simulations provide a comprehensive understanding of how a REC can operate efficiently and sustainably.

One of the primary applications of simulation tools in the feasibility stage is determining the optimal sizing of renewable energy installations and storage systems. Studies like those by Weckesser et al. [27] and Secchi et al. [39] highlight how modelling techniques such as multi-objective optimization can balance the trade-offs between investment costs, renewable energy production, and storage capacity.

In this context, the use of Mixed Integer Linear Programming (MILP) models is common for optimizing investment decisions. Terlouw et al. [40], for instance, applied MILP to optimise EA in community energy storage systems, evaluating different battery technologies for cost-effectiveness in REC environments. These simulations allow decision-makers to determine the most cost-efficient investment in terms of both renewable generation (e.g., solar PV, wind turbines) and storage technologies (e.g., lithium-ion batteries, thermal storage), considering the energy demand patterns of the community.

Additionally, feasibility simulations often include sensitivity analysis, which helps assess the impact of fluctuating factors like EPs, weather conditions, and regulatory changes on the economic viability of the REC. According to Dimovski et al. [41][42], these simulations are particularly useful in ensuring that the community can remain economically viable under different market conditions, making them a key component in risk management for RECs.

Once a REC is established, ongoing simulations help in optimizing energy management by providing detailed forecasts of energy generation, consumption, and storage needs. Techno-economic models are used to simulate how RECs can optimize their participation in energy markets and demand response programs. Studies such as those by Ghaemi and Anvari-Moghaddam [43] emphasize the importance of these simulations for predicting and scheduling energy flows in peer-to-peer trading environments, enabling RECs to maximize economic returns.

For daily operations, dynamic simulations based on real-time data (such as weather forecasts and grid conditions) help RECs decide when to store excess energy, when to consume locally, and when to sell energy back to the grid. Gu et al. [44], for instance, propose a data-driven stochastic optimization framework that uses probabilistic forecasting to optimize energy sharing in RECs with integrated storage systems. These models enable communities to dynamically adjust their energy strategies based on real-time conditions, ensuring the most efficient and economically beneficial use of available resources.

Furthermore, virtual energy storage simulations, as discussed by Oh [26], allow for more efficient management of shared storage resources within RECs. By modeling how energy storage can be distributed virtually across a community, these simulations help RECs avoid the cost of installing large, centralized storage systems while still benefiting from storage optimization at the grid level.

Another crucial use of simulation tools in RECs is the evaluation of long-term scenarios, particularly in relation to grid integration and the evolution of energy demand over time.

According to Sale et al. [24], long-term simulations allow RECs to project how their energy production and consumption will evolve in response to changes in technology, regulations, and member participation. These models often use agent-based simulations to assess how individual behaviours within the community impact overall energy use, allowing for more precise demand forecasting and load balancing.
Additionally, life-cycle analysis (LCA) is frequently incorporated into long-term simulations to evaluate the environmental impacts of the REC over its lifetime. Ascione et al. [45] used LCA to assess the potential for energy communities to reduce their carbon footprints and greenhouse gas emissions by maximizing the use of renewable resources and energy-efficient technologies.
Simulations of RECs often aim to balance multiple objectives, such as minimizing costs, reducing emissions, and maximizing energy autonomy. The use of multi-objective optimization models helps to address these competing goals by identifying Pareto-optimal solutions, where no single objective can be improved without worsening another. For example, Grasso et al. [25] propose a Pareto optimization strategy to cluster prosumers in RECs, balancing technical constraints such as distribution-level grid limitations with the economic benefits of energy sharing.
Multi-objective optimization is particularly useful when dealing with diverse community needs. For instance, a REC may need to balance the interests of members who prioritize cost savings with those who value environmental impact. As pointed out by Terlouw et al. [40], using optimization techniques allows RECs to navigate these trade-offs and devise strategies that satisfy all stakeholders.
Numerous software tools are available to conduct REC simulations, each with strengths tailored to different aspects of community energy modelling. Some of the most widely used tools include:

- HOMER Energy: A popular tool for microgrid design, used to optimize the mix of RES and storage solutions for RECs. HOMER is particularly useful in techno-economic modelling for feasibility studies, as shown by Li, Hakvoort, and Lukszo [46].
- EnergyPLAN: A tool designed for energy system analysis, frequently used for modeling large-scale RECs. This software integrates renewable energy generation, storage, and energy consumption into a comprehensive model that can simulate grid interactions and policy impacts [47].
- PyPSA: An open-source simulation tool for energy system modelling that allows users to simulate both the technical and economic aspects of RECs. PyPSA is used for optimizing electricity grids, renewable energy integration, and energy storage, as noted by Weckesser et al. [27].
- RECON: Developed by ENEA, RECON (Renewable Energy Community Optimizer) is an open-source tool specifically designed to support the planning and optimization of RECs in Italy. RECON provides a user-friendly interface for assessing the technical and economic feasibility of RECs, optimizing energy production and consumption, and simulating various energy sharing strategies. It integrates local energy production (such as solar PV) with community energy needs, providing detailed insights into energy flows, SC, CSC, and financial returns. RECON functionality is well-suited for communities looking to maximize local energy autonomy and reduce dependence on external energy sources [48].
- MESSpy: An advanced Python-based simulation tool designed for Multi-Energy System Planning and Optimization. MESSpy allows users to model complex multi-energy systems, including electricity, heating, and cooling networks, and simulate interactions between renewable energy production, storage systems, and the grid. The tool is particularly suited for techno-economic analyses and supports both design optimization and operational simulations of RECs. MESSpy modular architecture also makes it adaptable for different scenarios sensitivity analysis. MESSpy was developed by the author of this thesis in collaboration with other colleagues in the research group. It was used for the simulations featured in the 4 papers

reported in this thesis, and is open source [49]. Its functionality is explored in more detail in the next chapter

To conclude this chapter, techno-economic simulations are indispensable tools for both the development and optimization of RECs. From determining the feasibility of investment in renewable energy technologies to managing daily operations and long-term strategy, simulations provide crucial insights that enable RECs to thrive. By incorporating multi-objective optimization, real-time data, and advanced modelling techniques, RECs can maximize their technical and economic outcomes while contributing to the broader goals of sustainability and energy autonomy.

1.2.8 MESSpy

Multi Energy System Simulation (MESSpy) is an advanced open-source Python-based simulation tool designed to perform comprehensive techno-economic assessments of multi-energy systems, ranging from RECs to large-scale industrial hubs. The tool is versatile and modular, allowing users to model interactions between different energy vectors, such as electricity, heating, cooling, and hydrogen production and storage.

MESSpy is structured around a flexible framework that supports a wide range of system configurations, from single-building energy systems to multi-player energy hubs, with the ability to model interactions among these entities. Its modularity makes it easy to adapt for various energy technologies, such as PV systems, batteries, HPs, and hydrogen production units, including electrolysers, fuel cells and storages.

The simulation tool operates on an object-oriented programming paradigm, allowing for easy modifications, extensions, and reusability of code. MESSpy was developed as part of a collaborative effort with the academic community and is publicly available under the EU Public License (EUPL) on GitHub [49]. Users can define their own case studies using JSON files, which store all necessary parameters, such as demand profiles, production data, weather conditions, and economic factors like CAPEX and OPEX.

MESSpy core strength lies in its ability to conduct techno-economic planning for complex multi-energy systems. It has been used in diverse projects, from evaluating single-family homes and local energy communities to large industrial facilities. Key features include the analysis of:

- Energy production and consumption balances for electricity, heat, and hydrogen.
- Techno-economic optimization of energy storage systems size, including lithium-ion batteries and thermal energy storage.
- Investment planning through net present value (NPV) and levelized cost of energy (LCOE) calculations, providing insights into the financial viability of energy projects.

In addition, the tool supports long-term planning, with a time horizon of up to 30 years, allowing for a detailed assessment of the aging effects on different energy technologies and their impact on overall system performance. It can also run sensitivity analyses to evaluate the impact of changing variables such as EPs and weather conditions on system performance.

MESSpy has been successfully applied in multiple contexts, including the simulation of hydrogen-integrated systems, as part of efforts to decarbonize hard-to-abate sectors like heavy industry. Its flexibility and wide-ranging capabilities make it a valuable tool for energy planners and researchers working on projects with multiple energy carriers, especially in the context of RECs and industrial-scale applications.

A full Step-by-Step Tutorial for Using MESSpy is available on GitHub page [49]. However, a short version is hereunder:

- Installation and Setup:
    - Install Anaconda, a Python distribution that simplifies the installation of necessary libraries, including numpy, scipy, and matplotlib.

- Clone or download MESSpy from the GitHub repository in ZIP format and extract it for easier access.
- Install the required Python libraries listed in the documentation, such as CoolProp, pvlib, and json, which are used for input files and weather data processing.

- Defining a Case Study:
  - Input files are created in JSON format, which store all technical and economic details. Key files include:
    - general.json: Defines the general inputs, such as location coordinates and time horizons.
    - studycase.json: The core file for the case study, containing production and demand profiles.
    - tech_cost.json: Lists CAPEX and OPEX for all relevant technologies.
    - energy_market.json: Specifies energy carrier prices.
- Running the Simulation:
  - Use the run_test.py script to execute the simulation. The solver processes the inputs and generates results, which include energy balances and system performance metrics.
- Post-Processing and economic analysis:
  - MESSpy provides extensive post-processing capabilities, including plots for energy flows, storage levels, and economic performance (such as LCOE and NPV).
  - Sensitivity analysis tools allow users to explore how changes in system parameters affect outcomes, producing maps and plots to visualize results.

In conclusion, MESSpy is a robust, adaptable tool for planning and optimizing multi-energy systems. Its application ranges from small-scale RECs to large industrial hubs, making it a valuable resource for simulating a wide array of energy scenarios.

1.3 Battery Energy Storage System

Battery Energy Storage Systems (BESS) have become an integral component of modern energy systems, particularly in the context of RECs. As RES like solar and wind are inherently variable and intermittent, BESS play a critical role in balancing supply and demand, ensuring that excess energy generated during periods of high production can be stored and used when demand exceeds production or when renewable sources are not available.
The ability of BESS to store energy and discharge it when required makes them essential for achieving energy SS, enhancing grid stability, and supporting decentralized energy systems. In the context of RECs, BESS enable communities to optimize their energy consumption, maximize SC of renewable energy, participate in energy markets, and provide grid services such as frequency regulation and demand response.
This chapter will provide a comprehensive overview of BESSs, starting with their key components and moving through the technical aspects of BESS modeling and aging. Following this, the focus will shift to management strategies, exploring both rule-based management approaches using tools like MESSpy and optimization-based strategies leveraging techniques like MILP to optimize the scheduling and control of BESS systems. By the end of this chapter, the reader will have a deep understanding of how BESS contribute to the efficient management of energy in RECs, ensuring both economic viability and sustainability.

1.3.1 BESS components

The BESS is composed of several key components that work together to store energy efficiently, manage its flow, and ensure long-term system stability. Understanding these components is essential for optimizing the performance and durability of the system. The main components of a BESS include:

- Battery Pack: The core of any BESS is the battery pack, which stores electrical energy. Among the various battery technologies, lithium-ion batteries are the most used due to their high energy density, long cycle life, and relatively fast response times. Lithium-ion technology is favoured for its ability to provide efficient charge/discharge cycles and lower self-discharge rates compared to other technologies like lead-acid batteries. Each battery pack consists of multiple cells, which are connected in series or parallel configurations to achieve the desired voltage and capacity. Over time, the performance of the battery pack is subject to degradation, which is influenced by factors such as the Depth of Discharge (DoD), operating temperature, and charge cycles.
- Power Conversion System (PCS): The Power Conversion System is responsible for converting the stored energy into a usable form, typically transforming direct current (DC) from the battery pack into alternating current (AC), which is compatible with the electrical grid and consumer devices. The PCS also handles the reverse process during charging, converting grid-supplied AC into DC for storage. This bidirectional functionality enables BESS to both store excess renewable energy and provide power back to the grid during periods of high demand. The efficiency of the PCS is critical, as it directly impacts the overall performance of the BESS by minimizing energy losses during conversion.
- BMS is essential for monitoring and controlling the operation of the battery pack. It ensures that the batteries operate within safe parameters by monitoring temperature, voltage, current, and State of Charge (SoC). The BMS also helps to prevent issues such as overcharging, over-discharging, and thermal runaway, which could degrade the battery or pose safety risks. Additionally, the BMS optimizes the charge and discharge processes to extend the life of the battery and improve the overall efficiency of the system.
- Auxiliary Systems: Auxiliary systems in a BESS include cooling systems, communication modules, and protection devices that ensure the stable operation of the system. Cooling systems are critical for preventing the battery cells from overheating, which can lead to performance degradation or, in extreme cases, safety hazards. Proper cooling can extend the life of the battery and ensure it operates at peak efficiency. These auxiliary systems also include sensors and communication interfaces that relay real-time data to the system operators, allowing for better system control and fault detection.
- Energy Management System (EMS): In larger and more complex BESS configurations, an Energy Management System (EMS) is used to manage the flow of energy between the storage system, the grid, and local loads. The EMS coordinates the charging and discharging of the battery pack based on energy demand, grid conditions, and the availability of renewable energy. It can also integrate demand response strategies and participate in energy markets by optimizing the use of stored energy to maximize economic returns.

Each of these components plays a vital role in ensuring the efficient, safe, and long-term operation of a BESS. The battery pack serves as the energy reservoir, while the PCS and BMS manage the conversion and regulation of energy. Auxiliary systems maintain safe operating conditions, and an EMS can provide advanced control over energy flows, making BESS a key technology for enhancing energy security and enabling the efficient integration of RES into decentralized energy systems like RECs.

In this thesis, new strategies for the EMS are proposed, aimed at optimizing energy management and enhancing the overall performance of BESS in RECs. However, to properly simulate, evaluate, and test these strategies, a comprehensive modelling approach that considers all the components of the BESS is required. This ensures that the proposed strategies are technically viable and economically effective, providing a reliable solution for future energy systems.

1.3.2 BESS modelling

Modelling a BESS can be approached through different methodologies, each addressing various aspects of the system behaviour, accuracy, and computational effort. Here we outline the key types of models frequently used in the literature for simulating BESS, drawing on the extensive research cited in the articles provided.

1. Electrochemical Models: Electrochemical models aim to represent the fundamental processes occurring within the battery cell, such as electrochemical reactions, ion transport, and thermodynamics. These models are particularly useful for understanding long-term battery behaviour, including degradation mechanisms, and they provide high accuracy in simulating the internal physical processes of batteries. However, these models often require significant computational resources due to their complexity.

   For example, Rancilio [50] emphasizes the utility of electrochemical models in accurately simulating battery degradation over time. He discusses how such models can track processes like solid-electrolyte interphase formation, lithium plating, and other reactions within the cell, providing insights into capacity fade and efficiency losses over time. Similarly, Bovera et al. [51] describe a validated modelling framework for BESS operations that includes electrochemical models, which can simulate battery efficiency under various operating conditions, including SoC and external ambient temperature.

   The study by Gonzalez-Castellanos et al. [52] also explores electrochemical models, highlighting their suitability for applications where high accuracy is required, such as in the design of the cell’s physical parameters and optimization of processes related to energy efficiency. These models can simulate the effects of temperature, charge/discharge rates, and other operational factors, making them essential tools for understanding battery behaviour in both utility-scale and behind-the-meter storage systems.

   Sakti et al. [53] developed an electrochemical model that includes internal losses and cell thermodynamics to simulate a utility-scale BESS. Such models are especially useful for understanding long-term battery behaviour, including degradation mechanisms like solid-electrolyte interphase growth.

   Electrochemical models, although computationally demanding, are indispensable for simulating and optimizing processes like degradation and energy conversion efficiency. These models are especially relevant for advanced applications where precise control of battery behaviour is critical, such as in EA, peak shaving, and providing AS. Therefore, integrating electrochemical models into BESS simulations allows for a more comprehensive understanding of battery performance, making them invaluable for long-term energy storage projects and market participation.
2. Equivalent Circuit Models: Equivalent circuit models (ECMs) offer a balance between computational efficiency and accuracy by representing a battery as a combination of electrical components such as resistors, capacitors, and voltage sources. These models abstract the electrochemical processes in the battery into electrical circuits that are easier to work with for system-level simulations. ECMs are widely applied in BMS for tasks like real-time state-of-charge (SoC) estimation and are also effective in energy management strategies for tasks such as peak shaving, EA, and grid stabilization.

   A prominent example of ECMs can be found in the work by Namor et al.[54], which utilized ECMs to simulate the energy dispatch efficiency of a lithium-titanate battery system for grid services. Another study by Bovera et al. [42] highlighted the use of ECMs for optimizing BESSs in real-time applications, showing their value in providing fast and reliable SoC estimation. These models are also instrumental for simulating dynamic processes in Li-ion batteries for applications like AS, as shown by Gonzalez-Castellanos et al [55], who provided an ECM-based model to represent transient behaviours such as ohmic losses and charge transfer resistance.

In another study, Hu et al. [56] developed ECMs to compare the performance of different Li-ion battery chemistries, offering insights into how varying resistance and capacitance values affect battery behaviour during real-world applications. These models have proven useful in both operational control and system optimization of battery storage systems. Additionally, empirical studies such as those by Rancilio et al. [57] and Bovera et al. [58] show that ECMs are often the preferred approach for real-time grid-connected BESS due to their simplicity and computational efficiency, especially when integrated into large-scale simulations of energy markets and grid stability services.

Moreover, ECMs are particularly suited for hybrid applications where batteries need to provide multiple services simultaneously, as outlined by Drummond et al [59]. These include frequency regulation, EA, and demand response, where fast computational performance is critical for real-time optimization. The flexibility of ECMs also allows for their integration into larger frameworks, such as the mathematical modelling approach presented by Nobile et al. [60], further proving their applicability in a wide range of energy storage scenarios.

3. Empirical Models: Empirical models are widely used in BESS simulations because they simplify the behaviour of the battery system by correlating input variables, such as SoC, current, and voltage, to observed outputs through mathematical or statistical techniques. These models rely on experimental data and historical performance to predict future battery behaviour. While empirical models are less computationally intensive than electrochemical or equivalent circuit models, they can suffer from a lack of accuracy when the battery operates under dynamic conditions or outside the range of the dataset on which the models were trained.

   One common approach involves using polynomial or linear regression models to predict battery performance based on past experimental data, as noted in Bovera et al. [61]. Such models are useful for early-stage feasibility studies, particularly when investigating how BESS can be optimized within a microgrid or REC. For instance, empirical models can provide insights into how BESS can perform EA, frequency regulation, and peak shaving with low computational effort.

   However, empirical models can become unreliable when applied to environments that differ significantly from the original test conditions, as pointed out by Rancilio et al. [57]. This is due to their limited ability to capture the complexities of real-time BESS operation. Despite these challenges, empirical models can be enhanced through careful validation with new experimental data collected under conditions closely resembling the operational environment of the BESS.

   In terms of practical applications, utilized empirical models to evaluate the performance of BESS under different grid scenarios. By correlating SoC with real-world operational conditions, they were able to forecast energy dispatch and predict the effectiveness of the BESS in responding to grid demands. This highlights the ability of empirical models to assist in optimizing grid integration strategies while maintaining computational simplicity.

   Additionally, in studies conducted by Bovera et al. [62], empirical models were used to optimize the provision of multiple services by BESS, including both EA and frequency regulation, showing that with proper parameter tuning, they can provide acceptable performance without the complexity of more detailed physical models.

4. Hybrid Models: Hybrid models aim to combine the accuracy of electrochemical models with the computational efficiency of empirical or equivalent circuit models. These models offer a balanced approach, integrating the precision of the physical and chemical processes represented in electrochemical models with the computational speed of empirical models. Hybrid models are particularly effective for simulating long-term storage operations or for

BESS applications that require fast responses in dynamic environments, such as participation in multiple energy markets.

One notable example is a study by Bovera et al. [61], where a hybrid model was developed to simulate a large-scale BESS. This model combined equivalent circuit and empirical techniques to balance the trade-offs between computational complexity and model fidelity. The hybrid approach was validated for applications such as frequency regulation and EA, showing significant improvements in both accuracy and computational efficiency.

Similarly, Spiller et al. [63] demonstrated the effectiveness of hybrid models in optimizing BESS performance in frequency control and EA applications. Their study utilized a combination of electrochemical and empirical models to simulate the dynamic behaviour of a BESS connected to a microgrid, focusing on short-term responses to grid frequency deviations while also accounting for long-term degradation.

Rancilio et al. [57] applied a hybrid modelling approach for multi-service BESS, combining equivalent circuit models with empirical data to optimize grid stability services. Their model was tested in real-world applications, demonstrating its versatility in handling various grid-related services such as peak shaving and demand response.

The flexibility of hybrid models allows them to be tailored to specific use cases, making them highly adaptable for different operational environments. By integrating multiple modelling techniques, hybrid models can provide enhanced accuracy for complex BESS applications without sacrificing computational efficiency.

Each of the above models serves a different purpose depending on the scope of the simulation or optimization problem. In energy management scenarios, Mixed-Integer Linear Programming (MILP) models are often used in combination with ECM or empirical models to optimize operational decisions, such as charge/discharge schedules and EA strategies. To summarize the trade-offs discussed Table 1 above, provides a comparative overview of the main modelling approaches, highlighting their respective strengths, limitations, and typical applications.

Table 1 Comparison of BESS modelling approaches.

	Description	Pros	Cons	Typical application
Electrochemical	Simulates internal chemical reactions and ion transport.	Highest accuracy, captures physical degradation mechanisms.	High computational cost, complex parametrization.	Cell design, detailed aging analysis.
Equivalent circuit	Represents battery as a circuit of resistors and capacitors.	Good balance of accuracy and speed, easy to implement.	Limited in capturing complex electrochemical phenomena.	Real-time BMS, system-level simulation.
Empirical	Uses statistical correlations from historical and experimental data.	Very low computational effort, simple formulation.	Low accuracy outside training conditions, limited generalization,	Early-stage sizing, rough economic estimate.
Hybrid	Combines physics-based elements with empirical data adjustments.	Optimizes trade-off between accuracy and speed.	Complexity in coupling different model types.	Multi-service optimization, long-term operation.

1.3.3 BESS ageing

Battery aging is the gradual deterioration in battery performance over time, primarily affecting capacity and efficiency. This process is inevitable, but understanding the mechanisms involved allows for improved battery design and better management strategies. Broadly, aging is classified into two main types:

- Calendar Aging: This type of aging occurs when the battery is at rest, meaning no cycling is performed. The battery ages simply due to the passage of time, influenced heavily by storage conditions such as temperature and the SoC. Calendar aging tends to result in the gradual loss of lithium inventory and an increase in internal resistance due to side reactions like the growth of the solid electrolyte interphase (SEI) film. Studies show that storage temperatures above 25°C significantly accelerate calendar aging [64].
- Cyclic Aging: This occurs due to repeated charge and discharge cycles. Every cycle generates heat and causes mechanical stress on the battery materials, leading to degradation. This includes loss of active materials (LAM) at the cathode and anode, increased SEI growth, and dendrite formation, which eventually compromise the battery ability to store and deliver energy. Studies like those from Lubello et al. [65] highlight that high-depth discharges and fast charge/discharge rates lead to faster cyclic aging [66].

The two primary factors that affect both calendar and cyclic aging are:

- Temperature: Higher temperatures exacerbate side reactions, increase SEI growth, and accelerate electrolyte decomposition. Xiong et al. [64] have shown that operating temperatures above 45°C can accelerate capacity loss by 10 times compared to operation at 25°C. At low temperatures, lithium plating can occur on the anode, causing safety concerns.
- SoC and DoD: Storing a battery at high SoC accelerates SEI growth, while operating at high DoD induces more stress, especially during rapid charging/discharging cycles. Studies like those by Bovera et al. [42] emphasize that batteries subjected to shallow cycles experience lower degradation; as can be confirmed also in the study of Namor et a. [54].

Various models are used to simulate aging, providing insights into how batteries will perform over time and under different conditions:

- Empirical models rely on historical data to predict how aging will affect the battery. These models are simple but may lack accuracy when used outside their initial conditions.
- Electrochemical Models simulate the chemical reactions within the battery to provide detailed insights into the aging process. Xiong et al. [64] use electrochemical models to simulate SEI formation and LLI, offering insights into how temperature and cycling rates contribute to aging .
- Hybrid Models, combining empirical and electrochemical models allows for balancing accuracy with computational simplicity. Bovera et al. [42] and Lubello et al. [65] discuss hybrid approaches that integrate aging mechanisms into optimization frameworks for BESS.

Lubello et al. [65] demonstrate that incorporating battery aging models into energy optimization strategies can lead to more efficient BESS sizing, particularly in solar home systems. Their work also highlights the significant impact of aging estimation on battery lifetime, particularly when accounting for fast cycling in high-renewable energy systems.

Xiong et al. [64] discuss how temperature plays a significant role in battery aging and propose advanced BMS strategies that adjust operation based on real-time temperature monitoring to mitigate aging. The studies also show that different chemistries (such as Lithium Iron Phosphate vs. Nickel Manganese Cobalt) age differently under identical conditions: while LFP batteries are more stable at high temperatures, NMC chemistries offer higher energy density but are more prone to degradation.

Bovera et al. [42] performed an experimental study demonstrating that empirical models can be used to assess the long-term performance of BESS in various grid services. Their findings underline the importance of including aging mechanisms in optimization models.

In the second and third articles included in this thesis, battery aging is a key consideration. Specifically, battery aging is integrated into the energy management model through a degradation-aware optimization approach. The model considers the impact of cycling on battery lifespan, incorporating an aging penalty to avoid excessive wear. This ensures that the optimal decisions balance short-term economic gains with the long-term sustainability of the battery. Sensitivity analyses were conducted to evaluate how different battery sizes, market prices, and REC configurations affect the degradation and overall performance of the battery. Aging is addressed in the models to preserve battery health while optimizing for CSC and EA. The models explicitly consider the trade-offs between maximizing energy use and limiting aging by managing the battery SoC and discharge cycles. This helps mitigate the impact of frequent cycling and extends battery life.

Both articles highlight that managing battery aging is essential for optimizing the performance of energy storage systems over time. Aging is not just a technical challenge but also a factor influencing the economic feasibility of storage investments. By considering aging in energy management system, the research ensures that the selected strategies minimize degradation while still achieving the desired economic and energy outcomes.

Battery aging has profound long-term economic impacts. Systems that fail to account for aging may face premature failure, significantly increasing operational costs due to higher maintenance and replacement needs. Furthermore, aged batteries contribute less to EA and grid balancing, reducing their economic returns over time. By considering aging, strategies ensure reduced total cost of ownership, improved energy efficiency, and extended system lifetimes. In the context of RECs, managing aging helps maximize CSC and improves financial sustainability, securing lower LCOE and maintaining optimal performance for decades. By accounting for aging in optimization models, this research emphasizes the importance of long-term planning. This ensures that economic and technical performance remain aligned, making BESS investments viable over extended periods, especially in markets like renewable energy integration and grid stabilization.

In conclusion battery aging is not only a technical issue but a core economic consideration that directly affects the feasibility and sustainability of energy storage systems. By integrating aging mechanisms into energy management systems, this research helps optimize battery performance over time while minimizing degradation. With these approaches, RECs can extend battery lifespan, reduce costs, and enhance the overall return on investment.

The next chapter introduces the management systems designed to implement these strategies, focusing on both rule-based and optimization-based approaches to maximize battery performance in real-world applications. chapter introduce the management systems designed to optimize battery performance through both rule-based and optimization-based approaches.

1.3.4 Battery Management Systems

BMSs are essential for optimizing the performance of BESSs within RECs. These systems can be categorized into two main types:

- Rule-based strategies, which rely on predefined rules to manage the battery operation.
- Optimization-based strategies, which use mathematical optimization techniques to achieve the best solution for battery management.

Both approaches can be further classified based on the integration level of information, such as real-time data or forecasted information (e.g., weather forecasts, load forecasts, or market prices). They can also be categorized based on the degree of component modelling, which can range from

simple battery behaviour models to more complex representations that consider battery degradation, grid constraints, and multiple interacting components.
The simplest BMS applies to a single household connected to a PV system. In this case, a basic rule-based strategy sets the charge or discharge setpoints of the battery using only real-time data from the household's PV production and load: via a real-time decision-maker, the battery is charged when PV production exceeds household consumption and discharged when consumption exceeds PV production.
Such a strategy can be improved by incorporating weather, load, or market price forecasts through an internet connection to appropriate forecasting services. This would enable the system to pre-charge or discharge the battery based on predictions. These improvements can be implemented either through a more complex rule-based strategy or by transitioning to an optimization-based approach.
As the complexity of the system increases, such as in an REC, rule-based strategies can be extended to include real-time information from other REC members. A centralized management system can coordinate energy sharing between households, optimizing the use of batteries within the REC. The first two articles of this thesis focus on rule-based systems for managing CSC in RECs. A novel real-time rule-based strategy is proposed to maximize CSC by balancing energy production and consumption across all REC members while coordinating the use of a fleet of batteries (in the first article) or HPs (in the third). Such a strategy requires a centralized communication system, which introduces additional costs that must be justified by the increased revenue gained from the improved management strategy. The two articles assess these gains in both economic and energy terms.
While rule-based strategies are simple and computationally efficient, they have inherent limitations:

- Scalability: As more data (e.g., forecasts or information from multiple users) is integrated into the system, developing effective rules becomes increasingly complex and challenging.
- Multiple objectives: Rule-based systems struggle to handle scenarios with competing objectives, such as maximizing both CSC and EA. Developing a rule that balances these objectives while also considering forecasts is difficult, and such systems are unlikely to find the true optimal solution.

This is where optimization-based systems come into play. These systems address the limitations of rule-based approaches by using mathematical techniques to identify the best strategy. Optimization problems consist of:

- Objective function: Defines the goal of the system (e.g., maximizing profit, minimizing energy costs).
- Constraints: Define the system operational limitations (e.g., battery capacity, grid constraints, maximum power limits).

The set of equations and inequalities describing the objective function and the constraints make up the optimisation problem, which can be solved using optimisation algorithms to find the values that make the objective function optimal. The description of the types of optimisation problems and algorithms that are used to solve them is beyond the scope of this thesis. However, it should be noted that in the field of battery management, the problems are of the LP type or at most mixed integer linear programming (MILP), i.e. they are composed of linear equations and inequalities on real or at most integer variables. This type of problem can be solved with confidence both in convergence and in finding the global optimum rather than possible local optimums, and this is crucial for engineering problems in which one is searching for the true solution. Non-linear problems have problems of non-convexity and therefore of convergence and computational cost, which is why many efforts are made in the literature to be able to linearise any type of problem.
LP Optimization-based BMS approaches are widely studied in the literature.

In the context of BESS operation within RECs some studies delve into scheduling optimization [67][68] while others highlight the need for multi-service community BESS models [69]: some contributions propose community BESSs for EA and Peak Shaving [70], participation in Capacity and Balancing Markets [71][72] or the Provision of Load Flexibility and Capacity Sharing [73].
In the context of utility-scale BESS and microgrid literature, the most accurate and comprehensive models are proposed. Some studies introduce scenario-based scheduling models for multiple services [74], addressing non-convexity by incorporating grid and battery losses. Real time control models formulated for multiple grid services are proposed in [75]. Other contributions propose a two-level control layer to prevent BESS saturation [76] or include AS (AS) provision [77].
Some studies apply metaheuristic methods for microgrid cost minimization [36], highlighting challenges in scalability and adaptability. Others focus on coordinated optimization for grid-connected microgrids, integrating RES and electric vehicles, though often with limited real-time responsiveness [78]. To address uncertainties the Tube-based Model Predictive Control for robustness and computational efficiency [79] is proposed; or a scenario-based approaches in multistage robust scheduling frameworks [80]. Multi-energy microgrid systems also extend BESS applications by integrating electricity, heat, and gas networks. Some works explore predictive scheduling for multi-energy balancing [76] or frequency constraints in islanded microgrids [81].
However, these studies rarely consider regulatory and community-specific frameworks, making them less applicable to RECs. That is why the third and fourth articles of this thesis were developed, to expand the advanced battery management methods found in the literature on microgrids and low utility scales to the REC context as well.
The third article in this thesis employs a LP-based optimization model to optimize the operation of a community battery within an REC. This model efficiently allocates battery usage to Maximize CSC by ensuring that local renewable energy is consumed within the community and at the same time enable EA, storing energy when prices are low and selling when prices are high. The LP model includes battery SoC limits for safe operation, charging and discharging power constraints based on battery specifications, market price forecasts for optimal trading, energy balance equations for REC-wide optimization.
This third article's model doesn’t include forecast uncertainties (e.g., errors in demand or RES generation predictions), neither grid constraints, neither real-time control, limiting real-world feasibility. To overcome these issues, the fourth article introduces a scenario-based model that incorporates grid and battery losses into a two-level control system, with a scheduling layer for long-term optimization and a real-time control layer for dynamic corrections.
This article also concludes the thesis with an experimental validation, bridging the gap between simulation and real-world deployment.
In conclusion the transition from rule-based to optimization-based BMS represents a major advancement in battery management for RECs. While rule-based systems are simple and efficient for small-scale scenarios, they become impractical as complexity increases. Optimization-based approaches, particularly LP and MILP, enable efficient management by integrating forecasts, balancing multiple objectives, and adapting to real-time changes. A comprehensive model incorporating scheduling and real-time control is crucial to ensuring efficient and economically viable battery management in RECs.

1.4 Energy markets

The ongoing transformation of electricity markets is driven by the increasing penetration of variable RES, the decentralisation of production, and the emergence of proactive consumers. This evolution requires a profound rethinking of the market structures traditionally designed for a centralised, predictable system.

This chapter analyses the current and future landscape of electricity markets, with a focus on the Italian regulatory and operational framework. It explores the functioning of the spot markets, (Day-ahead and Intra-day), the Dispatch Service Market, new capacity and storage procurement mechanisms, and the emerging decentralised models of flexibility procurement [82]. The objective is to provide a comprehensive overview of how these developments pave the way for active participation by DER, energy communities, and storage systems, setting the stage for the research work presented in this thesis.

1.4.1 Day-ahead market

The Day-ahead Market (DAM) [83][84] constitutes the principal platform for electricity trading in Italy and represents the first phase of the spot electricity market, where transactions are finalised one day before the actual delivery. It is organised by the Gestore dei Mercati Energetici (GME) who acts as a central counterparty to both buyers and sellers, ensuring transparency and security in market settlements. The DAM facilitates the scheduling of most energy deliveries for the following day, making it a crucial component in the overall functioning of the national electricity system and contributing to market liquidity. The DAM is structured as a zonal auction market. Currently, the market operates on an hourly resolution, dividing the trading day into 24 periods. However, following the implementation of the TIDE and European balancing guidelines (e.g., Regulation EU 2017/2195), the market time units are shifting towards a 15-minute resolution (quarter-hourly products). This transition is crucial to better integrate the variability of renewable sources and allow faster-response resources, such as batteries, to valorise their flexibility.
Operators can submit bids from 8:00 AM of the ninth day preceding delivery up until 12:00 PM of the day before delivery. Market outcomes are communicated by 12:58 PM of the same day.
Participation in the DAM is open to all authorised electricity market operators, including producers, consumers, traders, and aggregators (as REC may be). Participants submit offers specifying the quantity and price at which they are willing to sell or purchase electricity. Offers to sell state the minimum price acceptable, while offers to buy indicate the maximum price participants are willing to pay.
The market operates according to a marginal pricing mechanism. After the closure of bidding, GME aggregates all offers and arranges them in ascending order for sales and descending order for purchases. The intersection of these supply and demand curves determines the equilibrium price, known as the System Marginal Price (SMP), and the corresponding quantities accepted. Sellers offering below the SMP and buyers offering above the SMP are fully accepted, while marginal offers are partially accepted.
Given the Italian electricity market's zonal structure, SMPs are calculated individually for each zone, considering inter-zonal transmission constraints that can affect local supply and demand equilibrium. However, the National Single Price (Prezzo Unico Nazionale, PUN) is applied to buyers (with certain exceptions) to harmonise purchase prices across different zones, thereby mitigating disparities caused by geographical differences in generation and transmission capacity and promoting fairer competition across regions. The PUN is calculated as a weighted average of zonal SMPs based on the volume of accepted purchase offers.
The level of market prices, particularly the SMP, is influenced primarily by the variable costs of the marginal production units, which include fuel costs and CO2 emission allowance prices, as well as by any additional mark-ups applied by market participants. Historically, combined-cycle gas turbine plants have played the predominant role as marginal units, accounting for over 60 % of marginal price-setting events in 2023. This highlights the importance of diversifying the energy mix to enhance market resilience and support the energy transition.
In summary, the Day-ahead Market defines the preliminary scheduling of electricity flows based on economic merit, serving as the foundation for subsequent market phases. Following the DAM,

market participants can further refine their schedules through the Intra-day Market, which will be analysed in the next section.

1.4.2 Intra-day market

The Intra-day Market (IM) [83][85] constitutes the second phase of the Italian spot electricity market, operating after the closure of the Day-ahead Market. Its primary purpose is to allow participants to adjust their schedules closer to real-time to better match actual generation and consumption, accommodating forecast errors and unexpected operational changes, particularly those related to the variability of RES.

Organised by the GME, the IM maintains a zonal market structure like that of the DAM, and accounts for inter-zonal transmission constraints. Participation is open to all market operators, although units engaged in the Dispatch Service Market (MSD ex-ante) may face feasibility limitations imposed by Terna, the Transmission System Operator (TSO).

Since September 2021, the IM operates through a hybrid model combining scheduled auctions and continuous trading:

- Scheduled Auctions (MI-A1, MI-A2, MI-A3): Participants submit hourly offers which are matched based on supply and demand curves, similarly to the DAM.
- Continuous Trading: Outside of auction windows, market participants can submit, and match offers in real-time. Offers are accepted immediately if matching conditions are met, based on a first-come, first-served logic.

This hybrid structure enhances the flexibility of the market by allowing operators to continuously refine their positions based on updated forecasts, thus improving the overall system responsiveness.

Participants can submit different types of orders specifying quantity, price, and execution conditions:

- NON (normal order): Can remain in the order book if not matched immediately.
- IOC (Immediate or Cancel): Must be matched immediately or cancelled.
- FOK (Fill or Kill): Must be entirely matched immediately or cancelled.
- AON (All or Nothing): Must be fully matched immediately or stay in the order book.

These options offer a greater degree of operational flexibility to market participants, enabling them to strategically manage their portfolios.

Market prices in the IM generally follow trends set by the DAM, although they may diverge due to real-time changes in system conditions. Historical data show that auction sessions still capture most traded volumes, while continuous trading is predominantly utilised in the final hours before delivery.

In summary, the Intra-day Market provides essential flexibility to market participants, improving the accuracy of energy schedules and enabling better integration of intermittent RES. The continuous refinement of market positions during the IM phase lays the groundwork for the subsequent balancing actions managed through the Dispatch Service Market (MSD), which will be discussed in the following section.

1.4.3 Dispatch service market

The Dispatch Service Market (Mercato Servizi Dispacciamento MSD) [82][86] plays a critical role in ensuring the safe and reliable operation of the Italian electricity system. Unlike the DAM and IM which focus on energy trading, the MSD is dedicated to the procurement of AS essential for real-time system balancing and network security.

The MSD is divided into two phases:

- Ex-ante MSD: Conducted after the closure of the DAM and IM, it aims to pre-secure upward and downward reserves, manage intra-zonal congestion, and prepare a dispatchable system configuration. This phase allows the TSO Terna to arrange necessary flexibility margins and solve potential network issues in advance.
- Balancing Market (BM): The final market stage where Terna activates resources in real-time to correct unforeseen imbalances and restore sufficient system reserves.

Maintaining the real-time balance between electricity injections and withdrawals is crucial for keeping the system frequency close to 50 Hz. Variations in load, unforeseen generator outages, and the inherent variability of renewable production necessitate continuous balancing interventions.

Historically, participation in the MSD was restricted to significant programmable units (above 10 MVA). However, recognizing the growing importance of distributed and renewable resources, the Integrated Text on Dispatching (TIDE) has been reformed. The new TIDE, approved in 2023 and effective from 2025, removes the "relevance" criterion, enabling broader and technology-neutral participation, including distributed generation, storage systems, and aggregated loads, in line with the EU Balancing Regulation [87][88][89][90][91].

The MSD is organized into six sub-phases, with the primary one being MSD1. During MSD1, operators submit offers from 12:55 PM to 5:00 PM on day D-1, with results communicated by 9:45 PM. After MSD1, continuous sessions allow further offer submissions up to one hour before real-time delivery.

The services procured through the MSD include:

- Primary, Secondary, and Tertiary Frequency Reserves: Essential to stabilize system frequency immediately after a disturbance and restore balance progressively.
- Congestion Management: Resolving intra-zonal congestion that could compromise network security.
- Real-time Balancing: Addressing short-term imbalances between production and consumption.
- Voltage Regulation: Ensuring that voltage levels throughout the network remain within safe operating limits.
- Load Shedding and System Restoration Services: Providing mechanisms for system recovery after severe faults.

It is important to note that not all AS are remunerated through the MSD: services such as primary frequency regulation, load disconnection, and system restoration are mandatory and not traded on the market.

Offers in the MSD are structured relative to the scheduled program resulting from DAM and IM. Each resource must make available all its upward and downward modulation margins. Offers are submitted in steps (up to three for MSD ex-ante, up to four for BM), with each step's price being non-decreasing.

Unlike DAM and IM, which operate on a "pay-as-cleared" basis, the MSD uses a "pay-as-bid" remuneration scheme. Accepted offers are paid the exact price submitted by participants, resulting in multiple clearing prices for different services and sessions.

The accepted selling offers (upward reserve) represent a cost for Terna, as generators are paid to increase production beyond scheduled levels. Conversely, accepted buying offers (downward reserve) generally represent a revenue for the TSO. In this case, generators or aggregators pay the TSO to buy back the energy they were scheduled to produce but will not, effectively saving on fuel or opportunity costs. The TSO accepts the offers that maximize this revenue (highest bid price to buy back).

Prices observed in the MSD generally correlate with those from the DAM, although prices in the real-time balancing phase (BM) tend to be significantly higher due to the urgency and short notice required to adjust production or consumption.
The net cost borne by Terna for ensuring system security through the MSD is fully recovered from end consumers via the "uplift" fee, a specific item included in the electricity bill.
In summary, the Dispatch Service Market is fundamental for maintaining continuous system stability in the face of growing renewable integration and increasing system complexity. The ongoing reforms towards broader participation and technological neutrality prepare the MSD to better meet the challenges of a future, highly renewable electricity system.

1.4.4 Capacity and Storage Procurement Mechanisms

In addition to the Energy Markets and the Dispatch Service Market, Italy has implemented dedicated mechanisms to ensure system adequacy and to promote the development of new capacity resources, including storage systems. These mechanisms provide long-term economic signals essential for sustaining investment in flexible and reliable infrastructure, supporting the integration of RES.
The Italian Capacity Market [92][93], operational since 2019, aims to ensure that sufficient generation capacity is available to meet future electricity demand, including appropriate reserve margins. Organised by Terna through competitive auctions, the market allows participation by existing and new generation units, as well as demand-side resources and foreign units.
Participants offer capacity (in MW) voluntarily, subject to compliance with environmental standards such as a maximum emission index of 550 gCO_2/kWh. Successful bidders enter reliability option contracts with Terna, committing to offer their capacity into the energy and ancillary service markets and refunding any positive difference between market prices and a predetermined strike price. This design mitigates excessive profits during high price periods and contributes to consumer protection.
Contract durations vary: one year for existing units and up to fifteen years for newly built units. The remuneration structure adopts a marginal pricing system (pay-as-cleared), with fixed annual premiums per MW secured through auction.
Recognising the critical role of storage in supporting renewable energy integration, Italy launched in 2024 the Meccanismo di Approvvigionamento di Capacità di Stoccaggio Elettrico (MACSE) [94][93]. This mechanism promotes the development of new storage infrastructure by providing long-term contracts with fixed premiums, determined through competitive auctions.
MACSE distinguishes itself from the traditional Capacity Market by focusing exclusively on energy storage, including lithium-ion batteries and pumped-hydro projects. Storage facilities selected through MACSE auctions are remunerated based on the energy they can store (€/MWh per year) and must make their capacity available for two purposes:

- Provision of time-shifting products: enabling energy shifting across hours via a dedicated GME market platform.
- Participation in the Dispatch Service Market (MSD): contributing to real-time balancing.

This innovative mechanism provides investment certainty for storage developers and is internationally recognised as a pioneering model for promoting large-scale storage deployment.
Together, the Capacity Market and MACSE represent strategic pillars of the Italian approach to securing system adequacy and flexibility in a decarbonised energy system. They deliver critical long-term investment signals while ensuring that new resources, particularly storage systems, actively contribute to energy and ancillary service markets, thus supporting grid stability and energy transition objectives.

1.4.5 The Evolution of the Electricity Dispatching

The ongoing transition towards a decarbonised energy system, characterised by the increasing penetration of non-programmable RES and distributed generation, necessitates a profound evolution of electricity dispatching models. Traditionally based on large programmable plants, the Italian electricity system is now adapting to a scenario dominated by small, dispersed units feeding into networks originally designed for passive operation. In response to these changes, the new "Testo Integrato del Dispacciamento Elettrico" (TIDE) represents a cornerstone reform aimed at ensuring the secure, efficient, and sustainable operation of the future electricity system [87][89][90][91].

The TIDE, approved by ARERA with Deliberation 345/2023/R/eel [88], radically redefines the organisation of the dispatching service. Its main objectives include promoting open, technology-neutral access to balancing markets, ensuring operational security, and harmonising Italian regulations with the European framework. Among the most significant innovations:

- The abolition of the "relevance" criterion (formerly applicable to units ≥ 10 MVA), enabling all units, regardless of size, to participate actively.
- The introduction of portfolio bidding, allowing aggregation of multiple small units into virtual structures.
- Full alignment with European balancing platforms (PICASSO for aFRR, MARI for mFRR, TERRE for RR), enhancing market integration.
- The transition to a 15-minute settlement period: Aligning the imbalance settlement period (ISP) and market time units with European standards to incentivise faster and more precise balancing actions.
- A clear separation between energy trading roles and ancillary service provision, with distinct obligations for different actors.

The TIDE introduces a dual responsibility model:

- BRP: Responsible for trading in energy markets (DAM, IM) and for covering any imbalances against scheduled programs.
- BSP: Responsible for providing balancing and redispatching services upon request from Terna and executing activation instruction.

Each unit must be associated with both a BRP and a BSP, though the roles can be covered by the same or different entities. The BSP is economically responsible for service provision and operational compliance, while the BRP manages market trading and settlement of imbalances.

The reform establishes new aggregation models to facilitate broad participation:

- UAS (Unità Abilitata Singolarmente): Large units able to act individually.
- UVAN/UVN (Unità Virtuali Abilitate/Non abilitate Nodali): Aggregates of units connected to a common node of the electricity grid.
- UVAZ/UVZ (Unità Virtuali Abilitate Zonali): Aggregates across a wider geographical area.

These models lower entry barriers for small and distributed resources, enabling them to provide AS and balancing capacity, either individually or through aggregation.

RECs emerge as key players under the TIDE framework. By aggregating generation and consumption at local level, RECs can act as flexible resources, participating in balancing and ancillary service markets, optimise local energy use, reducing grid congestion and supporting system stability.

By combining distributed generation, proactive consumers, and storage, RECs can actively support grid balancing, making them a cornerstone of the future dispatching system.

The new dispatching model fosters a highly dynamic and decentralised electricity market. Prosumer participation, energy communities, aggregators, and storage operators can seize

opportunities to provide value-added services. Flexibility becomes a tradable asset, enabling more resilient, efficient, and sustainable grid operation.
The TIDE markets a historic shift towards a fully open and decentralised electricity dispatching system. Energy communities and storage systems are set to play a central role, not only as passive consumers or isolated producers but as active providers of flexibility, contributing to a secure, efficient, and decarbonised energy future. In this evolving context, new initiatives such as local flexibility markets are emerging as practical applications to enhance distributed resource participation, a topic that will be explored in the next section.

1.4.6 Pilot projects for Distributed Flexibility and Self-Dispatching

In parallel with the reforms introduced by the TIDE, Italy is pioneering several pilot initiatives aimed at unlocking the potential of DER at both the transmission and distribution levels. These projects provide practical applications of the new dispatching philosophy and offer critical insight into the evolving role of aggregators, storage systems, and energy communities.
Local flexibility markets (LFMs) aim to provide Distribution System Operators (DSOs) with operational tools to manage network congestion, voltage regulation, and other critical grid needs without relying solely on traditional network reinforcements.
Through platforms managed by the GME, flexibility services are procured competitively, with DSOs acting as buyers and Balancing Service Providers (BSPs), including aggregators, energy communities, storage operators, and distributed generators, acting as sellers.
RomeFlex [95], managed by Areti in Rome, focuses on upward flexibility procurement using contracts that combine availability and utilisation payments. Services are provided by distributed resources such as PVs, batteries, and demand response assets.
EDGE [96], managed by E-Distribuzione, operates in selected areas such as Cuneo, Benevento, Foggia, and Venice. It targets both upward and downward flexibility needs, particularly in regions with high renewable penetration. The project leverages an adapted version of the PicloFlex platform for service procurement.
Both initiatives validate the feasibility of local flexibility procurement and demonstrate how distributed assets can play a strategic role in maintaining grid stability while deferring costly infrastructure investments.
Complementing local flexibility markets, Terna has launched a pilot programme for self-dispatching and self-balancing based on the aggregation of distributed resources into Unità Virtuali per l'Auto-Bilanciamento (UVB) [97][98].
Through this scheme, aggregators voluntarily commit to maintaining a predefined balance between injections and withdrawals for each fifteen-minute interval, autonomously managing deviations without direct intervention from the TSO. Successful adherence to the commitments leads to reduced dispatching charges, while failures incur penalties.
This innovative model further decentralises system management and explicitly recognises the role of proactive distributed resource management. Storage systems, flexible loads, and RECs can thus become fully integrated participants in balancing and ancillary service provision.
The pilot projects RomeFlex, EDGE, and the UVB self-dispatching experiment are fully consistent with the research directions developed in this thesis. In particular, the fourth article anticipates and supports the evolution towards a system where storage systems embedded within energy communities actively participate in local and national flexibility markets and aggregators dynamically manage portfolios of distributed assets through sophisticated self-balancing algorithms.
New control codes and operational strategies must be developed to enable the seamless integration of DERs into real-time market operations.

The experiences gained from these pilot initiatives offer not only validation of the theoretical models proposed but also a glimpse into the practical challenges and opportunities that lie ahead. The next section will summarise the connections between the thesis contributions and the future trajectory of electricity markets, with a specific focus on the evolving role of storage systems within energy communities.

1.4.7 Alignment of the research work with the evolution of electricity market

Chapter 1.4 illustrates how the Italian and European electricity markets are undergoing a profound transformation. Driven by the need to integrate increasing shares of variable renewable energy and distributed resources, the system is evolving from a centrally dispatched model to a decentralised, flexible, and participatory architecture.

The evolution of the Day-ahead and Intra-day Markets, the reform of the Dispatch Service Market under the TIDE, and the development of capacity and storage procurement mechanisms lay the foundation for broader participation of new actors. Local flexibility markets and self-dispatching pilots provide tangible examples of this decentralised vision in practice.

In this evolving context, the research conducted within this thesis aligns perfectly with the trajectory of market development, particularly focusing on the following key aspects:

Active Role of Storage Systems: Batteries are no longer seen merely as passive energy buffers but as dynamic assets capable of providing flexibility services. The models developed in the thesis demonstrate how storage systems within energy communities can be optimally managed to provide these services, anticipating the role envisaged in local flexibility and UVB markets.

Empowerment of Energy Communities: RECs are recognised as critical actors in the new markets. The thesis highlights how RECs, through aggregation and intelligent management of distributed assets, can actively participate in energy markets, fully exploiting the opportunities opened by the TIDE reform.

Need for Advanced Control Codes and Algorithms: The transition towards decentralised dispatching models necessitates the development of sophisticated control systems capable of managing heterogeneous portfolios of distributed resources in real time. The thesis addresses this challenge by proposing innovative management strategies and algorithms that are fundamental to enabling full participation in emerging flexibility markets.

Overall, the work carried out anticipates and supports the regulatory and market trends towards a smarter, more resilient, and more inclusive energy system. The models, simulations, and strategies presented not only confirm the feasibility of these developments but also provide concrete tools and insights to accelerate their practical implementation.

1.5 Role of forecasts

In the context of RECs and DES management, accurate forecasting is critical to both the design and operation of local energy systems. Forecasts are used not only to anticipate the generation and consumption behaviour of members, but also to support the planning of community-scale assets, such as batteries or thermal storage, and to inform the real-time management of these systems.

This thesis makes extensive use of forecasts in two key areas. The first concerns the generation of synthetic load and generation profiles, particularly in the absence of real historical data. These profiles are used in techno-economic simulations and storage sizing exercises. The second relates to operational forecasting short-term and real-time predictions used in the optimisation-based scheduling and control strategies developed in the latter part of the work. The following subsections provide an in-depth discussion of these two forecasting domains

1.5.1 Forecasts for profiles generation

The ability to simulate realistic load and generation profiles is essential when designing and assessing the performance of a REC, especially given the prevalence of old-generation meters that do not provide quarter-hours data or when the access to new-generation meters is not possible. Two main forecasting paradigms are typically adopted for this purpose: bottom-up and top-down approaches. The key features, inputs, and limitations of these two methodologies are compared in Table 2.

Table 2 Comparison between bottom-up and top-down load profile generation approaches.

	Top-down	Bottom-up
Input data	Aggregated stats, reference profiles, electrical and gas monthly bills	Surveys, appliance ownership data, user habits
Methodology	Disaggregation of total energy using standard curves	Stochastic simulation of individual appliances
Output data	Smoothed and standardized profiles	High-resolution synthetic profiles
Scalability	High: minimal data required, fast deployment	Low: data-intensive, complex implementation
Accuracy	Low on user diversity, misses peaks	High: captures non-contemporaneity and habits
Limitations	Inaccurate for Self-Consumption analysis	Strongly dependent on survey data quality
Use in thesis	Bills used as main constraint for the LoBi method in [P1] and [P2]. ARERA standard profiles are used in [P3] and [P4].	Used to generate occupancy and appliance patterns as inputs for the LoBi method in [P1] and [P2].

Bottom-up methods construct synthetic profiles by aggregating the estimated behaviour of individual appliances and users. These techniques often rely on detailed inputs such as surveys and appliance ownership data to simulate load on a minute or hourly basis. In this thesis, bottom-up models were implemented in the first and second studies using appliance-level surveys to derive household-specific consumption profiles through stochastic simulations. These methods are robust in capturing user-level diversity but require extensive input data. Some excellent open-source software and methodologies are available [100][101][102][103][104][105][106]. However, as highlighted in Table 2, the effectiveness of these models can be hindered by the variability of survey-based data and the complexity of implementation across large user bases (low scalability).
Top-down approaches, conversely, start from aggregated or macro-level data, such as national statistics, standard load profiles, or monthly energy bills, and disaggregate these into time-resolved profiles using predefined patterns. They are advantageous when high-resolution consumption data are unavailable and allow for faster deployment in real-world case studies due to their high scalability. Top-down techniques often use reference profiles, such as those obtained through statistical observation campaigns or from official surveys of network operators [107][108][109][110][111][112][113][114], which are then scaled and adjusted to match observed energy. Despite being easier to apply, pure top-down models tend to overlook user-level diversity and intra-day variability, which are critical to accurate modelling of SC and CSC.
To overcome the respective limitations of the aforementioned approaches, this thesis introduces LoBi (Load Profiles from Bills), a novel hybrid methodology developed by the author and released as open source [99]. The method utilizes monthly electricity and gas bills as the primary top-down constraint to ensure the total energy volume is real. It then redistributes this energy across hours using bottom-up drivers:

- For electricity: Data is shaped according to occupancy profiles (generated via Markov chains using the StROBe tool) and constrained by the specific Italian time-of-use tariff slots (F1, F2, F3).
- For heating: Gas consumption is converted to thermal energy and redistributed based on Typical Meteorological Year (TMY) temperatures and occupancy.

By combining top-down robustness (bills) with bottom-up customization (occupancy and stochastic appliance usage), LoBi was able to generate realistic profiles used for the simulations in Papers 1 and 2. Conversely, Papers 3 and 4 adopted standard top-down profiles provided by ARERA [111]. This choice was driven by the need for high scalability (simulating RECs with hundreds of members in [P3]) and result generalizability (creating a reproducible benchmark for the control algorithm in [P4]), objectives that would have been impractical with a survey-intensive bottom-up approach.
LoBi is publicly available on GitHub [99].

1.5.2 Forecasts for scheduling and control

Forecasting plays a pivotal role in the operational management of energy storage systems, especially in the context of community-scale batteries supporting RECS. Accurate predictions of local energy consumption and PV production are essential for enabling both day-ahead scheduling and real-time control of storage systems. In this thesis, two forecasting horizons are considered: longer-term forecasts, typically used as input for optimisation-based scheduling algorithms, and short-term forecasts, necessary for real-time control systems that respond to unexpected deviations.
In the third article of this thesis, a deterministic forecasting approach is adopted to simulate the performance of a community battery participating in EA and CSC. Day-ahead forecasts of load and PV generation are assumed to be perfectly accurate and used as inputs for an optimization model that computes an optimal battery charging/discharging schedule. While effective for techno-economic assessment, this approach does not account for forecasting errors, which may compromise arbitrage profitability and dispatchability (DIS).
To address this limitation, the fourth article introduces an advanced scheduling framework based on multi-scenario forecasts. Here, uncertainty in both PV production and load demand is represented through a finite set of probabilistic scenarios. The MILP model is reformulated to minimise the expected cost across all scenarios, producing a robust day-ahead Dispatch Plan (DP) that is resilient to forecasting errors. This method reflects the stochastic nature of distributed energy systems and enables a more realistic modelling of community battery behaviour under uncertainty.
In addition to day-ahead scheduling, accurate short-term forecasts are required for real-time control. The second control layer developed in the fourth article operates on a rolling horizon, using updated forecasts of PV generation and load to continuously adjust the battery set point.
The real-time control algorithm leverages:

- short-term irradiance forecasts (from nowcasting or numerical weather prediction models),
- load forecasting based on recent consumption trends,
- and a CoDistFlow-based grid model to estimate current power flows and losses.

By incorporating these predictions into a closed-loop control strategy, the battery can dynamically compensate for unforeseen deviations, thus improving compliance with the scheduled DP. This approach was tested on a real-life microgrid setup and validated under realistic forecasting uncertainty, demonstrating high tracking accuracy even under varying weather and demand conditions.

A wide range of forecasting techniques can be applied, depending on the available data, desired accuracy, and computational resources [115]. Classical statistical methods include:

- ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal ARIMA) models, which capture time-dependent patterns and seasonality in load and PV data.
- Exponential smoothing, useful for simpler trends with limited computational needs.
- Artificial Neural Networks.
- Support Vector Regression.
- Random Forests.
- Long Short-Term Memory networks, particularly effective for highly non-linear time series with complex temporal dependencies.

Alternatively, RECs and aggregators may rely on external forecasting services [116][117][118] that provide updated predictions via APIs, often based on sophisticated ensemble weather models or proprietary algorithms. While these services simplify implementation, their performance may vary depending on local conditions and often lack granularity for small-scale prosumers or communities.

In this thesis, forecasting models were implemented using a mix of in-house scenario generation methods (for robust optimisation) and simplified short-term predictive heuristics (for real-time control). However, the framework developed is compatible with more advanced forecasting engines and external data sources, offering a flexible and modular approach to REC energy management.

1.6 Problem statement and study novelty

RECs are expanding rapidly as literatures about them, yet two foundational gaps still constrain their design and operation.

First, stakeholders lack a fit-for-purpose, simulation-based techno-economic assessment workflow tailored to RECs, one that starts from realistic reconstruction of demand profiles and proceeds through energy-flow simulation to investment analysis under current incentives and tariffs. Existing studies often rely on generic profiles or partial models and do not provide a coherent, REC-centred pipeline that municipalities, associations or PV installation companies can use in their feasibility studies.

This work addresses this by formalising and testing a techno-economic assessment framework that can reconstruct load profiles from bills, surveys and standard curves when real data are absent, simulates hourly energy balances including storage system modelling, and quantifies stakeholder Cash Flow (CF) and investments under the Italian CSC scheme.

Second and more of interesting and deeper for research, while advanced scheduling and control methods exist for utility-scale grid-connected storage, there is no validated suite of algorithms conceived for the REC domain. i.e., for shared community batteries or coordinated fleets of member-owned batteries, which can simultaneously provide multiple services of SC, CSC and EA; but that in the near future they will also have to be capable of self-dispatching and local flexibility, as is starting to happen in some pilot projects, and in the somewhat more distant but not so distant future they will also have to be enabled to dispatching service as required by European Directives and by TIDE.

The literature lacked methods that a REC operator could deploy to operate storage assets within REC regulatory, and experimental evidence was notably missing. Our work fills this gap by progressing from centralised rule-based scheduling to optimisation-based scheduling and real-time control, culminating in the first experimental validation of a REC-specific multi-service BESS controller.

1.6.1 REC techno-economic assessment in realistic scenarios

One of the most pressing challenges in the development of RECs is the lack of empirical data to evaluate their economic feasibility. RECs are still at an early stage of implementation across Europe, and most have not accumulated sufficient operational history to derive robust cost-benefit analyses especially in configurations involving shared storage systems. As a result, stakeholders such as municipalities, associations and PV installing companies are often left without decision-making tools to understand whether and how to invest in distributed energy systems.

This thesis addresses this problem by developing a simulation-based methodology that can accurately replicate the technical and economic behaviour of RECs under realistic conditions. The simulations can consider real-world constraints such as Italian incentive schemes for CSC, current EPs, technical limitations of storage systems (e.g. thermal losses or battery ageing), and member-specific load and production profiles. These are either derived from monitored data or reconstructed from actual electricity bills, ensuring the realism of the simulated energy curves.

Within this framework, various configurations can be modelled and assessed, including individual producers with or without batteries, fleets of batteries coordinated by a central REC manager, shared community-scale batteries, HPs, various size for all these components and different configurations in terms of number of prosumers and consumers. Each configuration is evaluated based on key performance indicators such as energy balances, levels of CSC, financial returns from electricity bill savings and selling energy, battery utilisation, and grid independence.

By analysing these indicators, the simulations provide concrete answers to questions such as:

- Is it economically advantageous to install a PV, a battery or a HP in a specific building part of a REC?
- What is the most effective battery sizing strategy under current market conditions?
- How should storage be managed to maximise personal and community benefits?

It is possible to answer these questions using a framework of precise techno-economic simulations and, above all, it is possible to do so using two software packages that implement it, namely MESSpy and LoBi, which were developed during this research work, tested and improved through the studies carried out in the first two articles of this thesis, and made available open source for the stockholders of the REC domain.

This work offers replicable, open source and policy-relevant tools for public administrations, energy planners, and community groups to de-risk investment decisions and support the scalable deployment of RECs. By bridging the current knowledge gap with simulation-based evidence, it enables a more informed and accelerated roll-out of energy communities across Italy and beyond.

1.6.2 New strategies for storage systems management in RECs

The effective management of energy storage systems within RECs is a prerequisite for unlocking their full potential. Batteries and thermal storage systems are essential to increase SC and CSC but also to enable REC to the provision of additional services. Yet, RECs today lack concrete and validated management strategies tailored to implement a central management under their technical and regulatory context. Currently, distributed resources within RECs are controlled by local logics (standard BMS) designed to maximize individual SC. While rational for the single user, this uncoordinated approach is sub-optimal for the community. This thesis addresses this gap by adopting the perspective of a central REC planner, aiming to coordinate these assets to unlock the optimization of CSC and the provision of additional services such as EA e self-dispatching.

This thesis addresses this issue by proposing and analyzing a progressive suite of storage management strategies, ranging from rule-based coordination to advanced optimization-based control, implementing article after article increasingly advanced and complete models.

The first two studies explore centralized rule-based strategies for managing fleets of distributed storage assets. Specifically, a novel rule-based approach is proposed for scheduling lithium-ion batteries and thermal energy storage coupled with HPs considering what is happening on hourly base to all members of the community in terms of electricity fed and withdrawn to and from the national grid. These strategies, though simple, enable coordinated energy sharing and demonstrate significant improvements in CSC and grid independence. However, they also highlighted two critical economic barriers: first the high capital cost of individual batteries makes distributed investment often unfeasible under current market conditions; second the gain from CSC is very low.
Building on these foundations, the third and fourth studies execute a strategic shift towards community-scale batteries managed via optimization. This transition addresses the need to exploit economies of scale and to overcome the limitations of rule-based logic. The research thus evolves into a comprehensive optimization-based framework that allows for the consideration of high-value services such as EA and Self-Dispatching. Furthermore, it integrates forecasts regarding production, load and EPs in future hours, as well as grid constraints and battery ageing considerations. The proposed methods are an absolute novelty within the literature because no paper had so far proposed management methods at this level of comprehensiveness and depth that were developed specifically for the REC.
Furthermore, a key contribution to this field is the experimental validation of this strategy in a real-world microgrid, demonstrating its robustness and applicability in practice. The test confirms, for the first time in the literature, the feasibility of jointly delivering CSC, arbitrage, and self-dispatch through a single control system, proving the REC technical ability to act as a BRP.
In summary, this thesis proposes a scalable and replicable pathway for REC storage management:

- From simple but effective rule-based coordination in distributed systems,
- To sophisticated real-time optimization in shared infrastructures.

Together, these strategies provide REC operators and developers with a concrete toolbox to design, manage, and evolve storage systems in alignment with community goals, regulatory constraints, and technical capabilities.

1.6.3 Each study novelties

This section summarises the specific novel contributions introduced by each of the four studies composing this thesis. Each article tackles a different aspect of storage integration and management in RECs, offering original models, methods, or experimental insights that advance the state of the art.

[P1]: A new smart batteries management for Renewable Energy Communities

- Proposes a rule-based centralised strategy for managing a fleet of prosumer-owned batteries within a REC, aiming to maximise CSC without penalising individual users.
- Introduces a realistic simulation framework based on reconstructed load profiles from real electricity bills, under the current Italian regulatory scheme.
- Demonstrates the trade-offs between rule-based and optimisation-based strategies, showing that a simple rule-based approach can be effective and easy to implement in early-stage RECs.
- Performs a sizing analysis to determine optimal battery capacity based on CSC and economic return.

[P2]: Heat pumps and thermal energy storages centralised management in a Renewable Energy Community

- Extends the rule-based approach to thermal energy storage (TES) and heat pumps, proposing a centralised load-shifting strategy aimed at increasing CSC.
- Provides one of the first techno-economic analyses of TES in RECs, including the impact of lower average COPs and higher thermal losses at higher storage temperatures.
- Updates the load profile reconstruction method to reflect thermal dynamics and seasonal variations, making it more suited for heating-dominated use cases.
- Highlights the limited economic gain under current incentive schemes, motivating future policy improvements.

[P3]: Community Battery for Collective Self-Consumption and Energy Arbitrage

- Formulates a LP-based optimisation model for the operation of a shared community battery, capable of providing both CSC and EA services.
- Conducts a comprehensive sensitivity analysis on economic parameters such as battery cost (BC), electricity prices, REC size, and service stacking.
- Incorporates battery ageing into the optimisation model, allowing more realistic lifecycle economic evaluations.
- Demonstrates the importance of multi-service optimisation for financial viability in real market conditions.

[P4]: Self-dispatching a Renewable Energy Community by means of BESSs

- Introduces a two-layer control strategy (scheduling + real-time control) for community batteries providing CSC, arbitrage, and self-dispatching.
- Implements a grid-aware convexified AC-OPF model (CoDistFlow) accounting for network constraints in a low-voltage REC context.
- Models forecast uncertainty and real-time deviation to minimise dispatch errors against REC market bids.
- Validates the proposed control system in a real-world microgrid, representing the first experimental demonstration of REC self-dispatch with storage.

2 ORIGINAL CONTRIBUTION

2.1 List of Publications

P1. [119] M. Pasqui *et al.*, "A new smart batteries management for Renewable Energy Communities," *Sustainable Energy, Grids and Networks*, vol. 34, p. 101043, 2023, doi: 10.1016/j.segan.2023.101043.

P2. [120] M. Pasqui, G. Vaccaro, P. Lubello, A. Milazzo, and C. Carcasci, "Heat pumps and thermal energy storages centralised management in a Renewable Energy Community," *International Journal of Sustainable Energy Planning and Management*, vol. 38, pp. 65-82, 2023.

P3. [121] M. Pasqui *et al.*, "Community Battery for Collective Self-Consumption and Energy Arbitrage : Independence Growth vs . Investment," *Sustainability*, 2024, doi: https://doi.org/10.3390/su16083111.

P4. [122] M. Pasqui, F. Gerini, M. Jacobs, C. Carcasci, and M. Paolone, "Self-dispatching a renewable energy community by means of Battery Energy Storage Systems," *J Energy Storage*, vol. 114, Apr. 2025, doi: 10.1016/j.est.2025.115837.

2.2 Discussion

This section provides a critical discussion of the main findings and contributions presented in the four peer-reviewed articles included in this thesis. It aims to interpret the results in a broader scientific and practical context, explore the implications for RECs, and reflect on the evolution of the methodological approaches employed as well as the motivations that guided the author in choosing the topics to be covered in each article and the case studies used. The discussion is structured to first summarise the individual contributions and results of each study, explain why each study led to the choice of the next and clarify how the case studies were selected.

Then delve into a detailed techno-economic assessment of storage investments, followed by a cross-cutting analysis of methodological progression, regulatory relevance, and finally an exploration of open challenges and future research directions.

2.2.1 Overview of the Four Studies and Their Main Results

This thesis comprises four peer-reviewed articles that collectively address the technical and economic management of energy storage systems within RECs. Each study contributes uniquely to advancing both the scientific understanding and practical implementation of smart storage strategies in RECs, following a precise evolutionary path.

[P1] introduced a novel rule-based strategy for the centralized control of a fleet of residential batteries within a REC. The approach was tested using data of a real-world case study involving a small Italian REC. The proposed management increased the share of CSC by over 35 % compared to standard local battery operation. However, the comparison with an optimisation-based benchmark (deterministic MILP) revealed that, while robust, the rule-based strategy remains sub-optimal, highlighting a margin for improvement that only optimization can capture. Furthermore, the economic analysis proved that small-scale residential batteries are currently not cost-effective due to high specific costs (€/kWh), making the distributed investment model often unfeasible. This finding motivated the strategic shift in [P3] towards a centralized Community Battery.

[P2] extended the concept of centralized management to thermal energy storage systems coupled with HPs. Simulation results showed a 5 % to 8 % increase in CSC and improved grid independence, but also quantified the technical trade-offs, such as reduced average Coefficient of Performance (COP) and higher thermal losses. Crucially, the study demonstrated that economic benefits at the user level were modest due to low incentives, proving that CSC alone is insufficient to justify the complexity of thermal management. This limitation motivated the shift towards high-value services like EA in [P3].

[P3] executed a strategic shift towards a shared asset model to overcome the cost barriers identified in [P1]. It adopted a LP model for a Community Battery designed to provide both CSC and EA. Sensitivity analyses on BC and market prices confirmed that aggregating capacity allows for economies of scale. The key result is that enabling EA is essential for profitability, potentially halving the payback period compared to CSC alone, although a trade-off was identified, with a reduction in shared CSC when prioritizing arbitrage revenues.

[P4] represents the culmination of the research, bridging the gap between the theoretical potential of [P3] and real-world applicability. It proposes and experimentally validates an advanced two-layer energy management system (Scheduling ans Real-Time Control). This study is the first to demonstrate through a real-world experiment on a physical microgrid that a community battery can simultaneously perform CSC, EA, and Self-Dispatching (minimizing imbalance errors). By proving the technical ability to act as a BRP, this work validates that the economic potential identified in [P3] can be accessed in real markets without being eroded by imbalance penalties.

2.2.2 Motivation of the articles

[P1] originated as a natural extension of the author's master's thesis. In fact, the latter had identified a specific conflict between individual and collective objectives. The standard logics embedded in PV inverters (StBMS) are designed solely to maximize the prosumer physical SC. From the individual perspective, this is rational behaviour. However, from the perspective of the REC as a whole, this uncoordinated approach represents a sub-optimal inefficiency because it penalises CSC, reducing the incentives generated for the community. From this evidence arose the need to devise a control logic capable of aligning these interests, combining both SC and CSC, with the aim of increasing the latter without penalising the former (a win-win strategy). Furthermore, thanks to collaboration with the University of Brussels, it was possible to compare the results of our simulations with those obtained on the same case study by their MILP-based model. Since this latter approach is deterministic, its outcomes provided a benchmark, namely the best achievable results. The comparison showed that an optimisation-based MILP model indeed allows for better results than the rule-based strategy proposed in our work. This comparison, combined with the study economic finding that individual residential batteries are currently not cost-effective due to high specific costs (€/kWh), motivated the strategic shift in subsequent papers: transitioning from rule-based to optimisation-based models and from individual to community-scale shared assets to exploit economies of scale.

[P2] stemmed from two main motivations. The first was to test the new rule-based logic, which had shown promising results for electrochemical storage, also on thermal storage integrated with HPs. The second motivation was to collaborate with another research group within our department, namely the technical-physics one. The results, however, demonstrated that while the rule-based logic could be effectively adapted also to HPs, the economic margin deriving from their management for the purpose of enhancing CSC was very limited. For this reason and driven by the need to find more profitable business models for RECs, the HP technology was set aside in favour of focusing resources on advancing storage management. The goal became to develop increasingly sophisticated models capable of going beyond simple CSC and delivering high-value services like EA, in line with the requirements of EU directives.

[P3] represents the first LP model developed by our department for battery management. The decision to move from the multiple battery scenario of [P1] to a single shared battery was directly driven by the economic barrier identified in [P1]: since distributed investments was not profitable, the research pivoted to a Community-Scale Storage approach to leverage economies of scale. We started with a simple model, designed to manage a single battery and not incorporating uncertainty management (deterministic). Wanting nonetheless to provide a meaningful contribution, we focused the study on two aspects not previously explored: an in-depth evaluation of battery ageing in relation to the combined practices of EA and CSC, and extensive economic sensitivity analyses. Such analyses were crucial to understanding whether EA could provide the significant additional CF needed to make the storage investment competitive, bridging the economic gap left by CSC incentives alone.

[P4] addresses the final gap. It became clear that the models proposed in the previous three articles were incomplete. Although they allowed us to perform valuable techno-economic exploratory analyses, they exhibited operational limitations that prevented immediate real-world applicability. Crucially, a significant gap emerged regarding the economic validity of the results obtained in [P3]. The profitability of EA, identified as the key driver for investment viability, relies on the assumption that the REC can trade energy at wholesale market prices. In reality, accessing these revenues requires the REC to act as a BRP, bearing the financial responsibility for grid imbalances. The deterministic model in [P3] ignored this risk. Therefore, the motivation for the fourth study was to bridge this gap: it became essential to develop a model capable of managing forecast uncertainty and minimizing real-time dispatch errors (Self-Dispatching). Only by proving the technical feasibility of acting as a reliable BRP could the economic potential suggested in [P3] be validated in a real-world market environment. Given these considerations, and in light of the outstanding opportunity to undertake a six-month visiting period at EPFL in Lausanne, the final direction of this doctoral research became self-evident.

2.2.3 Case studies selection

Each of the four papers carries out simulations on slightly different case studies. Naturally, the choice of the case study was each time carefully assessed and then made by taking into account the data available, the specific research objectives of the paper, and also the possibility of turning the study into an opportunity for collaboration with other entities, such as energy communities, local companies, and research groups. The purpose of this paragraph is to summarise the case study employed in each paper and, above all, to explain the rationale behind its selection. Table 3 outlines the main KPIs of each case study.

Table 3: Article case studies.

	P1	P2	P3	P4	RECs' potential
PV total size [kW_p]	5 x3	50	100	30	inf
BESS total size [kWh]	2.5-10 x3	-	20-300	60	inf
HP total size [kW_{th}]	-	10 x10	-	-	inf
Prosumer numbers	3	1	-	-	inf
Consumer numbers	5	10	80-200	10	inf
PV properties	private	shared	shared	shared	private and shared
BESS properties	private	-	shared	private and shared	private and shared
HP properties	-	private	-	-	private and shared

During the preparatory phase of the first article [P1], the opportunity arose to collaborate with a local start-up: EnCo Energia Condivisa. At that time, EnCo was engaged in establishing the very first REC in our region. Our interest in collaborating with them was therefore obvious. From this collaboration emerged the possibility of using the small REC that was being created as a case study. The community consisted of only 3 prosumers and 5 consumers, with three PV systems of 5 kWp each and three batteries. Crucially, our study proved useful for them in assessing the installation of batteries, leading to the understanding that such investment was not economically convenient. This real-world negative finding was pivotal: it demonstrated that at the small residential scale, distributed batteries struggled to achieve a return on investment, motivating the later shift in the thesis towards larger, shared assets. Conversely, their data were useful for us to develop the LoBi methodology for simulating load profiles.

When deciding the case study for the second paper [P2], we were collaborating with a local PV installation company, which was overseeing the creation of a new rural REC. This company provided significant know-how on HPs. Considering the opportunity to collaborate and the attractive chance to increase the PV capacity in our analysis to 50 kWp (a larger REC composed of 10 consumers and one prosumer), it was decided to adopt this new case study.

[P3] does not employ a specific real case study, but rather a representative one based on official standard curves (ARERA) for Italian domestic consumers. The reasons are twofold. First, the paper is essentially a sensitivity analysis on several parameters to identify the economic break-even points for storage. Second, and most importantly, the decision to move from a scenario with multiple batteries (as in [P1]) to one with a single shared battery was driven by the specific need to solve the economic problem identified in [P1]. Since individual batteries proved too expensive, we needed a flexible, theoretical case study to test whether a Community-Scale Storage approach could restore economic viability through economies of scale and EA. Using standard curves allowed for a generalizable benchmark, providing validity and replicability to the results.

[P4] employs the experimental microgrid at the EPFL Distributed Electrical Systems Laboratory. Regarding the choice of case study, it reflects precisely the resources available: a 30 kWp PV system, a 60 kWh battery, and 10 consumers emulated via load emulators. This choice was strategic: to validate the hypothesis that a REC can act as a BRP, simulation alone was insufficient. We needed a physical environment with real grid constraints and real-time control capabilities to prove the technical feasibility of Self-Dispatching.

In conclusion, the selection of case studies was driven by a mix of strategic research needs, testing different scales (from residential to community) and different assets (distributed vs. shared), and valuable collaboration opportunities. While changing the case study limits direct comparability, it allowed the thesis to cover a broader spectrum of REC configurations, from small pilot projects to optimized community hubs.

2.2.4 Techno-Economic Feasibility of Storage Investments in RECs

A detailed techno-economic evaluation was carried out across the first three studies to assess the viability of investing in storage systems under realistic REC conditions. Although the fourth article was centered on control methodology, the other studies provide a strong empirical and simulated basis to assess financial impacts.

In [P1], simulations on a REC with 5 consumers and 3 prosumers with residential batteries (3 kWh to 5 kWh) demonstrated that smart rule-based management increased CSC by 35 % compared to local operation. While the raise in individual user revenue from CSC incentives alone remained modest (10 €/year to 15 €/year starting from a base of about 50 €/year), this is due to the limited incentive that the Italian government makes available, the REC-wide benefit can translate into a collective incentive gain. The CSC incentive is therefore best seen as a collective surplus, which, if enhanced through smart management, can finance social or environmental projects within the REC. Moreover, the methodology proposed is scalable: in larger RECs, the absolute value of this surplus increases proportionally, even if the percentage gain remains similar. Also, and maybe more importantly, the study showed that PV investment is already economically justified through physical SC and selling energy, regardless of the prosumer participation in a REC, although now investing in a battery is not cost-effective due to the long payback time owing to the still high initial costs. Is no accident, and the REC studied in [P1] then decided to install only the panels without the batteries. This conclusion serves as a turning point for the thesis strategy. The inability of individual residential batteries to generate a positive return on investment highlights that the path to storage viability in RECs lies in aggregation. This directly justifies the transition to the Community Battery model explored in [P3], where economies of scale and multi-service stacking are leveraged to overcome the cost barriers identified in [P1].

[P2] showed that, even without strong individual profitability, coordinated thermal storage management can provide a 5 % to 8 % increase in CSC and strengthen REC resilience. While individual user benefits raise remained below 5 €/year, the system-wide effects in terms of load shifting and renewable integration are significant. In contexts where heating and cooling loads dominate, such strategies could become critical, especially when thermal storage incentives or carbon pricing mechanisms are introduced.

[P3] analyzed the techno-economic potential of a community battery applied to a medium-sized REC with 80 to 205 users and a total PV power installed of 100 kWp. The battery is managed through a LP model to increase CSC and supply EA. The study explored two EP scenarios (low and high), tested various battery capacities (0 kWh to 300 kWh) and CAPEX values (200 €/kWh to 600 €/kWh). Key results highlight a distinct dichotomy depending on the services provided, as well as the importance of proper sizing:

- Scenarios without EA (CSC only): Dedicating the battery solely to CSC proves to be the most efficient solution for energy independence but lacks economic appeal. The investment becomes financially viable only under very specific conditions, namely high electricity market prices combined with low BC (below 200 €/kWh). At higher costs (400 €/kWh), the payback period extends significantly, often rendering the investment unfeasible.
- Scenarios with CSC and EA: Integrating EA significantly enhances investment feasibility. The simulations show that EA acts as a driver for profitability, making battery investment attractive even with capital costs around 400 €/kWh and across both high and low EP scenarios. Effectively, enabling EA approximately halves the payback period compared to the CSC-only scenario, making the battery a competitive asset.

- Importance of Optimal Sizing and REC Configuration: Economic viability is strictly dependent on the correct sizing of both the battery and the community itself. The analysis highlights a counter-intuitive finding regarding the number of consumers: maximizing the number of members is not always the optimal strategy. If the aggregate demand of consumers is too high during generation hours, it absorbs the entire PV production instantly. In this "saturated" scenario, there is no energy surplus available to charge the community battery, rendering it useless for increasing CSC (as it would only operate for EA by withdrawing from the grid). Therefore, the optimal configuration requires a balanced ratio between production and consumption, ensuring sufficient daytime surplus that the battery can store and shift to evening peak hours, thus maximizing the value of both CSC incentives and arbitrage.

These findings highlight the importance of multi-service stacking and strategic planning in determining the profitability of community-scale storage. Furthermore, defining the ownership and financing model is crucial for the practical implementation of such a shared asset. In this analysis, the battery is assumed to be owned by the community itself. The financing strategy could vary: the REC could use funds collected through territorial projects or accumulated incentives, seek external financing (e.g., banks or business angels), or launch internal crowdfunding campaigns among members. Consequently, the redistribution of the revenues generated by the battery, both from market arbitrage and increased CSC incentives, would logically depend on the financing model adopted and the investors' expected return.

[P4], while not including new economic simulations, provides the essential technical validation for the economic results obtained in [P3]. The profitability of EA, identified as the key driver for investment viability, relies on the assumption that the REC can buy and sell energy at wholesale market prices. In reality, accessing these prices requires the REC to act as a BRP, which implies bearing the financial responsibility for grid imbalances. By experimentally demonstrating that a community BESS can simultaneously perform CSC, EA, and self-dispatching (minimizing real-time dispatch errors), [P4] proves that the REC can effectively manage the operational risks of being a BRP. Thus, [P4] substantiates the economic feasibility suggested in [P3], confirming that those theoretical margins can be accessed in a real market environment without being eroded by imbalance penalties.

2.2.5 Cross-Study Synthesis: From rule-based simulation to real-time optimization

The real guiding thread of this thesis is the evolution of the models proposed across the articles towards the construction of an increasingly comprehensive framework, capable of delivering multiple services and being used for both scheduling and real-time control. Completeness and complexity, however, go hand in hand. Indeed, to enable batteries to provide more services it is necessary to increase the model inputs, which requires two things. The first is, obviously, the deployment of an IoT infrastructure able to manage the collection and transfer of such data, which entails a cost. The second is the formulation of linear-programming (LP) models capable of handling multi-objective functions and a large number of possible solutions, something impossible for a rule-based approach.

The objective of this paragraph is to clarify the guiding thread along which this thesis evolves by explaining in detail the progression of the proposed models in terms of deliverable services, inputs included in the model, its logic and typology, its use, and the type of test for which it was employed in the studies of this thesis. Table 4 serves as the reference for the following explanation.

Table 4: Service stacking and model evolution through articles.

	St	P1	P2	P3	P4	RECs' potential
Services						
Self-consumption	X	X	X			X
Collective self-consumption		X	X	X	X	X
Energy arbitrage				X	X	X
Ageing control				X	X	X
Self-dispatch					X	X
Local flexibility						X
Dispatch services						X
Model inputs						
Local prosumption	X	X	X	X	X	X
REC prosumption		X	X	X	X	X
Prosumption forecasts				X	X	X
Energy price forecasts				X	X	X
Forecasting uncertainty					X	X
Grid status and constraints					X	X
Model type						
Rule-based	X	X	X			
Optimization-based LP				X	X	X
Model aim						
Real-time control	X	X	X		X	X
Scheduling				X	X	X
Test performed						
Simulation	X	X	X	X	X	X
Experimentation					X	X

To begin the explanation, it is essential to clarify a fundamental point: namely, what the standard logic (St in the table) is, according to which all residential batteries are currently controlled. This is important because it represents the starting point from which all the other models evolve. Such logic is managed by the inverter connected to the battery; it is rule-based, very simple, and designed to maximise SC. It works as follows: the energy produced by the PV system is first used to satisfy the load; if there is surplus, it is stored in the battery until its maximum SoC is reached, and any remaining surplus is inevitably injected into the grid. On the other side, the energy required to satisfy the load is first supplied by the PV production; if insufficient, it is taken from the battery until its minimum SoC is reached, and if more is needed, it is drawn from the grid. This logic is rule-based, i.e. based on ifs, on rules, that is, on a limited number of well-defined scenarios. Such logic can be implemented with only a few lines of code and requires, for its operation, only two real-time inputs: production and load, whose sum is called prosumption. It operates in real time without using any information regarding the rest of the REC, nor forecasts, let alone data from the grid itself. This logic works very well for individual SC and represents the baseline for prosumer cost savings. However, from a collective perspective, it represents a missed opportunity, as it does not align injection/withdrawal profiles among members to maximize shared incentives. This logic can be implemented both for simulations (it is included in MESSpy) and in real machines. In fact, it is the most widespread control logic for batteries worldwide. Nevertheless, it is possible to do better.

An improvement of this logic is proposed in [P1] and consists in integrating, into the standard logic, information about the production and consumption of the other REC members, namely the REC prosumption. Using this information, it is possible to extend SC to the maximisation of CSC by simply adding one more rule to the standard logic: if another member of the community is withdrawing energy, prioritise grid injection, for the sake of sharing, over charging the battery.

This logic remains very simple and [P1] has demonstrated its effectiveness; it does, however, require an IoT infrastructure capable of enabling communication between all inverters for data exchange. Such logic could be implemented in real-time control without major difficulties, but in [P1] it was used only for hourly simulations, due to the lack of resources to set up the IoT infrastructure necessary for a real experiment.

The model in [P2] is equivalent to those in [P1] but applied to thermal storage associated with HPs instead of batteries. The logic is straightforward: if there is surplus energy in the community, increase the heating of the thermal storages of the HPs. This logic too could be implemented without major difficulty for real-time control through the installation of an IoT infrastructure suitable for data exchange among REC members. In the paper, however, it was used only in simulation.

[P3] introduces, alongside CSC, the practice of EA. Performing EA means planning the charging and discharging of the battery, and the corresponding withdrawals and injections of energy into the grid, in order to maximise revenue from selling electricity and minimise expenditure on its purchase. To do this, an algorithm capable of performing scheduling is required, using as inputs the forecasts of prosumption and EPs over a time horizon of several hours, typically at least 24. This cannot be achieved with a rule-based logic due to the dimensionality of the problem: indeed, the size of each variable corresponds to the time horizon, making it impossible to define a finite set of rules that could cover all possible scenario combinations and identify the optimal solution. This, however, can be done mathematically by formulating an optimisation problem using LP. Such a model allows for the determination of optimal solutions to large-scale problems with very short convergence times. Thanks to LP, [P3] achieves optimal scheduling for the charging and discharging of a shared community battery, maximising a multi-objective function comprising the incentive from CSC, the purchase and sale of electricity, and a penalisation function that accounts for excessive usage in order to consider ageing and the future replacement costs. The model does this using forecasts of electricity prices, loads, and production from all REC members. These forecasts, however, are assumed perfect: the model is deterministic and does not account for forecast errors, i.e. the discrepancies that will inevitably occur in real time between predicted and realised values. From this perspective, the model is incomplete. Nonetheless, it proved very useful for simulations and techno-economic sensitivity analyses.

[P4] overcomes all the limitations of the previous papers, completing the simplifications previously adopted, and thus proposes a model encompassing all aspects necessary for real-world implementation. The LP model of [P4] considers not only forecasts, but also their uncertainty. Using a stochastic, scenario-based approach, [P4] bases its results not on a single forecast but on a multitude of forecast scenarios, with the aim of capturing the full distribution of forecast errors. In this way, scheduling results are robust, i.e. they account for all possible scenarios that may occur in real time. The model does this in order to maximise an objective function composed of the components already included in [P3] (CSC, EA, and ageing control), plus an additional component related to the DIS of the proposed scheduling, i.e. the ability to follow the schedule in real time. Indeed, the model proposed in [P4] can be used, and was used in a microgrid experiment, for real-time control of battery setpoints, based on the scheduling and on real-time data of actual outcomes. The goal of this model is to minimise dispatch error, i.e. to enable the community self-dispatch, avoiding imbalance penalties. Moreover, the models in [P4] are even more refined and precise, as they incorporate power grid modelling, including line losses due to cable resistances and physical constraints such as ampacity and voltage limits. Within the optimisation model, all these components are included thanks to the implementation of the well-known CoDistFlow, a framework developed at EPFL capable of linearising the entire grid model, thus making it possible to embed it within LP-based optimisation.

Crucially, the transition from [P3] to [P4] is not merely a technical refinement but a necessity for economic validation. Since accessing the arbitrage revenues estimated in [P3] requires the REC to assume the role of a BRP, the stochastic framework in [P4] provides the necessary tool to manage the associated risks. The two-layer model, scheduling and real-time control, was tested in a microgrid for 24 hours representing a small REC. The experiment was highly successful, demonstrating the model's effectiveness and its feasibility for real-time battery management within RECs to deliver the proposed services. In this way, the thesis reached its culmination, closing the synthetic loop of battery management models.

2.2.6 Regulatory Outlook, open challenges and future research directions

All studies were developed with close alignment to the Italian and European regulatory context, particularly the CACER Decree, ARERA TIAD, and directives 2018/2001 and 2019/944. [P1] and [P2] support current incentive structures for CSC, offering scalable solutions that work within the hourly net metering. [P3] anticipates REC evolution by showing how RECs could integrate EA as a secondary income stream, using the possibility of hourly supply and selling contracts. [P4] prepares the technological and operational basis for RECs to act as Balance Responsible Parties (BRP), responding dynamically to DP and grid signals. This is highly aligned with the vision outlined in the TIDE report and the Clean Energy Package's push for local energy actors in system balancing.

The model aligns with ongoing pilots by Terna and ARERA as explained in 1.4.6. But, as dispatch service markets expand, allowing broader access to small DERs and their aggregates, the methods proposed here, especially [P4], equip RECs to become credible and efficient participants in these markets and to play an increasingly important role in the energy landscape.

Naturally, the evolution of this research should move towards integrating into the model developed in [P4] the capability to provide services for the Local Flexibility Market and the AS Market (MSD). This entails evolving the REC role from a simple BRP (minimizing internal imbalance) to a BSP, capable of actively bidding flexibility to the TSO or DSOs to solve grid congestions (e.g., participating in UVAM - Mixed Virtual Aggregated Units). This was not included in the present thesis both for time constraints and due to lack of data. Indeed, although regulatory frameworks already define the rules and mechanisms for access to these markets, we are speaking of very recent pilot projects for which data are not yet publicly available. This makes it impossible to perform simulations, as no public lists of signals exist that could be replicated in a simulation environment. To develop research in this direction, collaboration with a BRP and/or an REC actually participating in such pilot projects would be crucial, in order to test the proposed models on real machines and leverage the experience and know-how of stakeholders already familiar with this market.

Regarding the broader Dispatching Services Market, regulation has not yet evolved to allow direct access to small stakeholders, although it does enable the participation of nodal or virtual DER aggregations. In practice, however, this is still not widespread. It is therefore unclear how aggregation mechanisms will operate, ranging from the rules for sharing economic revenues, to the IoT infrastructure (possibly based on standards) needed to enable such practices, to the redistribution of responsibilities and roles among the different stakeholders. In short, this is a fully evolving scenario, which deserves to be studied in depth and requires extensive research.

Another interesting development of this doctoral research would be a comparative study of all the models proposed in this thesis applied to the same case study. The reason why such a study has not been included here has already been addressed in section 2.2.3. However, to support and guide future work, some considerations can be highlighted. Such a study could use the standard load curves published by ARERA together with PV production curves from PVgis, supplemented by a forecast error distribution from which to generate predictive scenarios. EPs considered should be the average of recent years, while still retaining hourly and daily variability, which is crucial for evaluating EA. This study could and should be performed for several market areas, where loads,

production, and prices vary (as, according to TIDE, zonal prices will soon replace the National Single Price).
The comparative analysis could include sensitivity studies with respect to BC, sizes, and REC dimensions. At the same time, investment solutions based on virtually aggregated private batteries could be compared with solutions based on a community-owned shared battery. In doing so, it should be noted that the models developed in [P3] and [P4] can be adapted to manage a fleet of batteries instead of a collective one, but this requires specific modifications to the model. In particular, the objective function must be expanded to include bill savings from SC, prioritizing the physical SC of the individual owner before aggregating the remaining flexibility for community services. On this point, the author warmly encourages any researcher undertaking such work to reach out for collaboration.
In summary, the two natural directions for further research are: on the technical side, integrating the local flexibility market and BSP capabilities into [P4]; on the economic side, conducting a comparative study of all the models. Considering both the results and the limitations identified in the articles, other key research priorities include:

- High-Precision Forecasting ("Hawk Eye"): As highlighted in [P4], forecasts are the bottleneck. Future research must focus on advanced forecasting techniques, such as "Hawk Eye" systems (e.g., sky imagers combined with AI) to provide ultra-short-term, high-precision irradiance data, essential for minimizing dispatch errors.
- Scalability: most simulations focus on small to mid-size RECs. Larger systems with multiple assets and heterogeneous participants require advanced coordination strategies.
- Hybrid Systems Management: [P2] demonstrated the potential of thermal storage. Future works should aim for multi-energy optimization, coupling batteries not only with HPs but also with other assets like small hydroelectric plants or electric vehicle chargers. Hybridization allows for greater flexibility and resilience.
- Battery ageing: while considered in [P3] and [P4], more accurate degradation models would improve lifetime value prediction and investment planning.
- Real-world validation: [P4] demonstrates feasibility in a microgrid test, but broader validation under diverse network conditions and multi-battery configurations is required to demonstrate generalizability.

2.3 Publications

Following are the 4 publications in their final version as published in the respective journals.

Sustainable Energy, Grids and Networks 34 (2023) 101043

Contents lists available at ScienceDirect

Sustainable Energy, Grids and Networks

journal homepage: www.elsevier.com/locate/segan

A new smart batteries management for Renewable Energy Communities

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A R T I C L E I N F O

Article history:
Received 31 October 2022
Received in revised form 31 March 2023
Accepted 4 April 2023
Available online 9 April 2023

Keywords:
Energy system simulation
Renewable Energy Communities
Battery management
Load forecasting
Photovoltaic systems

A B S T R A C T

Based on the European Directive, the Italian Government has recently published the technical rules for accessing the service for valorizations and incentivizing shared electricity, kick-starting the setting-up of Renewable Energy Communities (RECs).

A techno-economic analysis is performed based on a real case in the city of Florence to show the benefits that the creation of a REC can bring to the stakeholders: consumers, prosumers, the national grid operator and third-party companies. Moreover, this study focuses on the role of batteries within a REC by comparing three different battery management systems (BMS).

The standard BMS (StBMS) is developed for individual prosumer self-consumption (SC) and not for REC collective-self-consumption (CSC), which is thus penalized by the presence of batteries. For that reason, a new smart BMS (SmBMS) based on REC real-time data monitoring is proposed. This solution guarantees the same level of CSC as in the case without batteries, and compared to the StBMS, it ensures greater REC energy independence from the national grid and leads to more incentives for all stakeholders, causing only a negligible economic loss for prosumers, as their individual SC slightly decreases.

The optimal BMS (OpBMS), based on deterministic knowledge of demand and production curves, could guarantee even greater REC energy independence and a better investment for all REC participants, but since it cannot be implemented, it is calculated only to be used as a benchmark to assess other BMSs and to explore the potential of forecasting based methods.

StBMS and SmBMS are simulated by Multi Energy System Simulator (MESS) while OpBMS by a Mixed-integer linear programming model (MILP).

1. Introduction

The concepts of REC and collective-self-consumption (CSC) have been introduced in Italy by the Regulatory Authority for Energy Networks and Environment [1], the ministry of economic development [2] and the ministry of justice [3] adopting Articles 21 and 22 of the European REDII Directive [4].

The Italian energy services operator (GSE) was appointed by the Italian Government to define the technical rules necessary for setting up a REC [5].

The REC is a legal entity composed of users belonging to the same low-voltage network that share the electricity produced by one or more systems powered by renewable sources, in this specific study photovoltaic panels. Open and voluntary participation in a REC is allowed for individuals, local or public authorities and small and medium-sized enterprises.

All configurations allowed for RECs involve the interaction with the electricity grid (Fig. 1), as it is not allowed to develop private grids for peer-to-peer energy transactions. All energy produced which is not self-consumed behind the meter of each utility is fed into the low voltage (LV) grid and it is paid based on 'Ritiro Dedicato' (RD) rates by GSE ([5]).

Part of this energy can also be recognized as CSC on which 110 €/MWh incentives are paid plus 8 €/MWh for the restitution of costs, not incurred for the management of the electrical system. The remaining energy ends up in the medium voltage (MV) grid. Each utility pays all the electricity withdrawn from the meter at

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https://doi.org/10.1016/j.segan.2023.101043

Abbreviations

CF	Cash flow
CSC	Collective-self-consumption
EnCo	'Energia Collettiva' (Third-party company name)
GSE	'Gestore Servizi Energetici' (Italian energy service operator)
LV	Low voltage
MESS	Multi-energy system simulator
MILP	Mixed-Integer Linear Programming
MV	Medium voltage
NPV	Net present value
PV	Photovoltaic panels
RAMP	Rural area multi-energy profile generator
RD	'Ritiro Dedicato' (GSE rate for energy fed into the grid)
REC	Renewable Energy Community
SC	Self-consumption
SmBMS	Smart battery management system (scenario)
StBMS	Standard battery management system (scenario)
OpBMS	Optimal battery management system (scenario)
PVrec	PV are installed in a REC, no batteries (scenario)

the price established with its distributor, whether it comes from MV or LV (CSC).

CSC corresponds to the energy produced and self-consumed by the entire REC on an hourly basis. It is defined as the minimum, in each hourly timestep, between the electricity fed into the grid by production systems and the electricity withdrawn from the grid by the end customers of the REC.

The purpose of RECs is to encourage the production of energy from renewable sources and to create social, environmental and economic benefits for the participants.

Literature review

The first operative Italian REC is located in the town of Magliano Alpi [6] and it consists of four public buildings, one commercial service and three residences. Photovoltaic panels are installed on the roof of the City Hall for a total of 19.4 kW_p and currently, no battery energy storage system is used. The developers claim to have obtained social, environmental, and economic benefits for all participants and emphasize the importance of developing smart control systems for the integrated management of generation sources and batteries to create more efficient and flexible scenarios.

Another Italian REC is in Monticello d'Alba, with a similar composition to the one in Magliano Alpi. It includes three municipal buildings, where PV panels are installed and ten dwellings. Its feasibility study [7] focused on two main aspects: the sizing of a single PV system and battery for the entire REC and the economic assessment of three business models defined based on a different distribution of the initial costs and revenues. All economic evaluations have been made from the point of view of the REC as a whole and as a third-party company, without investigating the economics of single prosumers and consumers. Moreover, the possibility that PV or batteries are installed in a single dwelling is not considered.

In both studies, demand profiles are obtained from synthetic load profiles based on general appliances usage statistics on a minute basis and then aggregated to hourly time steps.

A different approach to load forecasting, based on actual REC participant's consumption, was described and used in a study on the constitution of a REC from condominiums [8]. The work investigates a case study in Valle d'Aosta, a mountainous region in Northern Italy, and performs a techno-economic sizing of centralized PV panels, batteries and heat pumps. Results underline the importance of assessing the economic investment of individual citizens because, in the absence of the right forms of incentive, they may opt for an economic benefit rather than an environmental one, jeopardizing the potential benefit of energy community initiatives.

Starting from the Italian experience, a set of recent works dealing with battery management systems in RECs has been compiled and summarized in Table 1, whereas a thorough review on the topic has been conducted by Hossain Lipu et al. [9]. Each work has been distinguished from the others based on the following characteristics. First, whether the energy sources of the REC (be it PV, wind, or others) and the batteries are installed in a centralized (C) or decentralized (D) configuration. In the former case, a single energy source and battery system are serving the whole energy community, while in the latter each participant might install its own production and storage assets.

A distinction is then made on the Battery Management System (BMS), which is based on a set of predefined rules or mathematical optimization. In line with the definition given by Casalicchio et al. [10], REC can be virtual (Vir) or physical (Phy). Virtual RECs are in line with the Italian normative, and energy is always exchanged with the grid. CSC depends on contextual injection and extraction of energy from the grid from two distinguished REC participants. Physical RECs are composed of micrograds where energy is shared among participants and a single point of connection to the grid is present. Each work can then be focused either on energy management (Man), components' sizing (Siz), or both. Finally, the reference country for the analysed study case and the major modelling approaches employed in each work are listed in the last two columns.

RECs analyses are often divided into two approaches: rule-based simulation and optimization [11]. In the first, the energy balances of the system are solved with an established energy management system (e.g., [8,12,13]), while in the latter a deterministic linear or mixed-integer linear programming (MILP) is applied to find the optimal energy dispatch (e.g., [7,10,14–17]).

Rule-based battery control strategy compared with an optimization-based battery control can lead to a lower cost for prosumer both in the case of shared battery storage [18] and in the case of an energy communities involving decentralized storage system [19].

The main role of battery management for a REC is to perform self-consumption and collective self-consumption, but energy arbitrage and services to the local grid can also be considered, such as load levelling [20] and smoothing [21] and peak shaving [22]. Moreover, ancillary services to the national grid could also be provided [23] in order to maximize the exploitation of available storage capacity and increase economic returns. Nevertheless, this study focuses only on ensuring self-consumption and collective self-consumption.

Aims and elements of novelty

None of the works cited addressed the main problem described in this study: installing batteries in an REC penalizes CSC if they are managed by StBMS. Therefore, this work aims to investigate how different BMS affect the energy balances and the economics of RECs. The Italian regulatory context is taken as a reference and a real-world case study is considered, as to ground the analysis on realistic assumptions and obtain new insights into the regulation itself by considering all stakeholders point of view: prosumers, consumers, third-party companies and national grid.

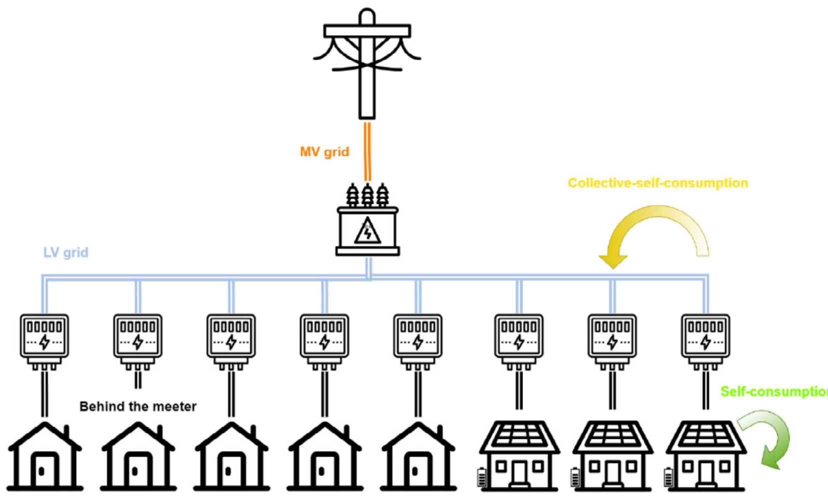

Fig. 1. Study case grid diagram.

Table 1
Literature review.

Ref.	Energy source	Battery	BMS	Phy/Vir	Man/Siz	Country	Methods
Ascione et al. [24]	C	C, D	Rule-based	Vir	Siz	Italy	Energy Plus Exhaustive search
Casalicchio et al. [10]	D	D	Optimization	Phy, Vir	Man, Siz	Italy	MILP
Cielo et al. [7]	C	C	Optimization	Vir	Man	Italy	MILP
Fernandez et al. [25]	C, D	C	Optimization	Phy	Man	Australia	MILP Bi-level optimization (Stackelberg game)
Fina et al. [12]	D	–	–	Phy	Man	Austria	Simulation
Fioriti et al. [26]	D	D	Optimization	Phy	Man, Siz	Italy	MILP Game theory
Gul et al. [27]	C	C	Optimization	Phy	Man, Siz	Italy	SAM optimization
Henni et al. [28]	D	D	Rule-based	Phy	Man	Germany	Simulation
Korjani et al. [29]	D	C	Optimization	Phy	Man	IEEE 906-bus	Genetic algorithm
Minuto et al. [8]	C	C	Rule-based	Vir	Siz	Italy	Simulation
Mustika et al. [19]	D	D	Rule-based Optimization	Vir	Man	France	Simulation YALMIP
Norbu et al. [18]	C	C	Rule-based Optimization	Phy	Man, Siz	UK	Simulation MILP
Roberts et al. [30]	C	–	–	Phys	Man	Australia	Simulation
Secchi et al. [31]	D	D	Rule-based	Phys	Man, Siz	IEEE 906-bus	Simulation Non-dominated Sorting Genetic Algorithm-II
Weckesser et al. [17]	D	D	Optimization	Phys	Man, Siz	Denmark	LP
Present work	D	D	Rule-based Optimization	Vir	Man, Siz	Italy	Simulation MILP

Key novelties of this study are:

- Demonstrate that the presence of batteries in a REC penalizes the CSC if they are managed with a StBMS.
- New SmBMS for RECs.
- Comparing different BMSs for RECs.
- Comparison between simulation and MILP optimization methods.
- Assessment of a REC with a decentralized storage system, in which each prosumer has its own battery.
- Focus on each stakeholder's investment.
- New method to generate load profiles.

2. Materials and methods

2.1. Reference study cases

The REC considered in this study is a residential neighbourhood, aiming to become an energy community, located in the countryside of Florence. The community consists of 3 prosumers and 5 consumers (Fig. 1). The project is under development by the start-up "Energia Collettiva" (EnCo), through which participants' data are collected.

The PVs sizes are determined based on the space available on a car park roof, whose angle of inclination is 10° and azimuth is 0°. Lithium-ion batteries sizing are performed to maximize each prosumer's investment, as explained in 3.1.

Table 2 summarizes case study information.

2.2. Load forecasting

The meters installed in the eight dwellings considered are old generation, so load profiles are not available, and it is necessary to generate them using a forecasting technique. Thanks to the collaboration with EnCo it was possible to submit a survey to the REC participants asking them about their habits in using household appliances. These kinds of information are used as input for a bottom-up simulation programme to simulate loads. After that, the generated profiles have been top-down validated and corrected according to the electricity bill of the participants.

Bottom-up simulation

Each household is subjected to a survey, in which it is asked what appliances are present in the dwelling and how often they are used. In addition, it is asked an average of at what time these are used. This information is used as input for a bottom-up simulation software [32] that simulates, minute by minute

Table 2
Study case information.

Stakeholder name	Role	Annual demand [kWh]	PV size [kW_p]	Battery size [kWh]
p1	Prosumer	1891	4.5	2.5
p2	Prosumer	10 341	6.0	10.0
p3	Prosumer	1695	4.5	3.0
c1	Consumer	1232	–	–
c2	Consumer	1374	–	–
c3	Consumer	2743	–	–
c4	Consumer	2791	–	–
c5	Consumer	1378	–	–
EnCo	Service provider and REC manager			
	Total REC demand: 23 070 kWh			
	Total REC production: 20 840 kWh			

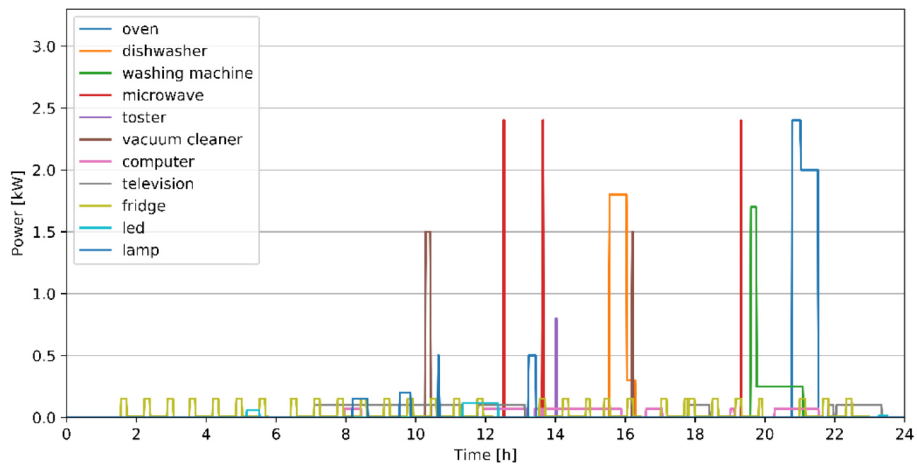

Fig. 2. Daily load simulation minute by minute of each appliance.

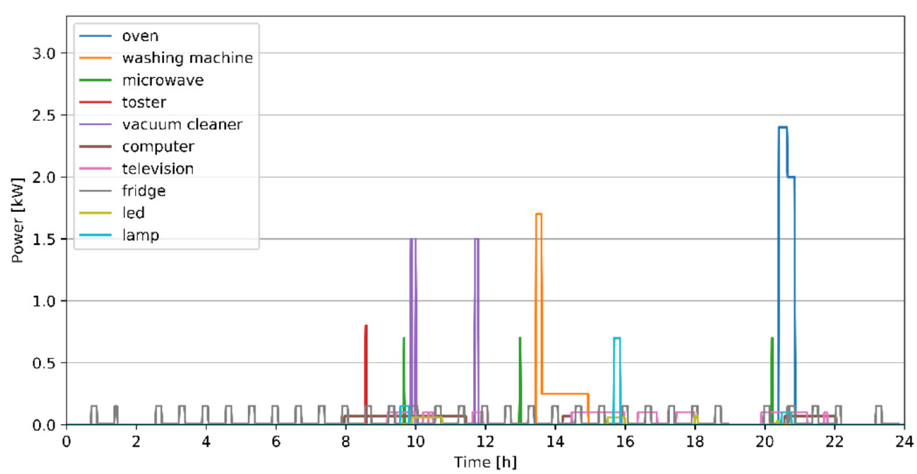

Fig. 3. Another daily load simulation minute by minute of each appliance.

throughout the year, the switch on and the switch-off of each appliance with a degree of randomness. The curves that the software can generate are shown in Fig. 2, Fig. 3, Fig. 4, and Fig. 5 using as example p1 simulation data.

Figs. 2 and 3 show how a daily load can be composed. Each appliance requires a different power and its switches on and switches off happen considering both survey information and a certain degree of randomness. For that reason, every day is different, the times in which the appliances are used change and some of them could also not be used.

By increasing the number of simulations, it is possible to observe the characteristics of the electrical demand of each dwelling, in terms of the average curve and required powers. These characteristics reflect survey information. Figs. 4 and 5 show, with a blue line, the medium load minute by minute of p1; the first figure considering a one-week simulation and the second one a whole year. The skylines are the daily profiles overlapping.

Average profiles, power required, and total energy demand are different from dwelling to dwelling because each one has different appliances and uses them at different times and frequency.

The main advantage of using a bottom-up method like this is that it allows replacing the random behaviour of people inside the dwellings by generating realistic loads. Moreover, the non-contemporaneity of each dwelling load, is a fundamental aspect

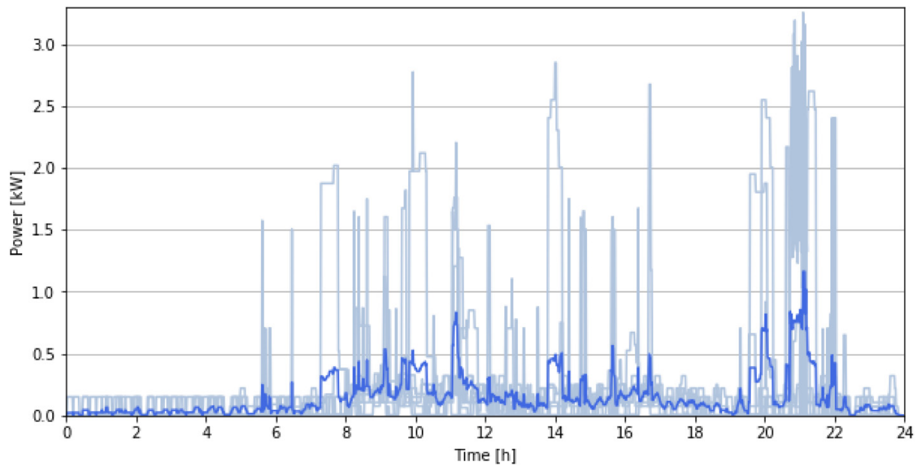

Fig. 4. Weekly load simulation: average curve and overlapping days.

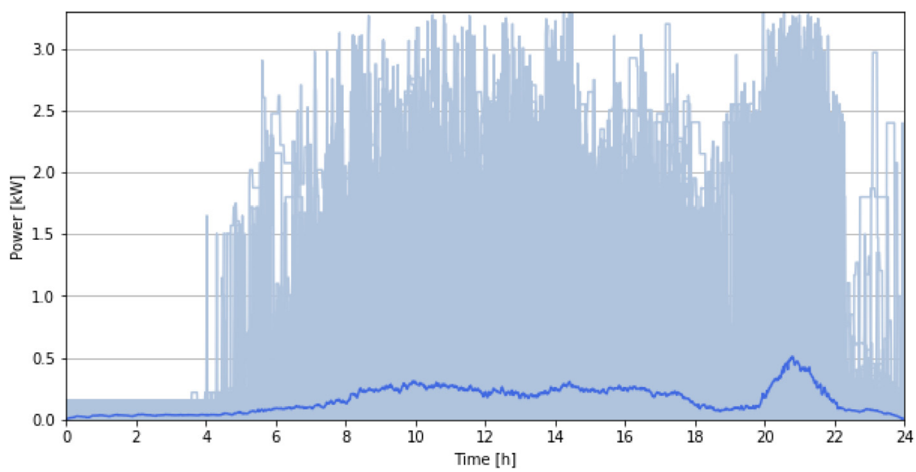

Fig. 5. Yearly load simulation: average curve and overlapping days.

Hours	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Week days	F3	F3	F3	F3	F3	F3	F3	F2	F1	F1	F1	F1	F1	F1	F1	F1	F1	F1	F1	F1	F2	F2	F2	F2
Saturday	F3	F3	F3	F3	F3	F3	F3	F2	F2	F2	F2	F2	F2	F2	F2	F2	F2	F2	F2	F2	F2	F2	F2	F2
Sunday	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3	F3

Fig. 6. Time slots according to Italian legislation.

to calculate the CSC. On the other hand, this approach does not include seasonality, it is subjected to errors due to initial assumptions, and the validity of the generated curves strictly depends on survey reliability, which varies from case to case. To adjust these sources of unreliability a top-down validation method is also used.

Top-down validation

Bottom-up simulation results are compared with electricity bills information, i.e., the consumption of each month, divided into the three time slots, defined by Italian law: F1, F2 and F3 as they are defined in Fig. 6.

Therefore, for each dwelling, 12 *x* 3 (month *x* timeslot) values are used to validate simulation results and correct them making consumption more realistic. As an example, Table 3 shows the p1 simulation results and p1 bill for some months of the year.

Starting from the simulated loads, the energy required in each time slot for each month is calculated, and these values are compared with those of the bills. Consequently, it is calculated where and how much energy to add or remove to make the simulated curve balance consistent with the bill information. These energies are randomly distributed on an hourly basis, as shown for a single day in Fig. 7. For instance, in the case represented, demand in F1 is overestimated, while in F2 and F3 it is underestimated.

The aggregation of the time step from minute to hour is a computational necessity of the following simulations. It is also justifiable considering that the CSC, which is the main object of this study, is defined on an hourly basis. The hourly profiles, averaged over a simulation year, are shown in Fig. 8. Total demands reflect electricity bill information and profiles result from survey information. Each dwelling has a different load, some concentrate the demand in the morning and during the evening while others have a more distributed demand. Due to the presence of electric vehicles, p2 demand is greater than the others and it is also high during the night hours, as verified in the bill.

Table 3
Case study p1 bottom-up simulation results vs bill information [kWh].

Month	F1		F2		F3	
	Simulation	Bill	Simulation	Bill	Simulation	Bill
January	58	70	56	66	39	96
February	51	49	42	49	46	60
…	…	…	…	…	…	…
December	51	55	50	56	48	72
Total	612	531	549	590	522	770

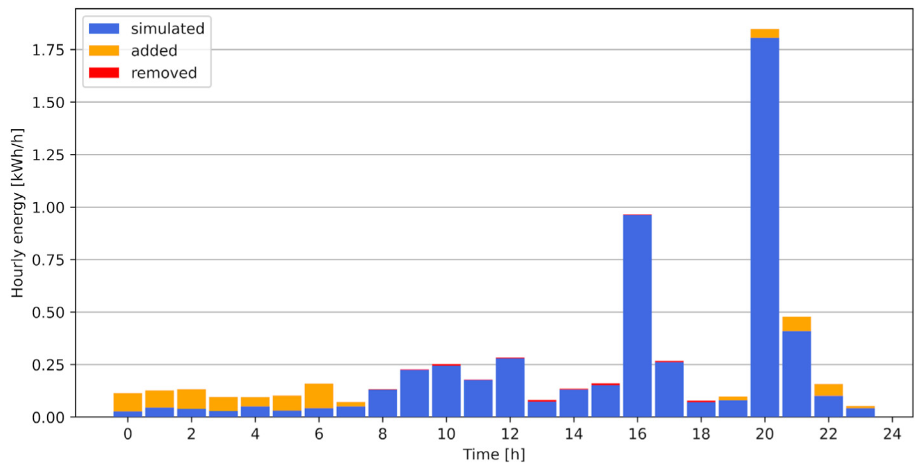

Fig. 7. One-day load curve correction.

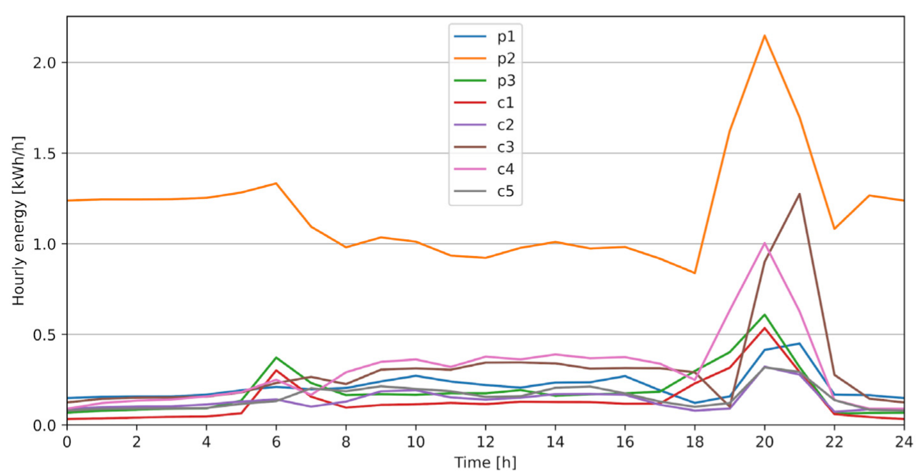

Fig. 8. Average daily profiles of each user dwelling.

2.3. Economics

The cost of PVs and batteries is covered by prosumers, who own them. Consumers, on the other hand, have no cost to bear either for the installations or for being able to participate in the REC and use the surplus of prosumer's energy. Their participation in the REC allows for an increase in CSC and the associated incentive, which is then distributed among both prosumers and consumers, as explained in paragraph 2.4.

The economic assessment of prosumers' investment is based on the Net Present Value (NPV), calculated for 20 years (y) using Eq. (1). Evaluating the evolution of the NPV over the years allows an accurate assessment of the investment by considering the NPV_{20} (Eq. (2)) and the payback time.

$$NPV_y = NPV_{y-1} + CF_y/(1+i)^y \quad (1)$$

$$NPV_{20} = -NPV_0 + \sum_{y=1}^{20} CF_y/\,(1+i)^y \quad (2)$$

$$CF = Into\ grid \cdot RD + SC \cdot E_{price} + CSC \cdot CSC_{rate} - O\&M \quad (3)$$

NPV_0 is the initial investment, CF_y is the cash flow of one year, and i is the annual interest rate set at 4%.

The initial investment is calculated according to the costs in Table 4 which are indicated by EnCo and therefore represent the Italian market as of September 2022; prices include main and additional components and installation costs. The 50% of the investment is refunded by the Italian Government in 10 annual instalments. In most cases the client can assign this credit to the seller, thus paying only half or a little more, of the initial investment cost.

The cash flow is calculated with Eq. (3), according to the rates in Table 5, and against the "business as usual" scenario in which

Table 4
Total installation cost of components.

Component	Total installation cost*
PV	1400 €/kW$_p$
Battery	800 €/kWh

*50% of total installation costs are refunded.

no renewable energy system is installed, and each household purchases all electricity from the grid and receive no incentives. Therefore, the cash flow related to a prosumer's investment is composed of the energy fed into the grid and therefore sold to the GSE at the RD tariffs, and of the self-consumed (SC) energy that is not purchased from the grid at energy price (E_{price}), as in business as usual.

Part of the energy fed into the grid is recognized as CSC on which incentives of 0.118 €/kWh [5] are disbursed and then distributed among REC members.

O&M can be considered zero for a residential installation.

The medium rate of RD is estimated at 0.15 €/kWh in March 2023 [33]; consequently the energy purchase tariffs is estimated to be at least 0.40 €/kWh. This last assumption is made by comparing the historical prices RD and the costs in participants' bills. Despite these estimates, the values used for the economic analysis are lower (fourth column of Table 5) so as to make the analysis more robust by simulating a 'worst-case' scenario. Obviously, making an accurate estimate of these prices is impossible, but it is worth noting that the economic gains reported below could be even much higher in scenarios of high prices, such as those experienced in 2022 due to geopolitical conditions.

2.4. Redistribution of collective-self-consumption incentives

CSC is calculated as follows:

$$CSC = \sum_{h} min(into\ grid_h, from\ grid_h) \tag{4}$$

Where into grid$_h$ and from grid$_h$ are electricity fed to and withdrawn from the grid by the entire REC at each hour (h). The total is multiplied by the value of the incentive and redistributed among the participants of the REC according to rules defined during its establishment. In this study, a meritocratic method that rewards who contributes most to CSC is proposed.

CSC$_h$ is attributable both to producers and to consumers: for example, if 10 kWh are recognized as CSC$_h$, this means that at least 10 kWh are fed into the grid and at least 10 kWh are withdrawn from the grid. The contribution of the 10 kWh fed into the grid is divided between the households that fed energy into the grid at hour h, in proportion to how much each fed. And the 10 kWh withdrawn are proportionally attributed to the dwellings that withdrew energy at hour h. Based on this principle, it is possible to calculate for each household how much it contributes to CSC as a consumer and how much as a producer. Consumers can only contribute as consumers, while prosumers can contribute both as producers and as consumers.

Consequently, the incentives are distributed according to how much everyone contributes, but first the share of the contribution as a producer and the share of the contribution as a consumer must be established.

Moreover, a part will be probably retained by the REC operator. In this study, a division of 60% to consumers, 20% to prosumers and 20% to the REC operator is initially proposed. Later, the operator's share is further discussed.

2.5. Simulation and optimization models

MESS

MESS (Multi-Energy System Simulator) is a simulation model based on an analytical programming approach, meaning that it is based on a set of pre-defined rules and priorities applied at each timestep. The simulation approach and the modular development of the tool, allow to consider different strategies for the same component and to define more realistic management strategies to account for real-life, unoptimized behaviours of energy systems [11]. A more detailed description of the tool can be found in previous works of the authors, where the tool has been applied to residential energy systems with heat pumps [34] or considering battery ageing [35]. For this work, a new BMS (defined as smart BMS, or SmBMS) is introduced. MESS is an open source software published on GitHub [36].

MILP

The optimization model used to benchmark the performance of two different BMS has already been presented for an optimal scheduling problem in a precedent work of the authors [14]. In this study, the optimal dispatch of PV, batteries, heat pumps and electric vehicle (EV) chargers is calculated to minimize costs. An extension of this model, with the addition of the optimal investment planning to the optimal dispatch problem, was presented in [15]. This updated model is used in this study for the evaluation of one of the possible BMS to implement in the REC, with the only addition of the extra revenue stream coming from CSC. The main advantage of using a fully deterministic optimization approach is that, by giving the best possible solution, it can be used as a benchmark for evaluating the results of another approach that could be more easily implemented in real-life conditions. On the other hand, a control based on perfect foresight cannot be implemented in real-life conditions.

2.6. Simulated scenarios

Table 6 summarizes the scenarios simulated, their acronyms and the tool used to simulate them. The graphs in Fig. 9 are examples of a daily balance of a single prosumer and are useful to display the distinct roles of the battery according to different BMS, which are also described in Table 7.

In the PVrec scenario there are not batteries, so all the PV surplus is fed into the LV grid and part of it can be used by the REC and recognized as CSC, the remaining ends up in the MV grid.

If a battery is present and managed with a standard battery management system (StBMS), PV surplus is first used to charge the battery and then fed into the LV grid. Because of this, the prosumer SC increases but REC CSC decreases.

This happens with StBMS, but a different management rule can be used (SmBMS) which gives priority to fed energy into the grid to create CSC instead of charging the battery. SmBMS allows to obtain the same CSC of the PVrec scenario, but the

Table 5
Cash flow components.

Energy balance	Rate in 2022 €/kWh	Rate in 03/2023 €/kWh	Rate used €/kWh
Into grid	0.50 (RD)	0.15 (RD)	0.10 (RD)
Self-consumption	1.20 (E_{price})	40 (E_{price})	30 (E_{price})
Collective-self-consumption	0.118 (to share)	0.118 (to share)	0.118 (to share)

Table 6
Simulated scenarios.

Acronym	Scenario	Tool
PVrec	No batteries	MESS
StBMS	Standard battery management system	MESS
SmBMS	Smart battery management (real-time data monitoring)	MESS
OpBMS	Optimal battery management (perfect forecasting)	MILP

Table 7
Batteries management system in the simulated scenarios.

StBMS	SmBMS
If there is energy surplus Charge the battery If there is still energy surplus Fed energy into the grid Calculate CSC	If there is energy surplus If REC members are withdrawing energy Fed the energy they need into the grid (this create CSC) If there is still energy surplus Charge the battery If there is still energy surplus Fed energy into the grid Calculate CSC
PVrec (no batteries)	**OpBMS**
If there is energy surplus Fed energy into the grid Calculate CSC	Calculate the optimal scheduling based on perfect foresight to maximize REC profits. Calculate CSC

SC of each prosumer is slightly lower than the StBMS scenario because the battery does not always have the necessary energy to be charged as in StBMS. Unlike StBMS, SmBMS requires real-time data monitoring because it considers the energy balances of all the REC members.

Introducing one-year perfect production and consumption forecasts OpBMS can be performed, which calculates the optimal batteries' scheduling to maximize REC profits, that is the sum of the profits of all members. This results in solving the contrast between CSC and SC without establishing a priority but maximizing the former without reducing the latter. OpBMS guarantees the same SC as the StBMS but allows a greater CSC because, in some hour battery charging is delayed. This also ensures that less energy is fed into the MV grid. Unfortunately, OpBMS it cannot be implemented, so it is only used as a benchmark to evaluate other BMSs.

3. Results

Firstly, batteries are sized and secondly, results of the different BMS scenarios are analysed by comparing the different energy balances and their economic performances. The aim is to quantify the benefits that can be achieved by establishing a REC, installing batteries, and managing them with different BMS. At last, the third-party company point of view is also discussed.

3.1. Battery sizing

Each prosumer's battery is sized to maximize his NPV_{20} considering StBMS; results are shown in Fig. 10. Due to the difference in PV nominal power, total electrical demand and load profiles, the sizing is different for each prosumer. P2 needs a 10 kWh battery as its demand is significantly higher and so is the PV capacity; for p1 and p3, smaller batteries of 2.5 kWh and 3 kWh respectively are the best solution.

3.2. Energy balances

Fig. 11 and Fig. 12 are graphical representations of the annual energy flows in PVrec and StBMS scenarios. Looking from left to right diagrams show energy produced by prosumers' PV which becomes SC, CSC or energy fed into the MV grid. From right to left, the demand for electricity is met by energy from the MV grid, from the LV grid (CSC) or from PV or batteries (self-consumption).

Table 8
REC annual energy balances in **PVrec** scenario.

Energy balance	Value [kWh]	Value/production [%]	Value/load [%]
SC	3824	18.35	16.57
CSC	3594	17.24	15.58
Into MV grid	13 423	64.41	58.18
From MV grid	15 654	75.11	67.85

To create a national grid that is powered by renewable sources and at the same time stable, the amounts of energy that a REC withdraws from the MV grid and feeds into the MV grid must be minimal. In other words, the REC and so the LV grid should be as independent as possible. This also reduces energy losses due to MV transport.

StBMS is used as an example for all the three scenarios in which batteries are installed, as the differences would not be appreciable in this type of graphs.

Tables 8–11 summarize the main results of the four scenarios. Comparing PVrec with StBMS, the latter scenario increases the independence of the REC. This results in a drop of 26.4% of energy fed into the MV grid and a fall of 17.3% of energy withdrawn from the MV grid. This happens because the batteries increase the SC by 95.6%. Unfortunately, StBMS also leads to a 26.3% decrease in CSC, which is a symptom of an inefficient REC.

SmBMS is developed to solve this problem, indeed, it guarantees the same CSC as the PVrec scenario. As a consequence, the REC independence increases further: compared to the StBMS, the energy fed into the grid MV decreases by an additional 3.9% and the energy withdraws from the MV grid by an additional 3.8%. The only problem with this scenario might be that SC decreases by 6.1% penalizing individual prosumers. This will be investigated from the economic point of view in the next section.

OpBMS aims to find the optimal scheduling in terms of cost, which results in maximizing SC, reaching the same amount of StBMS, but with an additional increase of 20% of CSC. The total grid interaction in the OpBMS scenario also decreases further compared to StBMS, with a 5.4% reduction of energy fed into the MV grid and a 4.1% reduction of energy withdrawn.

Fig. 13 gives a summary of the total energy flows. In general, the MV grid remains the biggest contributor to the annual demand, followed by the SC, while CSC represents the smallest contribution in all the scenarios.

3.3. Economic assessment

Each REC member's investment is evaluated over 20 years using as reference annual energy balances shown in the paragraph above. 20 years is the period for which the GSE guarantees incentives on CSC from the time of REC establishment and is also the minimum expected lifetime for PV and batteries. Fig. 14 and Fig. 15 show the evolution of each member's NPV for PVrec and StBMS scenarios, while Tables 12 and 13 describe the exact cash

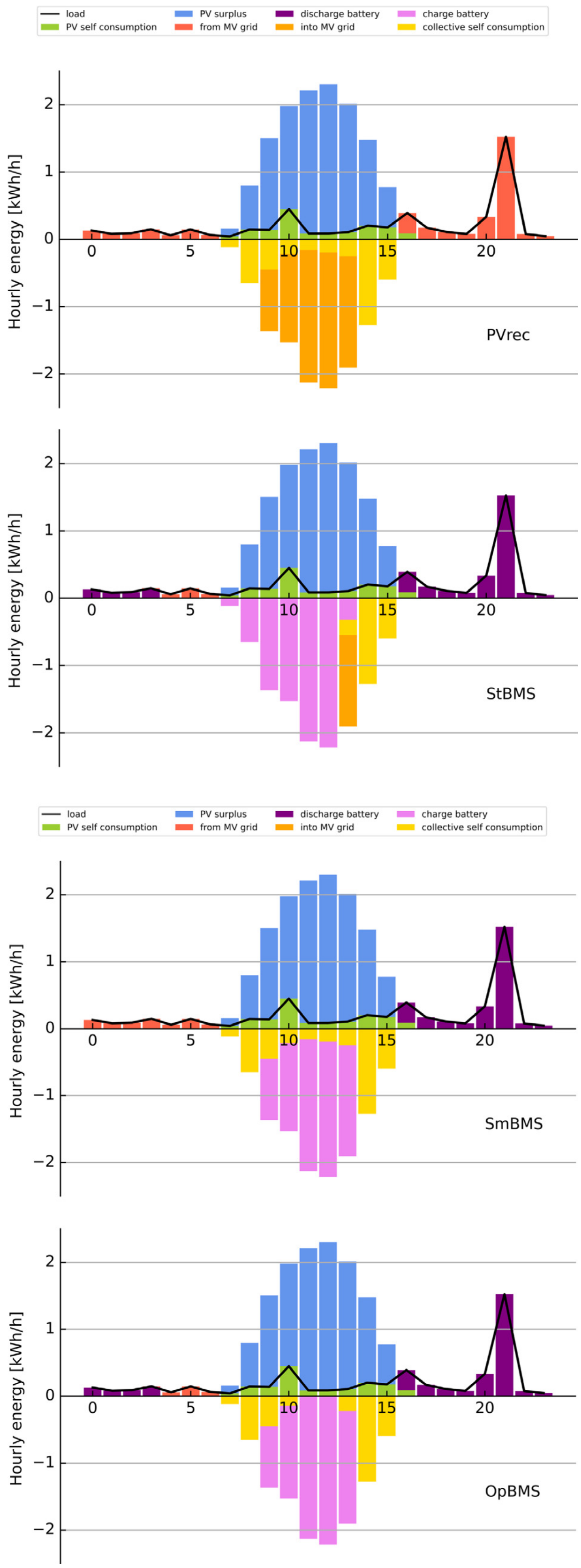

Fig. 9. Daily energy balances in different scenarios.

flow of prosumers and consumers respectively. Fig. 16 summarizes the prosumer's cash flow composition in different scenarios.

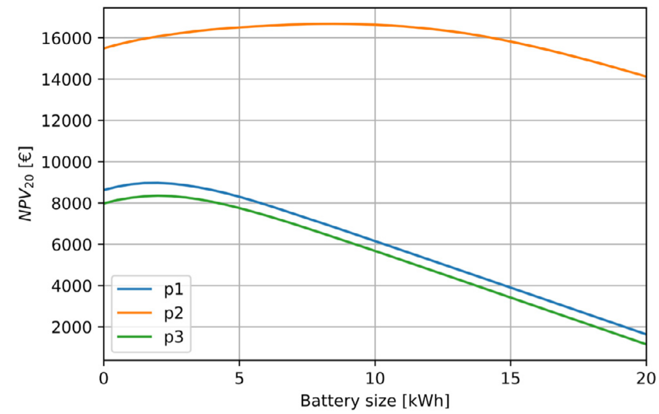

Fig. 10. Battery sizing.

Table 9
REC annual energy balances in the **StBMS** scenario.

Energy balance	Value [kWh]	Vs PVrec [%]	Value/ production [%]	Value/ load [%]
SC	7480	+95.6	35.89	32.42
CSC	2648	−26.3	12.71	11.48
Into MV grid	9872	−26.4	47.37	42.79
From MV grid	12 945	−17.3	62.11	56.10

Prosumers must repay the initial investment of PV and batteries, while consumers have no upfront expenses and receive for free their share of the incentive.

In PVrec scenario, p1 and p3 pay 6300 €, which they recover in 7 years, coming to get, after 20 years, about 8000 €and 7500 €respectively; the difference is obviously due to the ability to self-consume energy and thus to consumption profiles. P2 investment is different, as it has both higher demand and production. It has an initial investment of 8400 €, his payback time is about 5 years and after 20 years it gets more than 15,000 €. REC establishment provides the three prosumers with 39, 53 and 32 €of additional revenue per year and consumers with 25 to 68 €, depending on how much they contribute to CSC. These values would be much higher in REC composed of a larger number of members, capable of creating greater CSC.

In the StBMS scenario, income due to CSC incentives decreases for all members. Battery installation magnifies prosumer investment to 8300 €, 16,400 €and 8700 €respectively for p1, p2 and p3. P2 payback time increase for all three. But also, earnings increase: the magnitude of these depends on the difference between the cost of energy and the RD.

In SmBMS and OpBMS the variation in investments is very small compared to StBMS to be shown in NPV evolution over years (Figs. 14 and 15); it is therefore necessary to look at the detail of the cash flow components (Table 12 and Fig. 16).

In SmBMS, CSC incentives are the same as the PVrec scenario, but the prosumer's annual cash flow decreases by about 15 €. This happens because the increase in cash flow due to CSC and energy sold to RD does not compensate for the diminution of SC. This result proves that adapting an SmBMS that prioritize CSC rather than SC creates a negligible economic disadvantage for prosumers. This should, however, also be evaluated considering less usage and thus ageing of the batteries, assuming a refund for prosumers or simply considering it "a gift to the environment".

OpBMS guarantees the highest revenues for all three prosumers by optimally choosing between charging the battery and

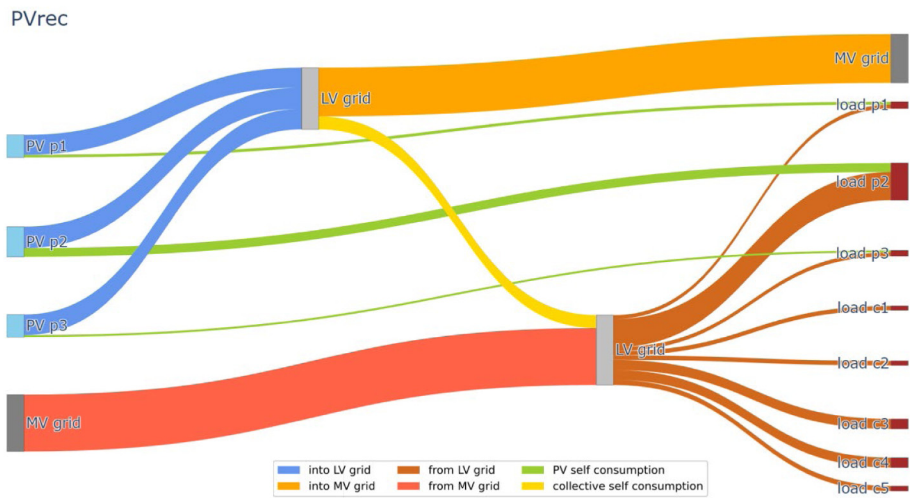

Fig. 11. Annual energy flows in **PVrec** scenario.

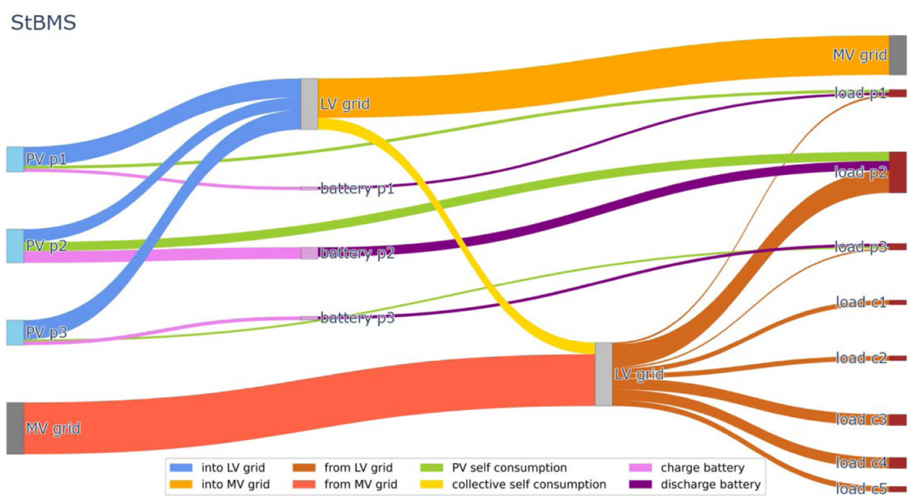

Fig. 12. Annual energy flows in the **StBMS** scenario.

Table 10
REC annual energy balances in **SmBMS** scenario.

Energy balance	Value [kWh]	Vs StBMS [%]	Value/production [%]	Value/load [%]
SC	7024	−6.1	33.70	30.44
CSC	3594	+35.7	17.24	15.58
Into MV grid	9490	−3.9	45.54	41.13
From MV grid	12 455	−3.8	59.76	53.98

Table 11
REC annual energy balances in **OpBMS** scenario.

Energy balance	Value [kWh]	Vs StBMS [%]	Value/production [%]	Value/load [%]
SC	7480	−0.0	35.89	32.42
CSC	3178	+20.0	15.25	13.77
Into MV grid	9342	−5.4	44.91	40.48
From MV grid	12 415	−4.1	59.55	53.79

selling electricity back to the grid, making it available for CSC. By doing this, OpBMS ensures the same SC as StBMS and at the same time makes it possible to achieve a higher level of CSC, providing more incentives to be shared among all parties.

3.4. Third-party company operator

Economic assessments above assume that the costs of setting up the REC are not borne by the participants but by a third-party company, in this case EnCo, who receives a percentage of the incentives on CSC to set up the REC and assumes the role of

Table 12
Prosumer's annual cash flow for different scenarios [€].

Stakeholder name	Scenario	RD	SC	CSC	Tot
p1	PVrec	545	239	39	823
	StBMS	469	426	35	930
	SmBMS	482	394	39	915
	OpBMS	469	426	42	937
p2	PVrec	588	736	52	1376
	StBMS	302	1434	17	1753
	SmBMS	329	1369	52	1750
	OpBMS	302	1434	20	1756
p3	PVrec	568	171	32	771
	StBMS	481	384	24	889
	SmBMS	497	344	32	873
	OpBMS	481	384	29	894

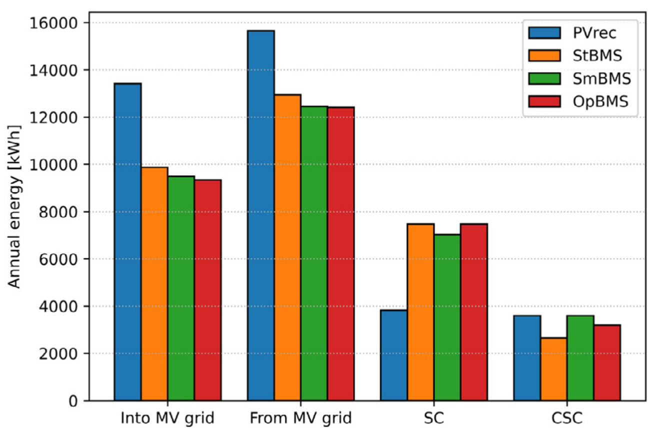

Fig. 13. REC annual energy balances comparing the four scenarios.

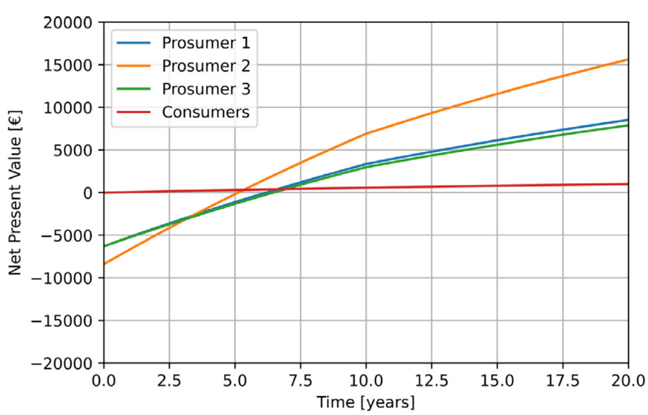

Fig. 14. Investment assessment of each REC member in **PVrec** scenario.

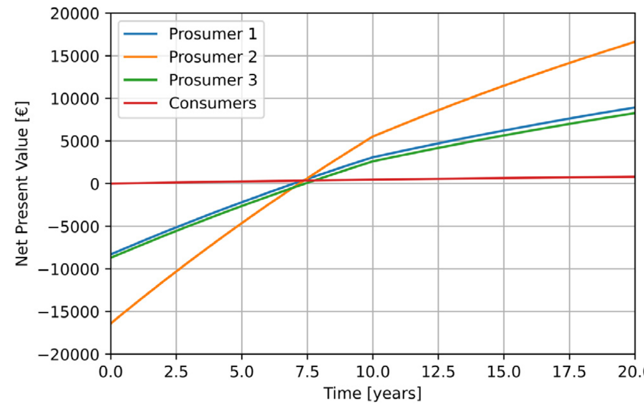

Fig. 15. Investment assessment of each REC member in the **StBMS** scenario.

Table 13
Consumer's annual cash flow for different scenarios [€].

Stakeholder name	Scenario	CSC
c1	PVrec	25
	StBMS	20
	SmBMS	25
	OpBMS	24
c2	PVrec	34
	StBMS	30
	SmBMS	34
	OpBMS	33
c3	PVrec	63
	StBMS	55
	SmBMS	63
	OpBMS	61
c4	PVrec	68
	StBMS	60
	SmBMS	68
	OpBMS	66
c5	PVrec	42
	StBMS	36
	SmBMS	42
	OpBMS	40

community manager. This income would like to be used partly to repay the initial investment and partly for public good works.

Table 14 summarizes the costs required to establish a REC. Here, it is evident how the role of a company like EnCo become very useful. In fact, due to legislation, to be operative a REC needs to be registered as legal entity to the authorities. Such a passage is full of bureaucracy and disincentive participants to deal with it. EnCo offers its support in matching the demand and the offer of service, like legal advisory. Furthermore, to properly allocate the generated tariff, EnCo installs a smart meter for each point of connection of the REC.

The cost of these meters and the constitution fee, visible in Table 14, are fully covered by EnCo to allow participants to enter the REC at zero cost. Administrative costs are mandatory and to be paid to GSE, therefore another support from third-party companies like EnCo is to manage such transactions and covering this expense with its part of the incentive.

Fig. 17 describes third-party company investment varying the percentage of retained incentive and the scenarios.

Fig. 17 shows that, considering actual Italian regulation, an 8-member REC with such a configuration is a good investment for a third-party company only if they keep a substantial share of the incentive on CSC. Indeed, the figure shows that the costs of establishing and maintaining the REC require almost all CSC incentives to be repaid. Or, from another point of view, incentives

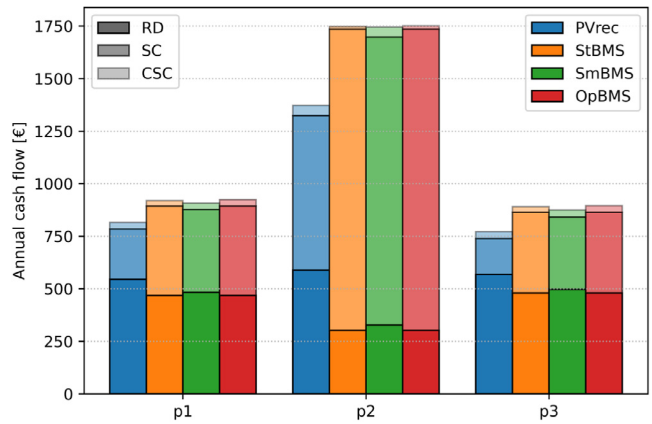

Fig. 16. Prosumer's annual cash flow composition for different scenarios.

Table 14
Costs of establishing and maintaining the REC.

Initial investment*	
Constitution fee	200 €
Meters	150 €/component
Administrative costs	
Fixed fee	4 €/component/y
Additional fee	30 €/y

*Deed is not necessary for a residential REC.

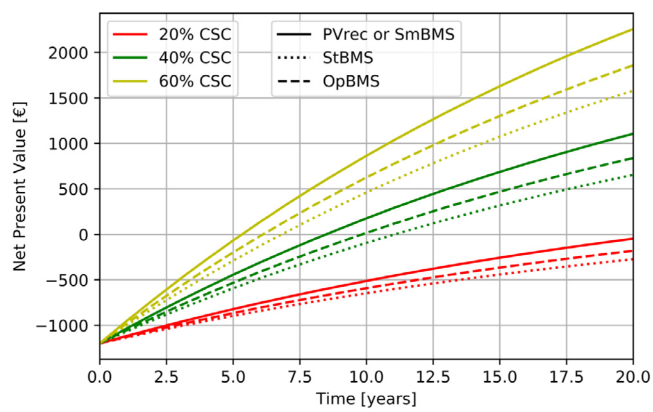

Fig. 17. Third-party company investment.

are too low. Despite this, the graph shows that a third-party manager should be incentivized to install SmBMS or to not install batteries because in these scenarios CSC is maximized and so is the incentive too. On the other hand, installing forecast-based systems to achieve the benchmark performance shown by the OpBMS should not be in the interest of a third-party company.

However, without any economic incentive SmBMS are still not economically convenient because of the costs of installing additional battery control systems. The government should incentivize them as they ensure greater stability of the national power grid.

4. Conclusions

A techno-economic assessment of a residential REC composed of 3 prosumers and 5 consumers is developed by comparing four different scenarios: PVrec, StBMS, SmBMS and OpBMS. PVrec does not include batteries; StBMS considers three batteries managed with a standard BMS which prioritizes SC; SmBMS considers a smart BMS which prioritizes CSC; and OpBMS finds the optimal operational schedule of batteries to minimize costs. The purpose is to assess different BMS benefits and problems from different points of view: prosumers, consumers, third-party company, and the national grid operator. The latter is interested in the development of REC as independent as possible from the MV grid, to reduce its instability and transport losses.

Results show that installing decentralized battery systems in a REC and managing them with a StBMS is a problem because CSC drop, and this limits the REC potential for energy independence from the MV grid. Therefore, the national grid operator should be interested in solving the problem through the addition of incentives to implement new BMSs. Also the stakeholders who only gain from the incentives that the GSE provides on CSC, consumers and third-party company, should be interested in finding a solution.

In this case study the decrease in CSC is 26.3%.

To solve the problem, it is necessary to manage batteries based on REC real-time data monitoring (SmBMS) or, even better, based on forecasts (OpBMS). The SmBMS proposed in this study guarantees to reach the same level of CSC of the case without batteries and compared to the StBMS allows greater REC independence: the energy fed into the MV grid decreases, as does the energy withdrawn. In this case respectively of the 3.9% and 3.8%. For those reasons third-party company, consumers and national grid operator should be interested in installing such a system. Only prosumers are slightly penalized by SmBMS as their SC decreases, but an accurate business model could provide reimbursement for this. According to these simulations, less than 15 €per year would be enough to reward them: a negligible amount.

To explore the potential of forecasting based methods the OpBMS based on the deterministic knowledge of production and consumption has been calculated as benchmark. This solution can guarantee no penalization for prosumers and a better REC independence from the MV grid, so the national grid operator should incentives such systems. But, from the point of view of consumers and a third-party company which earns by retaining a portion of the incentives on CSC, SmBMS remains the best system for managing batteries since it maximizes CSC. In addition, SmBMS is certainly less expensive than systems that require forecasting.

This proves for the umpteenth time that the economic interest and the environmental or population interest, are at odds. When that happens, governments have the responsibility to address it through the appropriate incentives. This study identifies a problem and uses a real case study to assess it and propose a solution by looking at both technical and economic perspectives. But energy and commodity markets are constantly evolving, as legislations and technologies; for that reason, studies such as these will always need to be updated. To facilitate this, MESS has been made open source on GitHub. The authors intend to follow the development of RECs around Europe and study new communities of different composition, not only residential one, by delving into topics such as centralized battery system and RECs as entities for the provision of multiple service to the grid. The REC that is the subject of this study will soon be realized and this will allow the SmBMS to be tested.

CRediT authorship contribution statement

Mattia Pasqui: Term, Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualisation. **Alex Felice:** Term, Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – review & editing. **Maarten Messagie:** Project administration, Funding acquisition. **Thierry Coosemans:** Project administration, Funding acquisition. **Tommaso Tiozzo Bastianello:**

Investigation, Resources, Writing – review & editing. **Duccio Baldi:** Investigation, Resources, Writing – review & editing. **Pietro Lubello:** Term, Conceptualization, Methodology, Validation, Formal analysis, Writing – review & editing. **Carlo Carcasci:** Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgements

Authors Felice A., Messagie M. and Coosemans T. were funded by the European Union's Horizon 2020 research and innovation programme under grant agreement No. 824342. Other authors did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Thanks to all participants of the renewable energy community understudy for sharing time and information.

Thanks to Alice Muzi for kindly reviewing the accuracy of the English language.

Thanks to EnCo for participating with passion, determination, and a clear mission: to give people back control over their energy, 100% renewable of course.

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International Journal of Sustainable Energy Planning and Management Vol. 38 2023 65–82

International Journal of
Sustainable Energy Planning and Management

Heat pumps and thermal energy storages centralised management in a Renewable Energy Community

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ABSTRACT

This paper examines a Renewable Energy Community (REC) made up of 10 dwellings that collectively self-consume energy produced by a photovoltaic field connected to a water purifier. Each dwelling heat demand is satisfied by means of Heat Pump (HP) coupled with Thermal Energy Storage (TES), which can be managed to perform load shifting and increase collective-self-consumption (CSC).

Techno-economic analyses are performed accounting for HPs' COP variation with temperature and part load operations, as well as TES heat dispersion. A new centralised control strategy for HPs is proposed and a sensitivity analysis is performed to assess the impact of varying TES system capacity.

The results show that the centralised strategy can increase the CSC by 12-30%, with TES sizes of 100-1000 litres respectively. But the electricity consumption of HPs increases by 2-5% due to higher storage system temperatures causing worse average COPs by 2.3-0.6% and higher thermal losses by 29-58%. As a result, REC's energy independence rise, as does the amount of CSC incentives, but electricity bills also increase. Comparing these trends shows that CSC incentives should be adjusted according to energy prices to ensure cost-effective outcomes for all stakeholders and encourage the adoption of similar centralised control strategies.

Keywords

Renewable energy community;
Collective self-consumption;
Load shifting;
Heat pump management;
Thermal energy storages

http://doi.org/10.54337/ijsepm.7625

Abbreviations

COP	Coefficient of performance
CSC	Collective-self-consumption
DH	District heating
HP	Heat pump
LV	Low voltage
MV	Medium voltage
PV	Photovoltaic
REC	Renewable Energy Community
SC	Self-consumption
TES	Thermal energy storage

1. Introduction

Based on the European Directive 2008/2001 [1], the Italian Government has recently published the technical rules for accessing the service for valorisation and incentive of shared electricity [2]. The concepts of Renewable Energy Community (REC) and collective-self-consumption (CSC) have been introduced by the Regulatory Authority for Energy Networks and Environment [3], the ministry of economic development [4] and the ministry of justice [5]. A REC is defined as a legal entity composed of users belonging to the same

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low-voltage (LV) grid that decide to share the electricity produced by one or more systems powered by renewable energy sources. This “shared electricity” is called CSC (see 2.2), and the higher it is, the less dependent the REC is from the medium-voltage (MV) grid.

This article presents a method for increasing the CSC by centrally managing a group of heat pumps (HPs) and thermal energy storage (TES) devices. The aim of this management strategy is to shift the load and make use of surplus energy from a photovoltaic (PV) field. In simpler terms, we propose to manage everything from a central location to store and distribute heat more efficiently, using surplus energy from a PV.

This article analyses an Italian residential REC consisting of 10 dwellings that are powered by a combination of the national grid and a centralized PV field. The REC uses a decentralized heating system, where each dwelling has its own air-to-water HP and TES system. These technologies can be managed through a centralized monitoring and management system that tracks real-time data such as power production, demand, and TES temperature.

Given the growing importance of RECs, PVs, and HPs in the future energy system, this paper’s findings are relevant not only to researchers but also to industry players, including manufacturers and operators. In addition, it should be noted that the management strategy proposed in this paper can be easily replicated for other energy communities beyond the case study presented here.

The following literature review will start from district heating (DH) concepts and move on to the use of decentralised HPs and their management. Finally, the emerging RECs will be discussed and the role of this paper in research will be clarified.

1.1. Literature review

This paper does not deal specifically with district heating (DH); however, the technologies examined in this study are widely studied and used in DH systems. Therefore, it is appropriate to begin the discussion by framing it in relation to the district heating sector. Indeed, according with Figure *1* the system analysed in this study can be compared to a high efficiency 5GDH system. The obvious difference is that the decentralised air-to-water HP systems considered do not use the heat in the pipeline as in DH systems, but the heat available in the ambient air. For more on the classification and evolution of DH systems, see [7].

DH systems are more efficient than individual heating solutions in areas with high heating demand, especially in Central and Northern Europe and North America.[8].

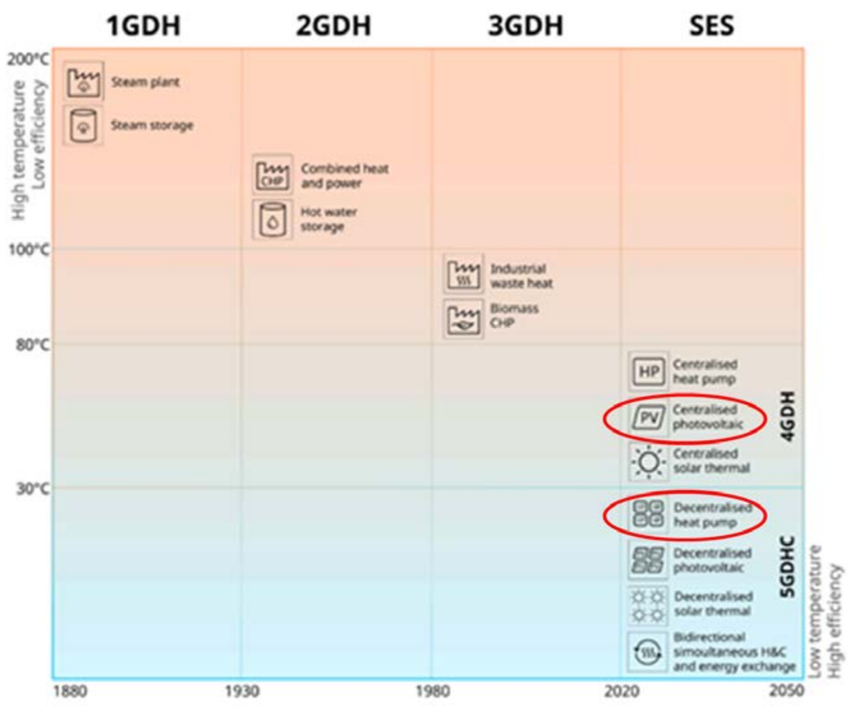

Figure 1: Evolution of DH systems over time [6] and case study placement.

However, conventional DH networks often suffer from high thermal losses through the pipelines due to high operating temperatures [9,10]. In case of low heat demand densities, losses in the distribution system are about 15% of the heat generated [11]. To address this issue, fifth generation DH (5GDH) systems operate at lower temperatures and integrate decentralized components, reducing thermal losses and enabling the use of renewable sources at low temperatures [6].

There are currently many studies on innovative solutions for DH [12]: One such solution is the integration of air-to-water heat pumps (HPs) and thermal energy storage (TES) systems with photovoltaic (PV) panels [13]. With smart management systems, TES can be heated during production peaks and the stored heat used during periods of high demand, contributing to load shifting and peak shaving [14]. While decentralized TES systems may offer better energy efficiency, they have higher investment costs [15], which can be offset through smart management systems that consider CO_2 emissions and increase energy independence from the grid [16].

The increasing use of HPs for heating homes [17] has led to a rise in the electrical load in the LV distribution grid [18] and put pressure on the grid's stability [19] and capacity [20]. The impact of a high penetration of HPs has been shown to be more problematic than a massive introduction of PV [21].

To address this, there is a need for greater flexibility in demand [22], which can be achieved through TES [23] or demand-side response schemes [24]. HPs can be used to heat the TES when energy is cheaper, which can significantly reduce operation costs [25]. To find the best strategy, factors like energy prices, COP, and thermal dispersion of the TES must be considered [26]. HP management strategies can be optimized based on daily forecasts [27], and the interaction between the HP, TES, and electrical storage should also be taken into account [17].

When comparing electricity and heat storage based on tariffs, there is a trade-off between prosumer benefits and grid impacts [28]. Both heat storage and batteries can have positive or negative effects on peak demand depending on the presence of capacity-based tariffs [29].

While research has shown that HPs can provide stability to the electrical grid in form of ancillary services and deliver cost savings, large-scale implementation is limited by the lack of aggregate control models [30]. The installation of a pool of HPs in a group of dwellings, as a REC, can significantly contribute to the reduction of issues connected to the extensive electrification of residential heating systems and will also make PV installation more cost-efficient [31]. In addition to PVs, HPs for RECs coupled with solar thermal or solar collectors [32] and hybrid systems with boilers [33] have been studied. However, the installation of a centralised heat pump management system requires accurate data collection and reliable weather forecasts, as well as smart HPs capable of receiving and implementing scheduling commands provided by a central supervisor [34]. Such a supervisor could be the manager of the REC itself, but currently, there is a lack of literature on methods that a manager of a REC could use to efficiently operate the REC and about the technical solutions that could be implemented.

Studies on RECs are focused on assessing the benefits that the establishment of a REC provides to all stakeholders, considering different REC configuration [35], different installed technologies [36] and business models [37]. The paper on the first REC created in Italy [38] merely shows the economic benefits to the REC participants provided by the current regulation, but concludes that the integration of REC can enhance energy efficiency and provide flexible services, which could be managed synergistically with the overall electricity system. A study [39] of a multi-criteria dimensioning of photovoltaics and batteries for REC was developed, taking into account different entities working together. In the conclusions it is suggested a potential benefit from thermal load management in a REC. Another study [40], deals with the impact of demand side management on REC as its composition varies. And again, the conclusions emphasise the importance of studying the electrification of thermal loads in RECs, in particular with a focus on the role of HPs. It has been demonstrated that centralised control of HPs can effectively address the challenges associated with the widespread adoption of electric heating in residential buildings and an optimisation algorithm for coordinating the operations of a pool of HPs has also been proposed [34]. However, this only aims to reduce peak absorption and does not perform an economic analysis that considers the point of view of individual stakeholders. Such an analysis was only conducted for the management of batteries in a REC, considering both role based method [41] and optimization method [42].

1.2. Paper novelty and structure

To the authors knowledge, no studies focused on the possibility to manage a pool of HPs through a centralised management system to increase RECs performances in both energy and economic terms. The aim of this paper is to evaluate such solution and to propose a centralised HP management system through the analysis of a real REC at the design stage. This study wants to prove that HPs and TESs can be used to store the surplus of PV production inside the REC, to increase CSC and decrease the dependence from the MV grid. This is a service for the national grid and so the grid operator should incentive it.

The study is structured as follows. Section 2 deals with the methodology and tools used to conduct the analysis. Firstly, a description of the case study (2.1) is provided, while the focus of subsection 2.2 is the Italian regulation on RECs and CSC. Load forecasting techniques (2.3) and the simulation tools employed (2.4) are then described. A specific focus on HP modelling is given in subsection 2.5 and on two different management strategies in subsection 2.6. Results are presented in Section 0. Subsection 3.1 shows the effects on REC energy balances of the two control strategies, while a sensitivity analysis is performed by varying the TES sizes in subsection 3.2, and the results of the economic assessment are presented in subsection 3.3. Finally, results are discussed, and conclusion is drawn in the last Section.

2. Materials and methods

In this chapter the reference study case is first presented (paragraph 2.1), followed by an explanation of the Italian regulations concerning collective self-consumption

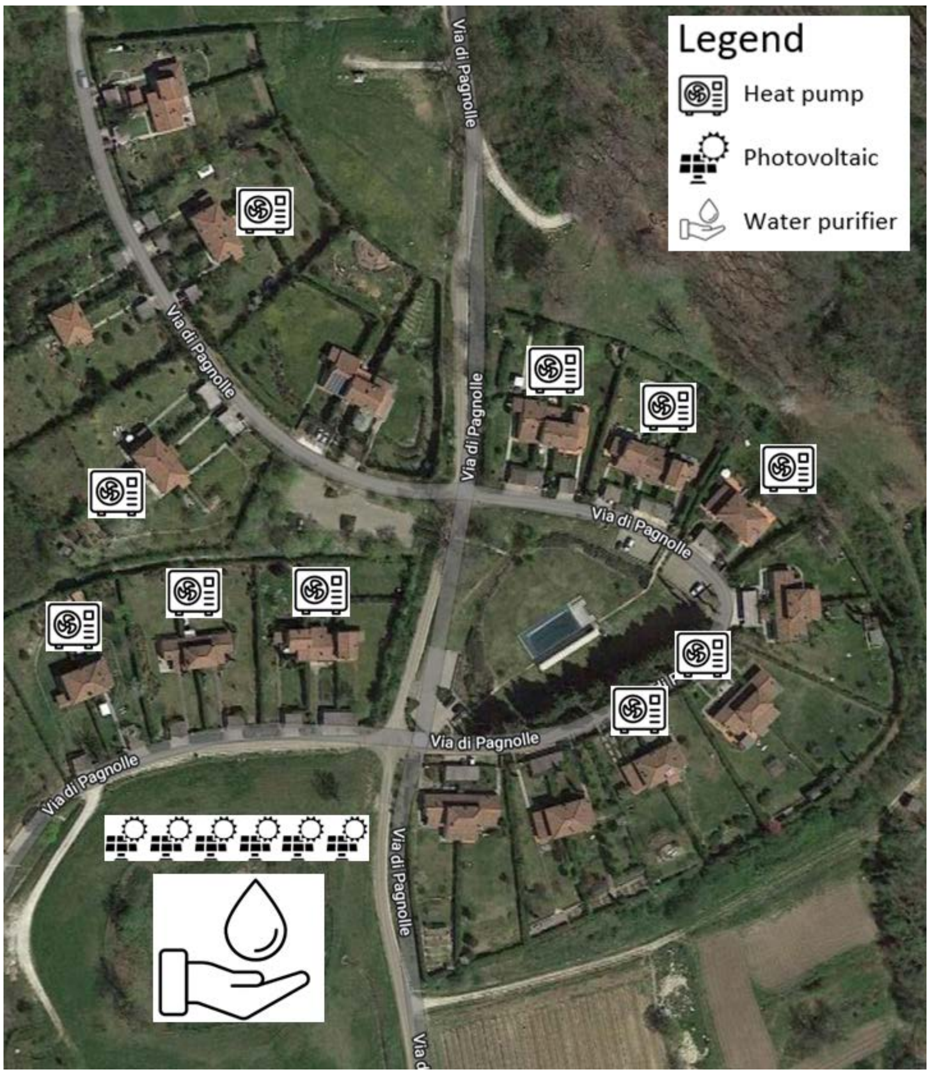

Figure 2: Case study: areal photo and installed technologies.

(paragraph 2.2). Next, a methodology for generating hourly load profiles in the absence of actual data is presented, using aggregated information from utility bills and surveys (paragraph 2.3). Paragraph 2.4 illustrates the tool used for the simulation of energy balances, while 2.5 focuses on HP modelling. Finally, paragraph 2.6 describes the two types of control strategies used to manage HPs and TESs: the standard one and the centralised one, which allows load shifting and the increase of CSC.

2.1 Reference cases study

The REC studied consists of 10 single-family homes in the Florence countryside and water purifier system, which provides clean water for houses (see Figure *2* and Table *1*). The electrical demand of the water purifier is 34.4 MWh per year and can be shifted to daylight hours by rescheduling the activity of the water pumping and purification systems. For these reasons, the homeowners decided to invest together in a centralised 50 kW_p PV system connected behind the meter of the water purified. The PV production is used primarily by the water purifier, yet the surplus of electricity can be used to cover the power demand of the dwellings. In each house, an air-to-water HP coupled to a TES system is installed for heating and domestic hot water, to cover the thermal demand which was previously satisfied with a gas boiler (Table 1 second column). A centralized HP management system is installed to better exploit the PV surplus and increase REC independence from the grid by increasing its CSC.

Table 1: Case study: electrical demand

Building	Electric demand home appliances [MWh/year]	Thermal demand heating and DHW [MWh/year]
Residential 1	2.4	8.7
Residential 2	5.1	21.4
Residential 3	1.5	8.8
Residential 4	6.2	15.9
Residential 5	4.5	14.7
Residential 6	2.6	21.3
Residential 7	1.8	22.8
Residential 8	9.2	5.2
Residential 9	9.8	33.9
Residential 10	5.5	18.6
Water purifier	34.4	-
Total	74.8	171.4

2.2. Collective-self-consumption under the Italian regulation

Figure 3 shows how REC works and what CSC is according to the Italian regulation. The REC is composed by 11 users: 10 residential buildings and the water purifier. Each user is connected via a meter to the LV grid and pays the bill for the electricity it withdraws from it (red arrow). Dwellings take all the energy they need from the grid. The water purifier, on the other hand, only withdraws part of the energy it needs from the grid because a good part of it is produced and self-consumed thanks to the photovoltaic panels installed behind its meter (green arrow).

In order for the electricity to be considered self-consumption, the consumption must be simultaneous to the

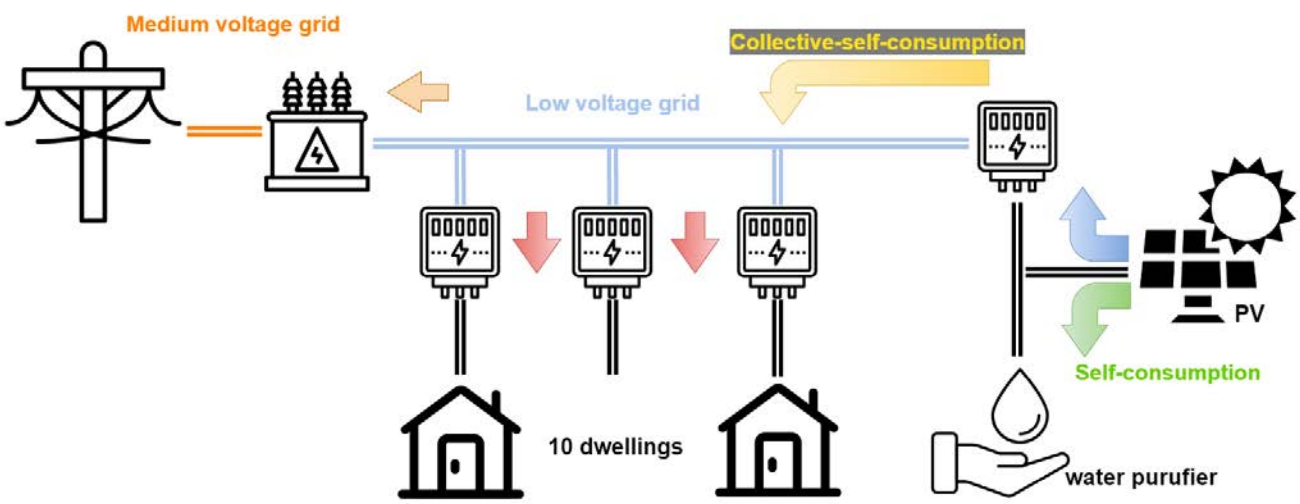

Figure 3: Case study: simplified electrical diagram to explain the Italian regulation.

production. When this does not happen or the production is greater than the consumption, the surplus of energy is fed into the grid via the meter and the Italian grid operator remunerates it (blue arrow) [43]. Part of the electricity fed into the grid does not leave the LV grid if there are users under the same LV grid who are withdrawing it (in this case study, the residential buildings). Only the electricity that is not consumed at the LV level is fed into the MV grid (orange arrow). According to the Italian regulation, if the user that feds electricity into the grid and the users that withdraw the electricity are part of the same REC, the part of electricity that remains within the LV grid is defined as CSC (yellow arrow). For each kilowatt-hour of CSC, an incentive of about 120 €/MWh is paid by the grid operator to the REC representative, who then redistributes the money among REC members according to the rules that each REC defines during its constitution [44].

CSC is incentivised because the higher the CSC, the lower the electricity exchanged between the LV and MV grids. Converting electricity from MV to LV and vice versa, as well as the transport through the grid, involves losses. In addition, the feed-in of PV-generated electricity might cause grid instability issues, due to the natural discontinuity of generation from this source. For these reasons, the possibility of increasing CSC must be studied.

2.3. Load profiles generation

Load profiles are one of the main inputs for an energy system simulation. For this analysis, one-year hourly load profiles of the 10 detached houses and of the water purifier are needed, electrical and thermal for the first, and only electrical for the second. These are not available, because the installed meters are old generation, so they must be simulated. Techniques to generate load profiles can be divided in two typologies: bottom-up and top-down approaches.

Bottom-up methods are based on modelling all the appliances of a building and simulating their use through stochastic algorithms [45–47]. These approaches have the advantage of reproducing detailed load profile and allow to assess load shifting impact of each single appliance [48]. On the other hand, they require a large amount of input data, which must be hypothesized or collected through surveys. This makes the results of simulations dependent on the quality of the collected data or on the researcher's assumptions [36]. In addition, using this approach for many buildings can be unpractical and time-consuming.

Top-down methods start from aggregated data, such as monthly energy consumptions, which can be read from electric and gas bills, and proceed to redistribute the consumption over different days and hours. The advantage is that the total demands are real, while the reliability of the daily profiles depends on the technique chosen to redistribute consumptions. This redistribution can be done by assumptions on the hours when people are present in the buildings or by using typical curves and existing bench-mark building energy profiles, which are then scaled to total consumptions [49,50]. Using typical curves to simulate multiple buildings could lead to a poor representation of the non-contemporaneity of the consumption of the members of a REC, which is what guarantees CSC. For this reason, a new top-down simulation method is proposed for this study and summarised in Figure *4***.**

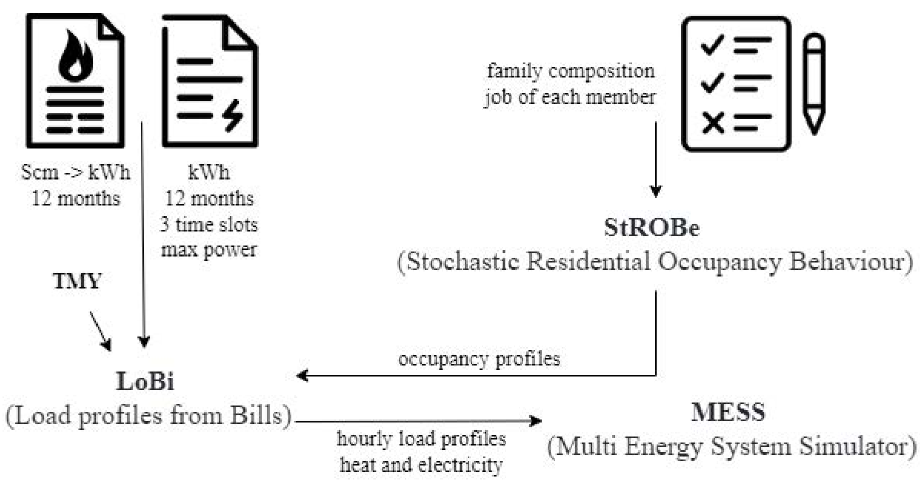

Figure 4: Load profiles generation workflow diagram.

This method consists of gathering one-year electricity and gas bills from each REC member and to have each of them fill out a survey. From the electricity and gas bills it is possible to read the consumptions for each month. For the electricity they are also divided into three timeslots, and the maximum power withdrawn is available. Electricity demand is in kWh, while gas demand is in Sm^3 and has been converted to thermal kWh considering a conversion factor of 10.69 kWh/Sm^3. The survey is used to collect data about occupants age and job status, which is then used as input for "StROBE" [51], an open-source tool using Markov chains to simulate occupancy profiles. These hour-by-hour profiles tell if people in the building are awake, sleeping or outside.

"LoBi" (Load profiles from Bills [52]) generates hourly load profiles. Monthly electricity demand is redistributed on hourly base considering time slots and using occupancy profiles as weights. Randomness is added by extracting values from a distribution that has as minimum the refrigerator power, as maximum the maximum power withdrawn from the grid, and an average that matches the total amount read on the bill.

To estimate heat demand, average hourly air temperature from a Typical Meteorological Year (TMY) [53] is used as weight to redistribute consumption.

Thermal and electrical load profiles of each building are then used as input for the simulation tool. Some examples of the generated profiles (electricity and heat demand of one of the ten dwellings) are shown in Figures 5 and 6. Since thermal demand was estimated from gas bills, it is not possible to know the exact breakdown of demand between heating and domestic hot water. However, a rough idea can be observed in Figure 6 considering that in summer the heating systems are turned off.

Cooling demand is not considered in this study because deals with hilltop country cottages which do not need it. Load shifting for heat demand can be achieved using TES, which increases the temperature from 40°C to 60°C. However, load shifting for cooling demand is not feasible in residential applications due to the limited temperature range. The cooling system requires 12°C, while the minimum achievable temperature by the HP is 5°C. This would require more powerful and costly HPs, as well as the use of glycol.

2.4. Simulation tool

MESS (Multi Energy System Simulator) is an open-source simulation software [54–56] that allows to assess the potential of an energy system by simulating hour by hour its energy balances. In a previous study [36] the model was validated by comparing its results with those of the model developed by Vrije Universiteit Brussel [31].

MESS inputs are the load profiles of each building, REC composition, geographical position and technical parameters. In this study MESS is used to calculate the REC energy independence from the MV grid by considering PV production, water purifiers and dwellings' demand, amount of SC, CSC, the electricity withdrawn

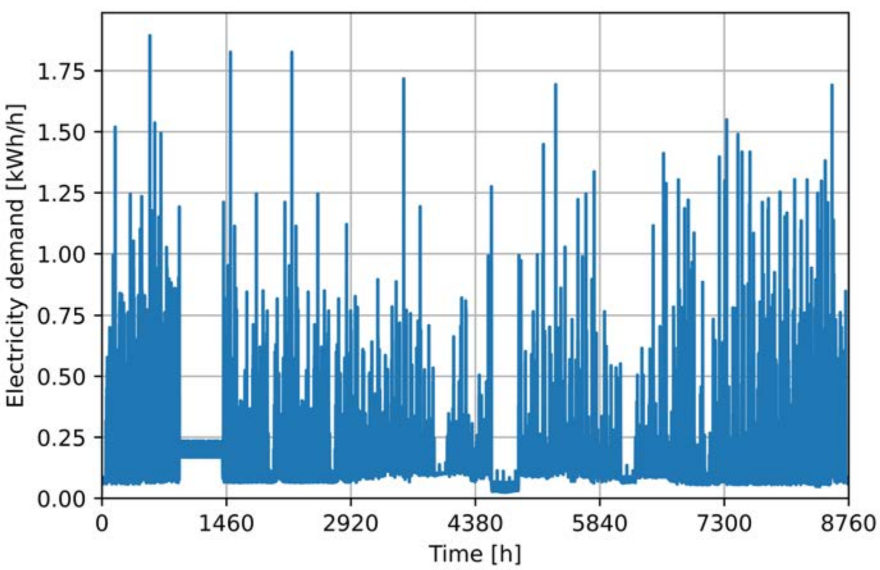

Figure 5: Hourly electricity demand of a residential building: a ppliances.

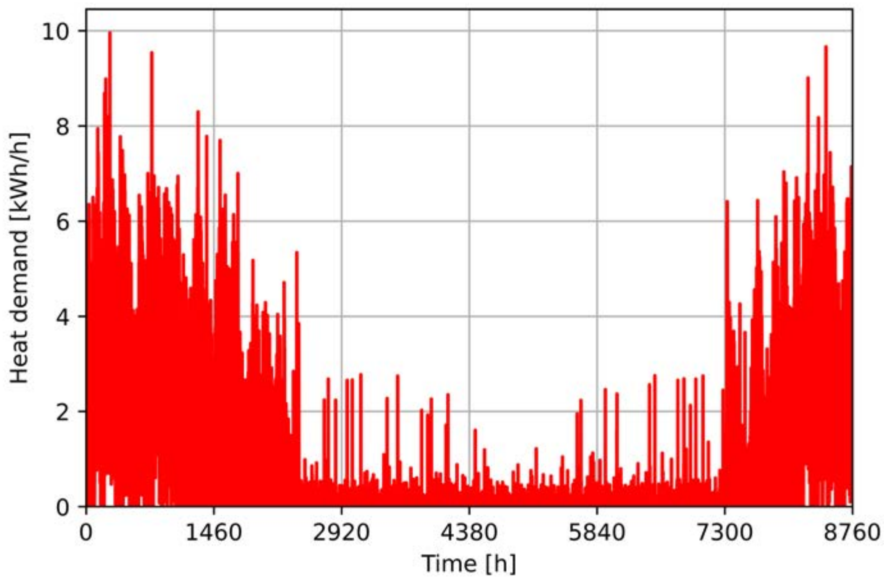

Figure 6: Hourly heat demand of a residential building: heating and DHW.

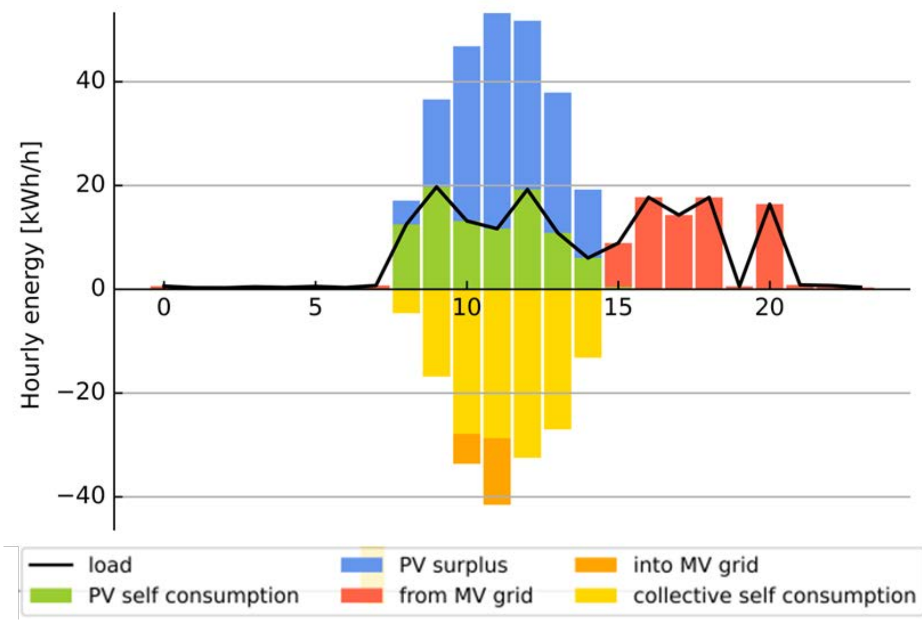

Figure 7: One day water purifier energy balance.

from the MV grid and the one fed into it (Figure *7*). Hourly balances are then aggregated to evaluate the annual amount.

2.5. Heat pump modelling

A function with one-minute time step, which simulates an air-water HP coupled with an TES, is introduced within MESS. The function inputs are the user's heat demand and the PV surplus and returns HP's electrical consumption. Two different control strategies are implemented: the HP follows the heat load, or the HP follows the PV production (paragraph 2.6).

Regardless of which strategy is used, the coefficient of performance (COP) is calculated as a function of ambient temperature, temperature of input water and load condition.

The HP model is developed starting from the performance of a scroll compressor from the Danfoss catalogue [57]. A compressor designed to produce 10 kW of thermal energy at nominal condition is taken as a reference. The Danfoss software gives the compressor performance as function of the evaporation and condensing temperature. A pinch point of 3°C on the water side and of 10°C plus 5°C of superheat on the air side have been assumed.

$$COP = f\left(T_{evap}, T_{cond}, load\right) \tag{1}$$

$$T_{evap} = T_{amb} - 15°\mathrm{C} \tag{2}$$

$$T_{cond} = T_w + 3°\mathrm{C} \tag{3}$$

Figure 8 shows the operating range. These values are implemented within the code in order to calculate the maximum water temperature achievable by the HP, given the ambient temperature. The requested water temperature, at each time step, is compared with the maximum allowable and the COP at design condition (6000 rpm) is hence calculated from regression curves supplied by the producer of the compressor (Figure *9*). In this way the design conditions of the machine are calculated for a size of 10 kW thermal. A corrective coefficient is then applied to the electric and thermal power, in order to consider HP of different sizes. Indeed, each dwelling in this case study has a different HP, sized according to its peak heat demand.

The HP can be regulated thanks to the inverter between 900 and 6000 rpm, allowing the HP to be used following thermal demand or PV surplus. In the former case, part load is defined as the ratio between thermal demand and the heat the HP provides at 6000 rpm, while in the latter, as the ratio between the electricity it uses and the electricity it would use at 6000 rpm. COP

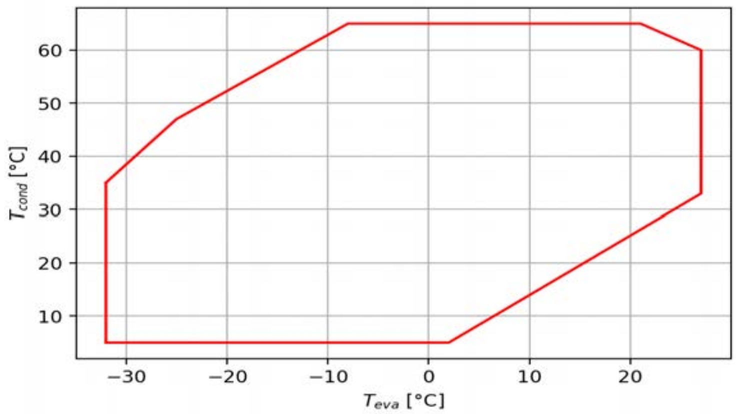

Figure 8: HP operating range.

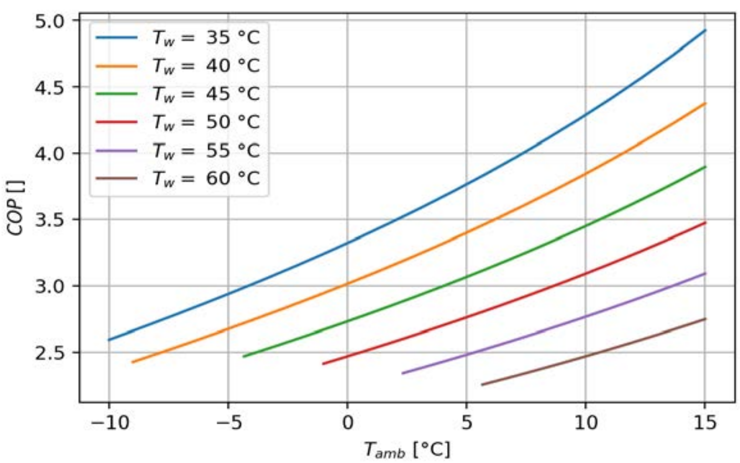

Figure 9: Design COP trend at 6000 rpm for the reference compressor.

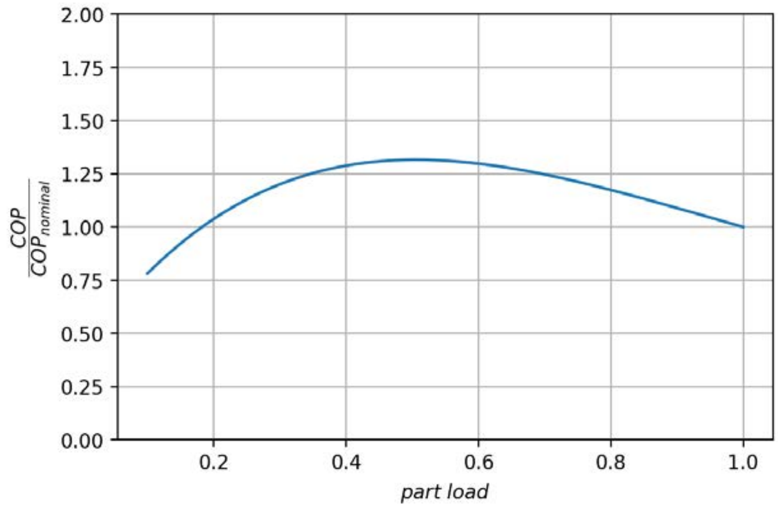

Figure 10: COP variation under partial load conditions.

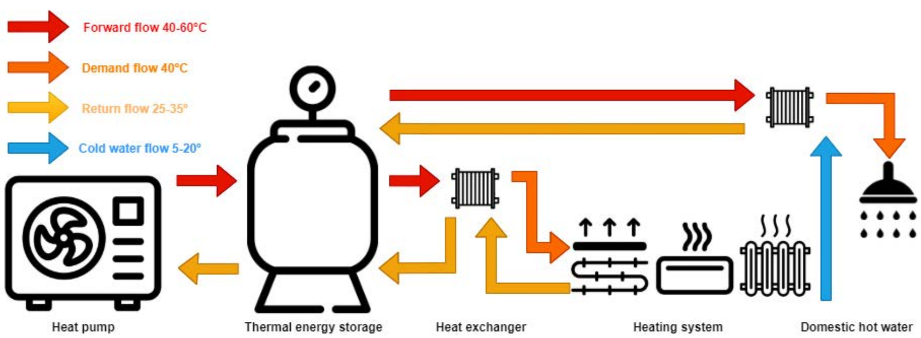

Figure 11: Simplified diagram of the heating system.

correction under these conditions is estimated according with [58] as shown in Figure *10*. This curve is the result of considering the effect of load regulation on the main HP components: heat exchangers, inverter, and compressor. The reduced flow rate causes the exchangers to be oversized, thus causing a reduction in the pinch points and therefore a benefit in terms of COP. On the other hand, when further decreasing the load, the efficiency of the inverter decreases. Therefore, the compressor has an optimal behavior in the middle of the machine's operating range. For high power, friction losses are high, while, for low power, leakage losses prevail.

There is a limit below which the machine cannot operate, approximately 15% of nominal load.

2.6 Heat pump and TES control strategies

TES is modelled considering U-values of 0.36 W/m^{2}K [29], corresponding to rigid polyurethane insulated commercial tanks. A stratification of 5°C between top and bottom is imposed To calculates the dispersing surface a geometry of a cylinder with a height three times its diameter is considered. The above are the only heat losses as the dispersion inside the pipes has been neglected, since these are inside the dwellings.

Interaction between HP, TES, heat demand and PV surplus is implemented in MESS. Two different control strategies are simulated and compared. Figure *11* shows a schematic representation of the system.

Standard strategy: HP follows heat demand.

When the building is to be heated or domestic hot water is required, hot water inside the TES circulates in the heat exchangers to heat return water from the heating system or cold water from underground. Demand flow temperature depends on the heating system type (fan coil, floor heating or radiator). For the simulation in this study a temperature of 40° is considered, but the results can be generalised to other working temperatures.

HP switches on to maintain a constant temperature inside TES, so HP must produce at each time step the same heat required by the heating system and by domestic hot water: HP follows heat demand.

If the heat required is lower than the heat generated by the HP at minimum load, the excess of heat produces an increase in the TES temperature. So, thanks to the TES the HP does not have to be switched off. If the temperature inside the TES reaches the maximum temperature that the HP can provide (above 60°, but depending on ambient temperature), the HP switches off. Before switching on again the HP, the heat demand is satisfied by the thermal energy stored inside the TES.

This strategy uses the TES only as inertial TES to reduce the number of HP switch-on events. Doing so, its efficiency and life-time increase [59].

Centralised strategy: HP follows REC PV surplus.

TES can also be used to store the energy produced by a PV system, which would otherwise end up on the grid. In this case the control strategy follows the PV surplus instead of thermal demand. If the thermal demand is lower than the thermal energy produced by the HP, the TES temperature increases. This mechanism goes on as long as there is a PV surplus or until maximum temperature is reached. Afterwards, the HP switches off and, if heat energy is required, it is taken from the TES.

If the TES is properly sized, this strategy allows to shift the load from evening to daily hours increasing SC.

This study deals with REC and CSC, one PV field and ten HPs. Therefore, to implement a control strategy able to harness REC PV surplus using HPs and TES, a centralised management is needed. The MESS operates as follows: if there is PV surplus, the HP with TES at the lowest temperature is switched on, in order to use the surplus and charge the TES. If there is more surplus, another HP is used. Using this selection criteria, the average temperature of all TESs is kept low. Consequently, COP are higher and heat dispersion lower.

3. Results

In this chapter the effect of using a centralised management on CSC and REC independence from the grid are shown in comparison with the standard management strategy. A sensitivity analysis is then carried out as the volume of TESs varies, followed by an economic assessment.

3.1. Centralised vs standard heat pump management

The following simulation considers TESs of 200 L, that is a standard size that can be found in market for residential applications. The three graphs in Figure 12 are the monthly balances of energy production (P) and demand (D). The former is in part self-consumed by the water purifier, and in part collectively self-consumed by the dwellings. The remaining part ends out of the REC, likely fed into the MV grid (it is assumed for simplicity that there are not utilities in the same LV grid of the REC that are not part of it). On the other hand, the demand is met by energy produced by PV which is SC or CSC and by energy withdrawn from the MV grid. It is clear how production and demand have an opposite trend over the year, the first is higher during summer while the second in winter, when heat demand is higher. Because of this, the surplus of energy that could be valued by a centralised HP management system is limited, yet should be considered.

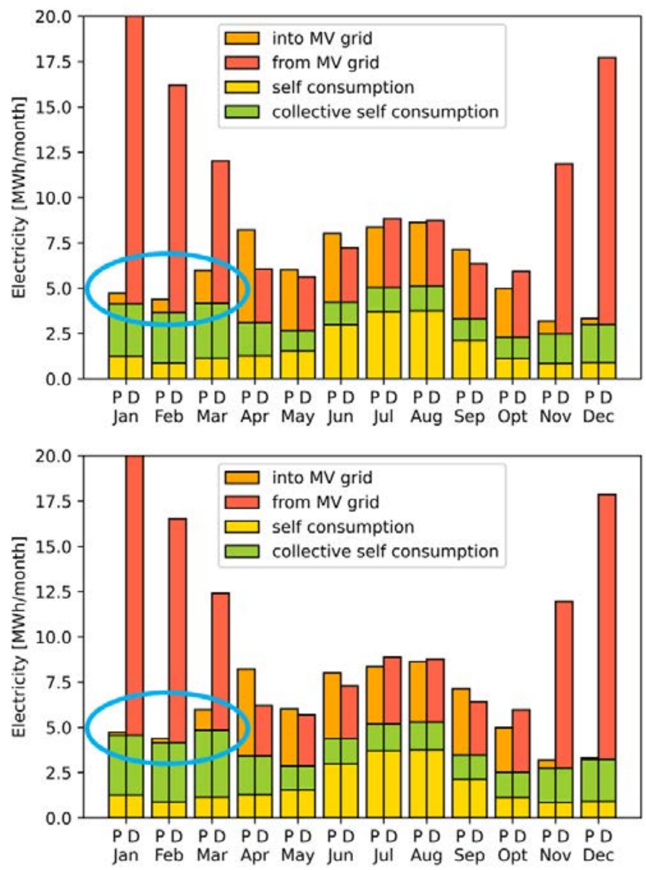

Figure 12: REC monthly energy balances: standard (above) vs centralised (under) management.

Looking at the winter months, it is possible to see that the energy fed into the MV grid with the standard strategy decreases and becomes CSC using centralised strategy. The same happens for the energy withdrawn from the MV grid, also if the total demand slightly increase. Effect on summer months is small because the HPs are used only for domestic hot water.

Table 2 summarise the REC annual balances comparing results of the two control strategies. The centralised one leads to a rise of CSC by 2.4 MWh. This amount of energy is produced and consumed inside the LV grid, so that the annual energy fed into the MV grid decrease by exactly 2.4 MWh. Charging the TESs using this energy, means not having to switch the HPs on again using energy from the MV grid when heat is required. Nevertheless, the reduction in electricity withdrawn from the MV grid (–1.0 MWh) is smaller than the reduction in the fed in one, due to the total demand increment (+1.4). This is caused by the increase of average temperature inside TES and the resulting deterioration in COPs and increase in heat losses.

Table 2: REC annual energy balances: standard vs centralised HP management.

	Standard	Centralized	
Production [MWh/year]	72.9	72.9	
Water purifier SC [MWh/year]	21.5	21.5	
Cottages CSC [MWh/year]	21.1	23.5	+ 2.4
Into MV grid [MWh/year]	30.3	27.9	– 2.4
From MV grid [MWh/year]	82.0	81.0	– 1.0
Demand [MWh/year]	124.6	125.0	+ 1.4

3.2 Sensitivity analysis

The previous paragraph has proven that a centralised management strategy can boost the REC energy independence from the MV grid, providing a service to the grid operator. This paragraph deals with a sensitivity analysis varying TES size from 100 litres to 1000 litres.

Figure 13 shows that increasing storage capacity, the possibility to perform load shifting using PV production surplus raises. In this way CSC grows decreasing the amount of energy the REC exchanges with the MV grid. From this point of view, the grid operator should promote the purchase of large TESs. Moreover, without a centralised system, HPs could not be switched on when there is a PV surplus of energy inside REC. In this case, it does not make sense to invest in large TES. Indeed, inertial TES of up to 200 litres are currently used and not larger TES useful for load shifting.

Figure 14 shows that heat generated by HPs is not dependent on TES size if no heat dispersions are considered (green lines). This is true for both the control strategies because the heat generated must be equal to the heat required by the users. But in real condition a higher TES means larger dispersing surface. For that reason, heat generated by HPs raises with TES size. Comparing standard with centralised management, the latter leads to higher medium temperatures inside TES and a consequently increase of losses and thermal energy needed.

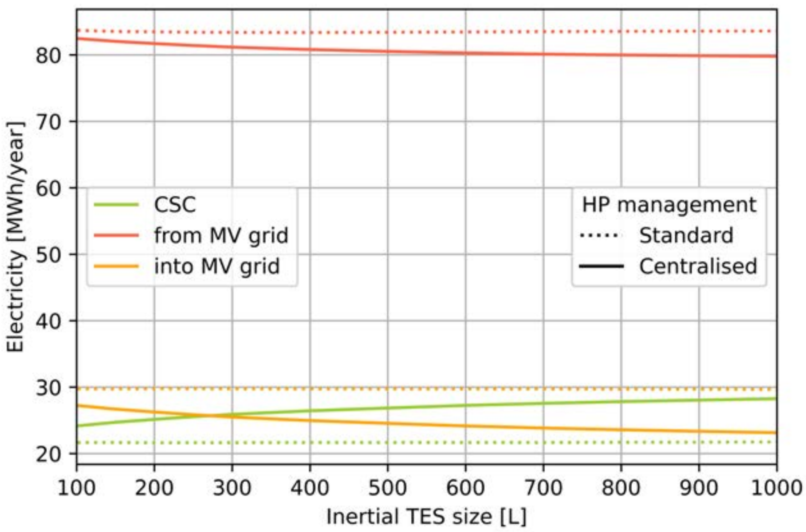

Figure 13: REC energy balances varying TES size.

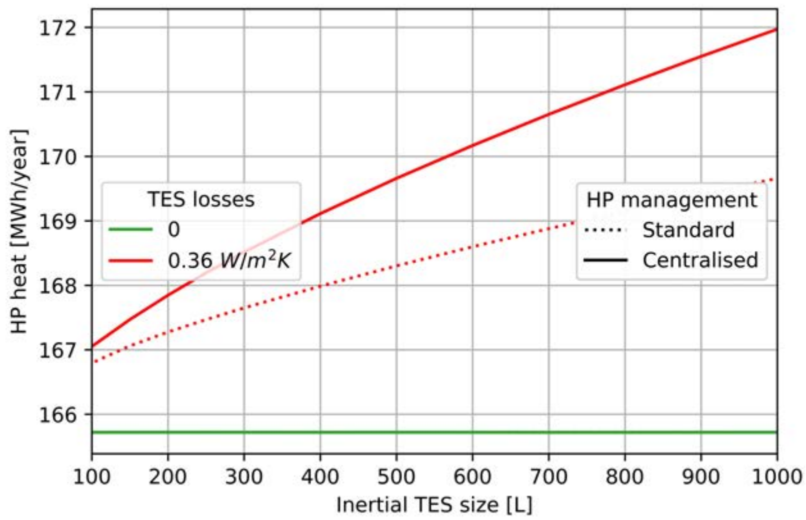

Figure 14: Heat produced by HPs varying TES size.

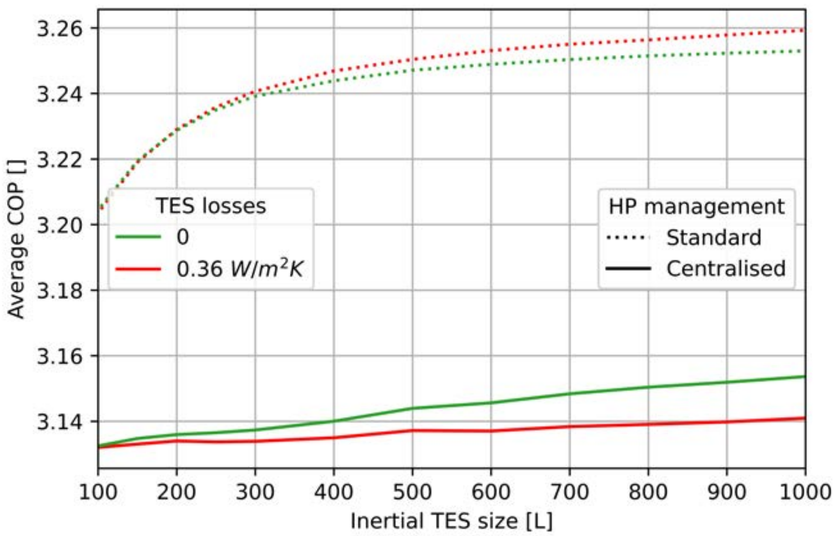

Figure 15: Average COP at which HPs work over year.

Looking at yearly average COP (Figure *15*), it is higher with the standard management because temperatures remain lower. With both strategies COP raises with thermal storage capacity because the medium temperature over the year inside TES goes down, but the trend is different. This happens because as the thermal storage capacity increases, so does the possibility to harness the energy produced by the PV with the centralised strategy. Doing so, TES temperatures rise. In the standard case, dispersion promotes COP by decreasing temperature. With the centralised control strategy, this consideration is no longer true because thermal losses involve more energy to be produced at high temperature and low COPs.

The consequence of thermal energy and COP trends is shown in Figure 16: without dispersion electricity consumed by HPs decrease with TES size because of the COP increase. Considering dispersion and standard control strategy, a minimum can be found. This is the result of two opposite effects: increasing TES volume, the COP increases due to decreased temperatures, but heat losses also increase due to increased surface area. With the centralised management the COP improvement is not sufficient to cope with the increase in thermal energy

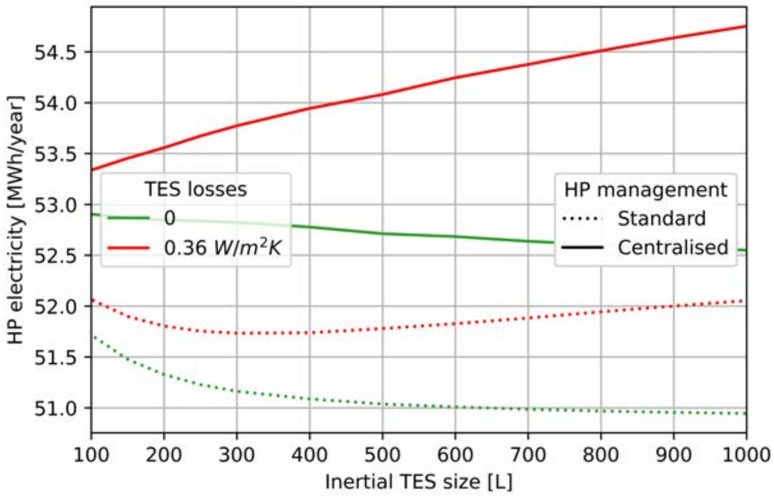

Figure 16: Electricity consumed by HPs varying TES size.

required due to heat losses. Therefore, the demand for electricity rises.

Analyses conducted thus far have shown that using a centralized management and increasing the size of TESs allows for increased collective self-consumption and energy independence of the energy community. Unfortunately, doing so also increases the electricity consumed by the HPs. The economic impact of these consequences is evaluated in the next section.

3.3 Economic assessment

Previous paragraphs have shown that the centralised HPs management allows to increase CSC, but at the same time increases electricity consumed by HPs. The PV field it is not under the same meter of the dwellings in which HPs are installed but is connected to the meter of the water purifier. For that reason, all the energy used to power the HPs has to be withdrawn by the grid and paid (doesn't matter if it comes from the LV or from the MV grid). This means that an increase in the energy consumed generates an increase in the electricity bill of the members of the REC which depends on the price of energy (See [60,61] to observe energy prices in the Italian market). This increase is offset by incentives on CSC of 120 €/MWh [44]. As Figure *17* shows, not to have an economic loss requires a scenario with low energy prices and large TES. The latter, by the way, costs more.

Considering that, a member of a REC would allow the REC manager or the grid operator to centrally manage its HP in order to increase REC energy independence from the MV grid only in scenario with low energy price. Hence, it's clear that, in order to make such system become real, an update of the regulation is needed to provide specific incentives for those who buy a TES and decide to make it available to provide a grid service.

4. Conclusions

This study assesses the possibility to use HPs and thermal energy storages inside a Renewable Energy Community to increase its collective-self-consumption and its independence from the medium voltage grid.

A REC consisting of ten dwellings sharing electricity generated by a 50 kWp photovoltaic field connected behind a common water purifier is considered. Their hourly load profiles are generated using a top-down simulation method from electricity and gas bills. Demand profiles are then used as inputs to an energy simulation software to perform techno-economic analysis. An HP model is used that considers the variation of COP as a function of ambient temperature, water temperature, and part-load conditions. Thermal losses within the TES are also considered.

Two different control strategies for managing the HPs of the ten cottages are compared. In the standard one, the HPs follow the thermal demand without considering whether the electricity used is produced by PV or must be withdrawn from the medium-voltage grid. On the other hand, a centralized strategy is proposed that allows the HPs to use the PV surplus to store energy within the TESs and use it when it is required later.

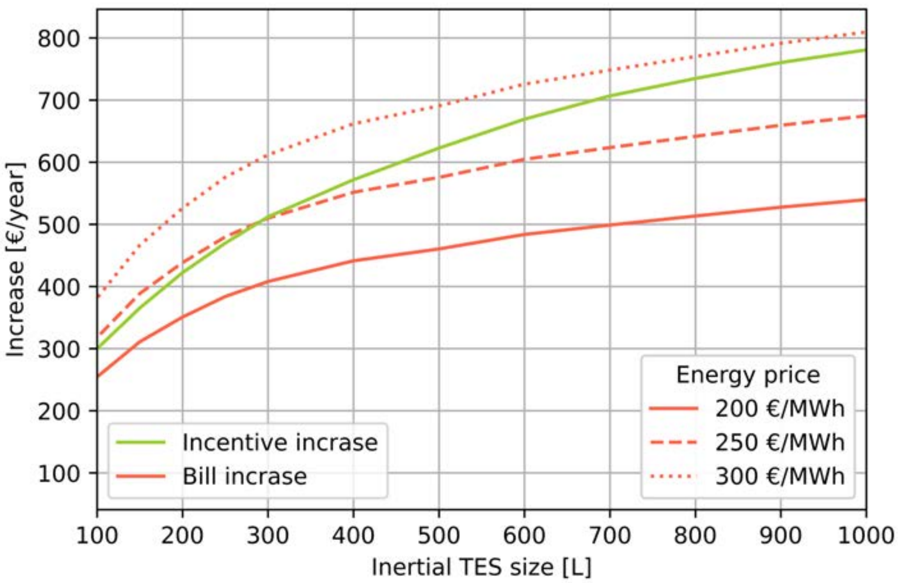

Figure 17: Economic assessment of centralised management varying TES size and energy price.

The centralized strategy leads to an increase in REC CSC, which corresponds to an equal decrease in energy fed into the MV grid. It also allows the energy withdrawn from the MV grid to decrease, but to a lesser amount. This happens because the total energy required by HPs increases, as the centralized strategy causes an increase in the average temperature of TESs over the year. As a result, COPs decrease, and thermal losses increase. By increasing the size of TESs, both collective self-consumption and electricity demand further increase.

Economic analyses show two opposing effects of using centralized management: an increase in electricity bills and an increase in incentives on collective self-consumption. The first is a cost, while the second is a revenue. The former depends on energy prices while the latter does not, since it is considered to be fixed. In a scenario with high electricity prices, centralized HP management is not competitive, yet it becomes so with low costs and large TESs.

In conclusion, the proposed solution can provide a service to the grid, but for its deployment to be favoured, it would be advisable to revise the incentives on CSC according to energy prices. Alternatively, or additionally, the purchase of large TESs with low dispersion coefficients could be incentivized.

The results of this study should be of interest not only to researchers, but also and especially to HPs developers, who could provide them with smart remote control systems, and to those who develop and use management systems for RECs. Implementing the solutions proposed would help the stability of the grid and also the earnings of REC members.

Future research could address centralized strategies for managing HPs that consider limiting values on temperatures and integration with other storage systems, such as latent heat technologies or electrochemical storage. Cold storage for cooling demand could also be investigated by introducing the use of heat pumps for sub-zero degree cooling.

In addition, the results simulated in this study will be compared with data collected from monitoring of the REC under study, which will be established soon.

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Article

Community Battery for Collective Self-Consumption and Energy Arbitrage: Independence Growth vs. Investment Cost-Effectiveness

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Abstract: Integrating a grid-connected battery into a renewable energy community amplifies the collective self-consumption of photovoltaic energy and facilitates energy arbitrage in the electricity markets. However, how much can energy independence really increase? Is it a cost-effective investment? The answer to these questions represents a novelty in the literature due to the innovative nature of the asset under consideration and the market and regulatory framework in which it is evaluated. Employing a net present value assessment, our analysis incorporated aging effects and conducts sensitivity analyses across various parameters: the number of community customers, electricity market prices, battery cost and size, and the decision to engage in energy arbitrage. Each scenario underwent a 20-year hourly simulation using an aging-aware rolling-horizon 24 h-looking-ahead scheduling, optimized with mixed-integer linear programming. Simulations conducted on the Italian market indicate that dedicating a battery solely to collective self-consumption is the most efficient solution for promoting a community's energy independence, but it lacks economic appeal. However, integrating energy arbitrage, despite slight compromises in self-sufficiency and battery longevity, halves the payback period and enhances the attractiveness of larger battery investments. The net present value is contingent upon the battery size, customer number, and market prices. Nevertheless, if the battery cost does not exceed 200 EUR/kWh, the investment becomes cost-effective across all scenarios.

Keywords: renewable energy community; battery energy storage system; scheduling; aging; collective self-consumption; energy arbitrage

Citation: Pasqui, M.; Becchi, L.; Bindi, M.; Intravaia, M.; Grasso, F.; Fioriti, G.; Carcasci, C. Community Battery for Collective Self-Consumption and Energy Arbitrage: Independence Growth vs. Investment Cost-Effectiveness. *Sustainability* **2024**, *16*, 3111. https://doi.org/10.3390/su16083111

Academic Editors: Filippo Bovera and Giuliano Rancilio

Received: 28 February 2024
Revised: 27 March 2024
Accepted: 1 April 2024
Published: 9 April 2024

1. Introduction

The electricity system is undergoing a shift from centralized to decentralized production. However, integrating decentralized renewable energy systems into the grid poses challenges due to resource intermittency. Battery Energy Storage Systems (BESS) and renewable energy communities (RECs) play crucial roles in tackling these challenges.

European directives incentivize active consumer participation in renewable energy production. RECs promote aggregation for energy production, consumption, storage, and sharing, often leveraging photovoltaic systems. Collective self-consumption (CSC), incentivized monetarily, encourages consumers to align usage with production, enhancing incentives and grid independence. REC not only focuses on CSC incentives but also seeks to engage in electricity markets. This study examines conditions for REC investment in a community battery to enhance CSC and participate in day-ahead and intra-day electricity markets through energy arbitrage (EA), aiming to profit by buying low and selling high.

1.1. Legislative Framework and Literature Review

The evolving EU energy policies, guided by regulations and directives, prioritize reducing greenhouse gas emissions and enhancing energy efficiency by increasing renewable energy sources (RES) in electricity production [1]. This transition toward RES integration in the grid focuses on two strategies: enhancing demand flexibility through Battery Energy Storage Systems (BESS) and fostering renewable energy communities (RECs) [2]. Directives 2019/944 [3] and 2018/2001 [4] facilitate citizen engagement with the electricity system, encouraging active involvement and aggregation within RECs. These communities engage in various market activities, including generation, consumption, sharing, trading, and providing flexibility services via demand response and energy storage. Member States, in compliance with these directives, are devising mechanisms to enable consumer participation in energy communities, offering incentives to expedite their deployment.

Italy has implemented REC legislation through specific legal provisions and regulations [5–9]. In Italy, a REC constitutes a virtual community where consumers and producers collectively produce, consume, store, and share energy from renewable sources. Energy sharing, termed collective self-consumption (CSC), is incentivized by the Italian government at approximately EUR 110/MWh and can be utilized for community activities or redistributed among members. To optimize CSC, a grid-connected BESS can be utilized [8,9], whereby energy withdrawn for subsequent feed-in is added to the collective self-consumption calculation. Participation in electricity markets is necessary for BESS to exchange energy with the grid, with operational details governed by Italian regulators [10,11].

There is a noticeable gap in the literature concerning Battery Energy Storage Systems (BESS) within renewable energy communities (RECs). While interdisciplinary literature on RECs is growing, it often overlooks the specific role of BESS within RECs. Conversely, extensive research exists on utility-scale grid-connected BESS providing multiple services, yet its application to RECs remains unexplored.

RECs across Europe vary due to factors such as energy technology, sources, and regional regulations [12,13]. They can be physically or virtually configured, with only the virtual option permitted in Italy, as it utilizes the national grid [14,15]. This study focuses on the virtual configuration, employing energy from photovoltaic panels or the national grid. Economic aspects dominate REC literature, comparing various business models and addressing incentive redistribution and cost allocation [16–21]. Some explore peer-to-peer trading, demand-side management, and REC composition and configuration [22–27]. The primary research question concerns the economic conditions necessary for REC viability and how stakeholders contribute to community sustainability [19,20,27,28]. While economic evaluations in these studies rely on energy simulations, few delve into the role of the battery. Some assess battery sizing's influence on self-consumption and REC gains [29,30]. Others investigate the battery's impact on the distribution grid, scheduling processes, and the possibility of aggregating multiple batteries or even heat pumps [31–36]. However, the use of grid-connected BESS within RECs remains underexplored. Contributions in this field propose community BESS for energy arbitrage and peak shaving [37]. However, these perspectives focus on Distribution System Operators (DSOs) rather than RECs and do not integrate collective self-consumption into scheduling algorithms. Moreover, the literature lacks assessments of investment costs and battery aging [38].

A review highlights the need for community BESS to cater to multiple services to optimize utility and economic gains [39]. However, the literature on BESS providing multiple services primarily focuses on utility-scale applications rather than RECs. These services can be classified into four mainstream categories:

- The provision of ancillary services (AS) to the grid operator to enhance the system reliability (e.g., frequency containment, frequency restoration, and replacement reserve).
- Dispatching, i.e., real-time coverage of dispatching errors.
- The achievement of local objectives, such as self-consumption and collective-self-consumption (CSC).
- Energy arbitrage (EA), i.e., buying and selling electricity to generate revenue.

Models in the literature mainly focus on AS and dispatching. Ref. [40] proposes a general framework for the scheduling and control of a BESS to provide multiple services and uses it in the problem of providing dispatchability. This problem is explored in more detail in [41], adding grid constraints and proposing a two-level control layer to avoid battery saturation. In [42], the provision of AS is also added to the problem's formulation. For a review of the possibility of providing AS using BESS focused on Italy's market and regulation, see [43]: a market price sensitivity analysis compared to the economic feasibility of the investment is performed. Instead, the BESS modeling methodology for stacking more than one ancillary service is described in [44]. A more comprehensive overview of how a BESS can provide multiple services and the programming methodologies used in various cases is beyond the scope of this article (see [45]).

Meanwhile, the use of a community battery for multiple services is overlooked, and scheduling algorithms for multiple services have not yet been applied to CSC and EA in REC literature.

1.2. Novelties

In this context, this paper's contributions can be summarized as follows:

- It introduces a new aging-aware rolling-horizon model for the hourly scheduling of a community battery. While existing battery scheduling models cover multiple services, integrating CSC and EA into these models is a novel addition. This novelty stems from the recent emergence of both CSC and EA concepts. The former is obviously related to the new appearance of RECs. The latter has only recently become feasible with the development of the intraday market, allowing bidding up to an hour before delivery based on reliable forecasts and knowledge of the day-ahead market prices.
- It conducts an extensive sensitivity analysis on various scenarios to explore the economic feasibility of investing in a community battery. Five key parameters are considered: community size, electricity market prices, battery cost, size, and the decision to engage in energy arbitrage. Such a comprehensive techno-economic analysis of this asset has not yet been proposed in the literature on RECs.
- Additionally, the scheduling model takes into account battery aging, as does the investment assessment. The combined effects of the provision of EA and CSC services on aging have not been previously studied.

1.3. Limitations

The primary limitations are as follows:

- Forecast errors are not considered. Indeed, scheduling assumes deterministic knowledge of future load and production. However, considering that scheduling is a rolling horizon and takes place one hour before delivery, i.e., at the close of the intraday market, forecast errors should be limited.
- Real-time control is not implemented, and at the same time, the costs of imbalances are not included in the economic calculation. This point is complicit with the previous assumption because if the forecasts are perfect, there are no imbalances and no need for a control to reduce them, performing dispatching.
- Simplified participation in the day-ahead and intraday markets is assumed, where all bids can be submitted at the closure of the latter market without differences in prices between the two markets. However, in reality, initial scheduling should occur at the closure of the day-ahead market, followed by continuous rescheduling during the intraday market as the delivery time approaches. The cost of rescheduling due to price differences between the two markets, albeit low in the Italian context, is not included in the economic evaluation.
- The provision of ancillary services in the balancing market is not evaluated, but it could certainly serve as an additional revenue stream for a community battery.

- The electricity grid is not modeled, which is definitely an aspect to consider to fully complete evaluations like those proposed. Scheduling without considering grid constraints could lead to bidding solutions that are technically undeliverable.

These limitations foreshadow future articles and the direction for further developments in broader research, positioning this study as an initial building block.

2. Materials and Methods

The chapter begins by introducing the selected case study for simulations, detailing the concept of a renewable energy community (REC) within Italian regulatory frameworks. It explains how a Battery Energy Storage System (BESS) can actively engage in collective self-consumption (CSC) and energy arbitrage (EA).

After the case study introduction, the BESS model is elaborated upon. A mixed-integer linear programming (MILP) approach is utilized to compute BESS scheduling, considering relevant parameters and techniques to address battery aging effects.

Next, the economic evaluation formulations are presented to assess the financial feasibility of the proposed system. Finally, simulated scenarios are introduced, followed by a comparative analysis of these scenarios in the Results chapter.

2.1. Case Study

A renewable energy community (REC) fueled by photovoltaic systems with an overall power of 100 kWp is examined, exclusively comprising residential customers. Photovoltaic power is the REC reference size and is kept constant during simulations. However, the results are scalable to RECs with higher production. On the other hand, battery size and number of consumers are the subject of sensitivity studies. According to the Italian regulation, collective self-consumption (CSC), which is the virtual self-consumption of the whole community, is an incentive at about 110 EUR/MWh. It is specifically defined as the minimum on an hourly basis between the feeding and withdrawal by all members of the REC. The energy withdrawn from a grid-connected Battery Energy System (BESS) for the purpose of subsequent feed-in (green row in Figure 1) is added to the energy withdrawn to calculate the CSC. This is why this article assesses using a BESS to increase the CSC and thus the incentive.

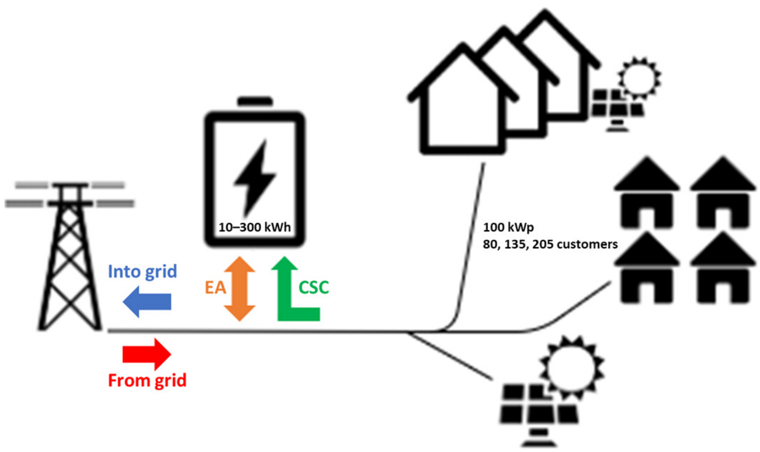

Figure 1. Case study definition.

In order to be able to exchange energy with the grid, the BESS must participate in electricity markets. In particular, this article considers participation in the day-ahead and intraday markets. This introduces the possibility of performing energy arbitrage (EA) by buying energy when prices are low and reselling it when they are high.

2.2. BESS Scheduling Model

According to the definition of CSC and the electricity market, the simulations performed have an hourly time step. However, in the near future, the market will become quarter-hourly. Considering that the intraday market closes an hour before delivery [46], the optimal battery scheduling for the next 24 h is calculated every hour, and the first hour is used as simulation. The scheduling problem is defined as a mixed-integer linear programming (MILP) optimization model. This problem is rolling horizon, because it is solved each hour, and it looks 24 h ahead. Such problem is solved for each hour of the yeas (8760 h) for 20 years, so each simulation is a combination of 8760 per 20 MILP optimizations. A deterministic knowledge of production, load, and energy price for the next 24 h is considered. These series serve as inputs for the MILP problems.

A thorough description of the scheduling optimization model follows objective functions (Equations (1)–(4)) and constraints (Equations (5)–(8)).

$$f_{obj}(E_{bess}) = \sum_{h=1}^{24} EA_h + CSC_h - AP_h \quad [€] \tag{1}$$

$$EA_h = E_{bess,h} \cdot EP_h \tag{2}$$

$$CSC_h = \min[E_{sur,h}, \max(0, E_{bess,h})] \cdot \mathrm{inc} \tag{3}$$

$$AP_h = \frac{|E_{bess,h}| \cdot AC}{2} \tag{4}$$

The objective function f_{obj} is an economic one. It is the sum on 24 h of the revenue obtained from energy arbitrage (EA) and collective self-consumption (CSC) minus an Activation Penalty (AP), which is linked with BESS aging and replacement cost. Aim of the optimization problem is to maximize the objective function.

The hourly energy BESS exchanges with the grid (E_{bess}) is the variable to be optimized: a vector of length 24 representing the scheduling of the battery. $E_{bess,h}$ is negative if the battery feeds energy into the grid, or positive if the battery draws energy.

EP_h represents the hourly Energy Price. The price is always negative, so if energy is withdrawn, the product $E_{bess,h} \cdot EP_h$ is a cost, while when it is fed, it is a gain.

The gain for CSC is the product between the value of the incentive (inc = 110 EUR/MWh) and the energy drawn from BESS that is counted as CSC. The latter is the minimum between the REC energy surplus ($E_{sur,h}$) and the energy drawn by BESS, i.e., the positive values of $E_{bess,h}$ (max(0, $E_{bess,h}$)).

The penalty due to activation linked with aging is the product of the amount of energy fed or withdrawn ($|E_{bess,h}|$) and the Activation Cost (AC) parameter, whose function will be explained in the next subsession.

The constrains of the model are the following:

$$SoC_{h+1} = SoC_h + E_{bess,h} \cdot \eta \tag{5}$$

Define the State of Charge (SoC) variable, which is dependent on parameter E_{bess} and considers an average charging and discharging efficiency (η) of 0.90 [47].

$$C_{max} \cdot DoD \leq SoC_h \leq C_{max} \tag{6}$$

$$|E_{bess,h}| \leq C_{max} \tag{7}$$

SoC and E_{bess} box constrains consider BESS maximum capacity (C_{max}) and depth of discharge (DoD). DoD is fixed to 0.10, while C_{max} is equal to size of BESS at the beginning of each simulation but then decrease due to aging effects. Therefore, it is assumed in Equation (7) that the battery can be fully charged or discharged in one hour, with an average q-rate = 1.

$$-E_{need} \leq E_{bess,h} \leq E_{sur} \tag{8}$$

This constraint obliges the battery to only be able to charge with the energy surplus of REC (E_{sur}) and to only discharge to meet the REC's energy need (E_{need}). This constraint is aimed at preventing EA through the purchase or sale of energy from outside the REC, which is not necessary for CSC. The constraint is active in scenarios with only CSC and inactive when EA is also desired.

There are also additional constraints and dummy variables in the model that serve for the linearization of the functions absolute value, minimum, and maximum.

2.3. BESS Aging Awareness

Figure 2 explains the effect of Activation Cost (AC) added to the MILP model (see Equation (4)) and its connection to BESS aging. Essentially, the AC value represents the minimum price difference required for executing a charge and discharge cycle to be advantageous. The division by 2 in Equation (4) precisely aligns the AC value with the buy-and-sell price difference. A high AC value corresponds to a low number of cycles, and vice versa (Figure 2c). However, a low number of cycles results in lower earnings in EA (Figure 2a). These effects can be evaluated over several years considering the Net Present Value (NPV) evolution (Figure 2b). Year after year, the available battery capacity decreases, and so does the cash flow. When end of life is reached, the battery needs to be replaced (decline steps in Figure 2b). As explained in the next paragraph, in the calculation of the NPV, a replacement is included as an additional cost that is subtracted from the regular cash. For this reason, in the year of replacement, the cash flow is negative, and in fact, there are "decline-steps" in the NPV graph in corresponding to the years when replacement is necessary. With high AC values, the battery ages more rapidly, but annual earnings are higher; with low AC values, the battery lasts longer, but the earnings are lower.

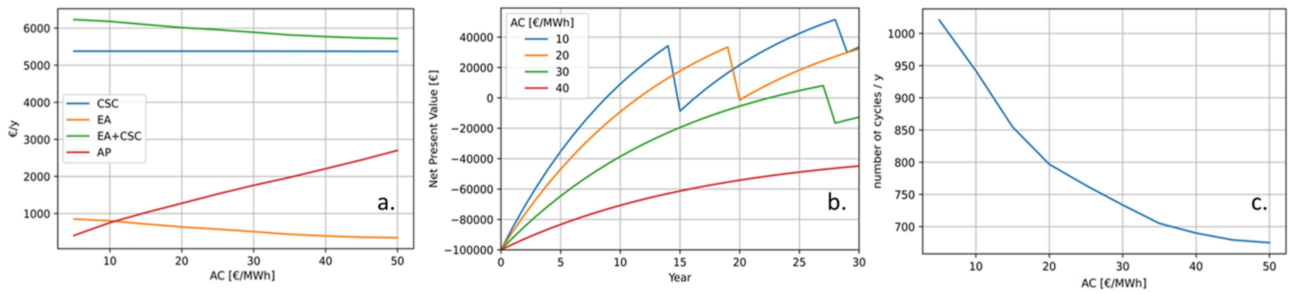

Figure 2. Effects of Activation Cost (AC) on collective self-consumption (CSC) and energy arbitrage (EA) cash flow (**a**), on Net Present Value (NPV, (**b**)), and on number of cycles per year (**c**).

To calculate battery aging, a rain flow counting method [48] has been used to calculate the equivalent number of cycles undergone by the BESS. Assuming that the BESS reaches its end of life after 8000 cycles with 80% remaining capacity [49], the available capacity is recalculated weekly in proportion to the number of equivalent cycles reached. Upon reaching 8000 cycles, the BESS is replaced (decline steps in Figure 2b). This empirical and macroscopic approach to calculating aging is considered sufficient for the purposes of this paper. While using equivalent circuit models or physical (i.e., electrochemical) models could provide more precise estimates of aging, they are difficult to generalize to different storage technologies and require higher computational costs. The proposed approach, however, is simple to implement; one only needs to write the rain flow counting algorithm and enter the end-of-life information on the battery, which is easily obtainable from any manufacturer. Although the aging estimate may be rough, it is sufficient for the purposes of this paper.

2.4. Economic Analysis

The economic assessment of BESS investment is based on the Net Present Value (NPV), calculate for 20 years (y) using Equations (9)–(11).

$$NPV_y = NPV_{y-1} + \frac{CF_y}{(1+i)^y} \quad (9)$$

$$CF_y = EA_y + CSC_y - Cost_{repl} \cdot R \quad (10)$$

$$NPV_0 = Size_{bess} \cdot Cost_{bess} = Cost_{repl} \quad (11)$$

NPV_0 represents the initial investment for BESS, and CF_y denotes the annual cash flow, encompassing the sum gains from EA and CSC. The annual interest rate, denoted as i, is set at 5%. When BESS replacement occurs (R = 1; otherwise, R = 0), replacement cost ($Cost_{repl}$) is incorporated into $CF_y \cdot Cost_{repl}$ is assumed to be equal to the initial installation cost (NPV_0), which is equal to $Size_{bess}$ per $Cost_{bess}$.

To facilitate the comparison of diverse investments with replacements occurring in different years, a transformation of NPV is employed in this study. Looking at the left-hand image in Figure 3, it is difficult to identify the value of the activation cost (AC) that determines the optimal NPV, because the choice depends on the specific year in which the NPV is compared. However, using the transform shown in the image on the right clarifies the most favorable AC value (i.e., ac = 35).

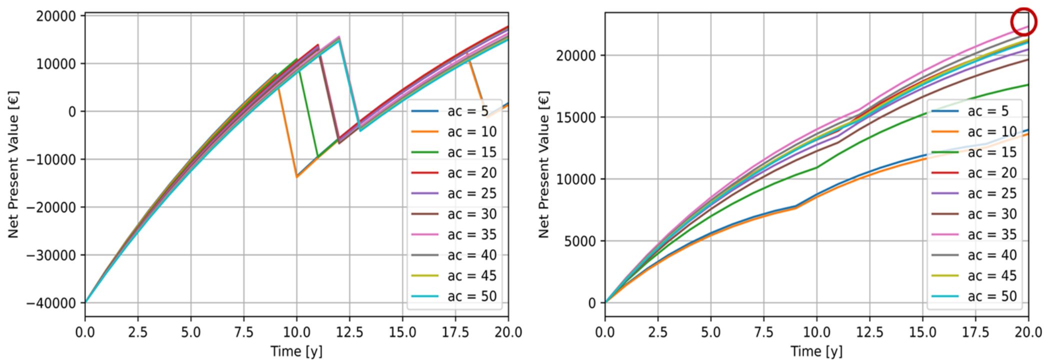

Figure 3. Effects of Net Present Value (NPV) (**left**) and NPV transformation (**right**) used to compare different Activation Costs (ACs).

The transformation used for NPV can be explained by observing Figure 4. The investment presented by the NPV line in blue can be transformed into the equivalent investment of the orange line, which does not have discontinuity due to the lack of replacement of the initial investment, which is equal to zero. To compute the transformation, it is essential to consider that both the initial investment cost and the replacement costs are not paid upfront. Instead, they are financed through a loan with a duration equivalent to the battery's lifespan and a loan interest rate chosen so that the original NPV and the transformed NPV are equal in the years when replacements occur. Thus, the transformed Cash Flow (CF*) for the transformed NPV must be recalculated with respect such conditions. Equations (12)–(15) synthesize how the NPV transformation can be calculated, where LF is the Loan Factor to be considered in the transformed cash flow.

$$NPV^*_y = NPV^*_{y-1} + \frac{CF^*_y}{(1+i)^y} \quad (12)$$

$$CF^*_y = EA_y + CSC_y – \mathrm{LF} \quad (13)$$

$$LF = \frac{Size_{bess} \cdot Cost_{bess}}{\sum_{y=0}^{lifespam_{bess}} \frac{1}{(1+i)^y}} \tag{14}$$

$$NPV_0 = Cost_{repl} = 0 \tag{15}$$

Figure 3 shows that the variation of NPV with AC values is not strictly monotonic but exhibits a global maximum (35 in the example), alongside several local peaks. This peculiar trend primarily stems from the non-uniform distribution of energy prices in the electricity market, which, contingent upon the AC value, impacts both cash flow and battery aging, consequently exerting further influence on cash flow. The outcome of such intricate interplay can only be computed through simulations employing a detailed time step and spanning a lengthy time horizon, such as those proposed.

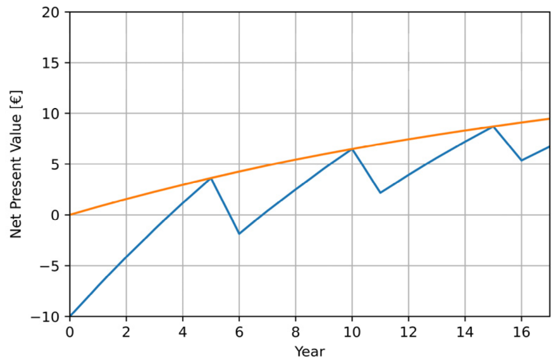

Figure 4. Net Present Value (NPV) (blue line) and NPV transformation (orange line).

2.5. Simulated Scenarios

This study encompasses the simulation of 36 distinct scenarios aimed at evaluating the impact of 4 key parameters (Table 1): number of customers in the renewable energy community (REC), energy price, battery cost, and the possibility of performing energy arbitrage (EA). The first parameter pertains to the REC energy surplus (E_{sur}) and needs (E_{need}), which the BESS can harness to derive gains through CSC. The second parameter influences earnings from EA. Battery cost ($Cost_{bess}$) has an impact on initial investment and replacement cost, and thus on NPV. Performing EA influences cash flow.

Table 1. Simulated scenarios.

Parameter	Scenarios
Customer number (CN)	80, 135, 205 residential customers
Energy price (EP)	Low and high prices (2020 and 2023)
Battery cost ($Cost_{bess}$)	200, 400, 600 EUR/kWh
Energy arbitrage (EA)	CSC + EA vs. CSC

Within each scenario, a substantial number of simulations are conducted to perform sensitivity analysis on two primary variables (Table 2): $Size_{bess}$ and AC. Therefore, for every combination of scenarios, $Size_{bess}$ values, and AC settings, a simulation spanning 20 years is executed. Within this simulation, each hour is an outcome of a MILP optimization process.

Table 2. Sensitivity analysis.

Variable	Range
Battery size ($Size_{bess}$)	20 to 300 kWh
Activation cost (AC)	5 to 60 EUR/MWh

Energy Price (EP) is an array comprising 8760 values, corresponding to the number of hours in a year, and is repeated over 20 years. Also, the vectors representing REC energy surplus (E_{sur}) and need (E_{need}), which are calculated depending on customer number (CN), have the same dimension. What evolves annually is the available capacity of the BESS, which diminishes due to aging. The procedure for selecting the two EP scenarios and the three CN scenarios (from which E_{sur} and E_{need} are dependent) is outlined below.

Considering the information about Energy Price (EP) in the Italian electricity market reported in Figures 5 and 6 [46], two different scenarios are selected. As a low-price scenario, the EP of 2020 is chosen as the worst-case scenario, and as a high-price scenario, 2023 prices are considered. The years 2021 and 2022 were excluded due to their excessive anomalies and randomness.

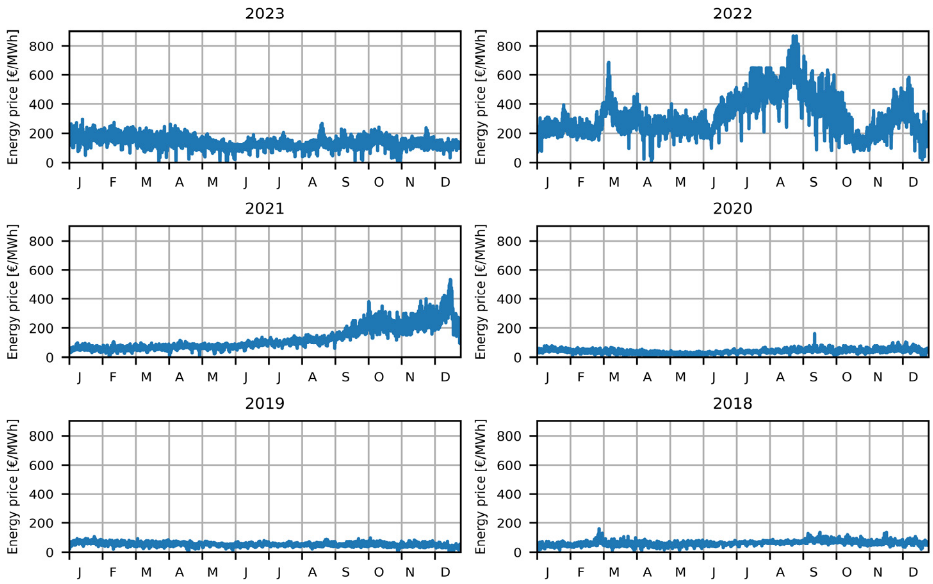

Figure 5. Hourly energy price in the Italian electricity market from 2018 to 2023.

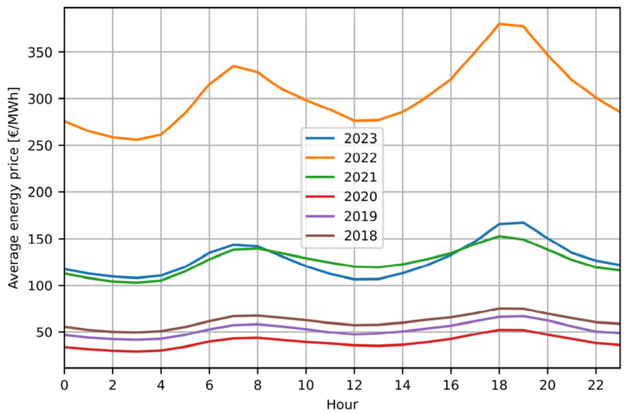

Figure 6. Average hourly energy price in Italian market from 2018 to 2023.

Dataset used for photovoltaic production downloaded from PVgis [50] are also from 2020 and 2023. This correspondence ensured that the price trends remained consistent with the fluctuations in production. The input parameters for PVgis included the geographical coordinates of Florence, a tilt angle of 30°, an azimuth angle of 0°, and losses of 14%.

To calculate the E_{sur} and E_{need} of the REC, in addition to the photovoltaic production series, the aggregated consumption series of all community customers is required. A load series representing a 3 kWp typical residential consumers from Tuscany is generated by utilizing average hourly profiles provided by the Italian regulatory authority [51] (Figure 7).

These profiles are differentiated based on the month and the type of day. The resulting load series is subsequently scaled by the number of customers within the considered REC, aggregating the total consumption pattern.

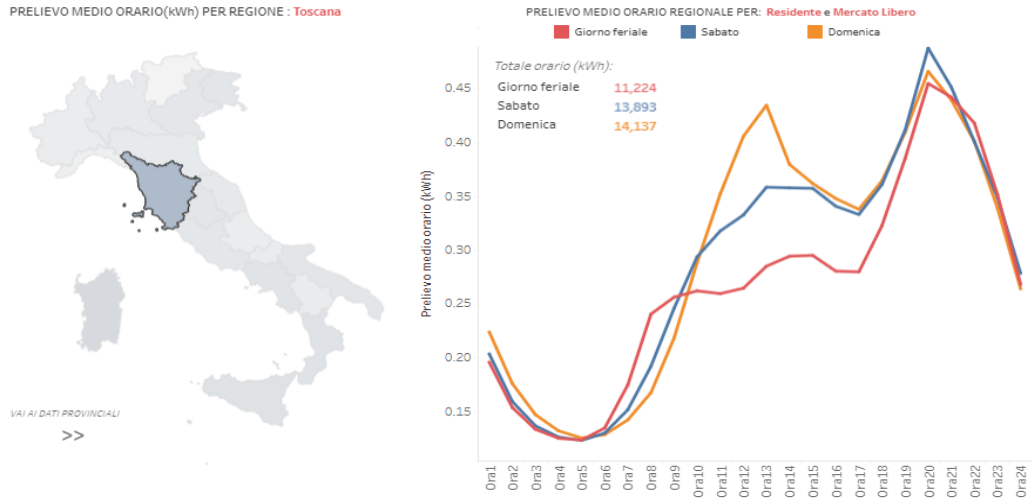

Figure 7. Average load profiles in January for a 3 kW residential customer in Tuscany.

Using the open-source multi-energy simulation software "MESSpy" [52,53], a sensitivity analysis was conducted on varying the number of customers within the REC (Figure 8). Based on this analysis, three scenarios were selected (Table 3) to be simulated with the BESS, representing collective self-consumption indices of 40%, 60%, and 80%.

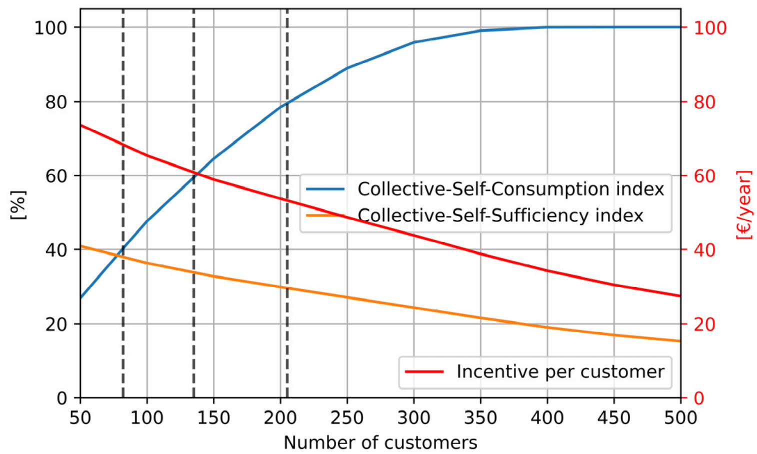

Figure 8. The 100 kWp REC key parameters, with varying numbers of customers.

Table 3. Three scenarios selected with regard to customer number.

Number of Customers [CN]	CSCi [%]	CSSi [%]	E_{sur} [MWh/year]	E_{need} [MWh/year]
80	40	38	82	89
135	60	34	55	160
205	80	30	27	258

Considering that collective self-consumption (CSC) is defined as the minimum between the energy injected into the grid by the community and the energy withdrawn (including that withdrawn from the battery), we consequently defined the following two relative indices: the collective self-consumption index (CSCi) is defined as the ratio of

CSC to the total electricity production from photovoltaic sources, while the collective self-sufficiency index (CSCi) is the ratio of CSC to the total energy demand of the customers. These two indexes are representative of the REC's independence from the national grid. On the other hand, the incentive associated with CSC is the multiplication of CSC by a value of approximately 110 EUR/MWh.

Figure 8 not only identifies three potential scenarios but also elucidates why evaluating a battery within future RECs is sensible: as the number of customers increases, so does the demand. With the withdrawal of electricity, the CSC, the total incentive, and CSCi rise while the CSSi diminishes. Moreover, the incentive per customer decreases. In practical terms, with more users, the metaphorical "pie" must be divided into more portions, leading to smaller individual slices. This observation highlights the impracticality of considering RECs with excessively high CSCi levels, suggesting that surplus energy (E_{sur}) will persist in future RECs. This raises the question of who will harness this surplus if not through grid-connected community batteries. Thus, the graph underscores that RECs will consistently have surplus energy, justifying the evaluation of introducing a BESS to harness and capitalize on this surplus.

3. Results

The outcomes are delineated across three segments. Firstly, we elucidated the impact of the Battery Energy Storage System (BESS) on renewable energy community (REC) energy balances. Secondly, we delineated the significance of the activation cost (AC) parameter with regard to battery degradation and the Net Present Value (NPV). Lastly, we conducted economic optimization of battery sizing within each scenario and appraised potential investments by performing energy arbitrage (EA) or dedicating the BESS only to collective self-consumption (CSC).

3.1. Energy Balances

Upon integrating a BESS into a REC, its grid independence increases. The collective self-consumption (CSC) and collective self-sufficiency (CSS) indices, reflecting REC autonomy from the grid, increase with larger battery sizes (Figure 9). However, the degree of increase varies with the performance of EA: the augmentation of CSS is constrained by regulations pertaining to access to incentives via the battery. Notably, while withdrawing energy during surplus periods is incentivized, injection during times of need lacks similar encouragement. Consequently, injections may not necessarily occur during these energy needs, which could otherwise enhance CSS, but rather during periods of elevated pricing. Conversely, in the absence of EA, the battery is limited to utilizing surplus energy from the REC and injecting it when required, thereby aligning the enhancement of CSC and CSS in this scenario.

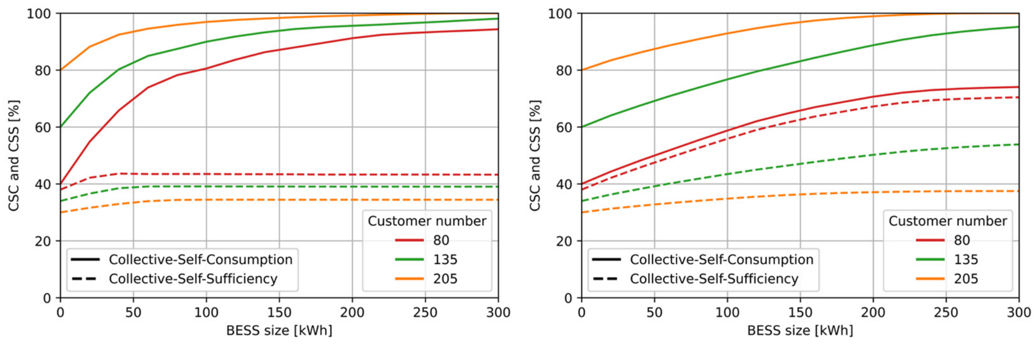

Figure 9. CSC + EA (**left**) vs. CSC (**right**): collective self-consumption index and collective self-sufficiency index with regard to varying battery size and number of customers.

Figures 10 and 11 underscore a key revelation from this study. The REC's reliance on the grid, considering the BESS as part of the REC, paradoxically rises instead of declining.

Over a 20-year span, both the energy fed into and withdrawn from the grid increase due to the battery's independent EA activities, notwithstanding decreases in energy exchange within the REC. To address this, the approach advocated in the right-hand graphs restricts the battery to charge solely from the REC surplus and discharge solely to meet community needs. This strategy of non-EA reduces overall energy fed into and withdrawn from the grid, thus mitigating REC energy dependence.

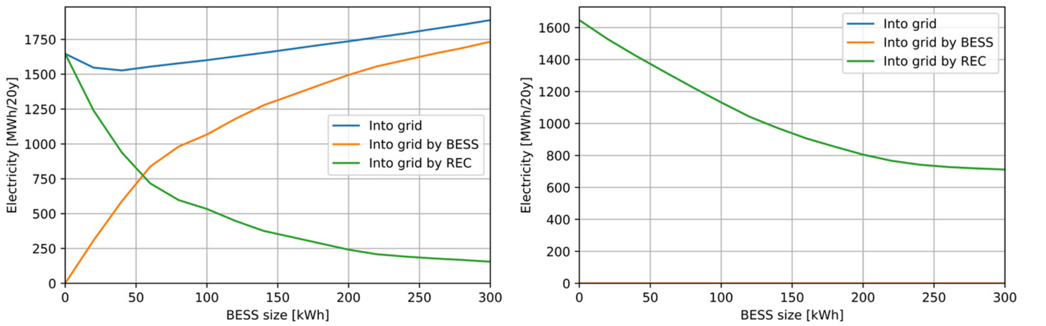

Figure 10. CSC + EA (**left**) vs. CSC (**right**): energy fed into the grid with regard to varying BESS size.

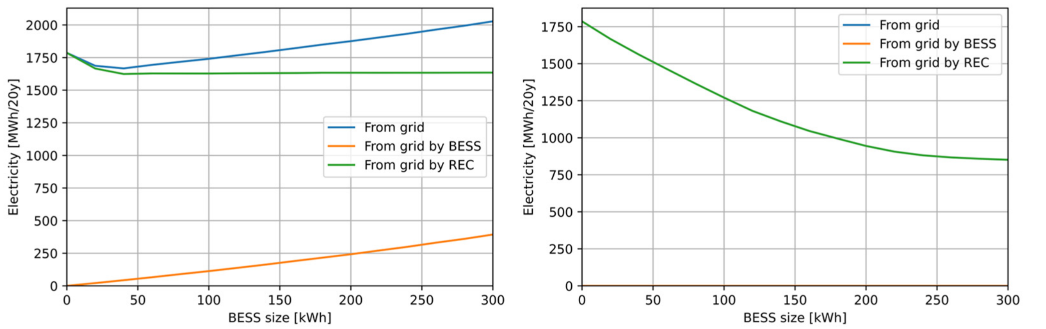

Figure 11. CSC + EA (**left**) vs. CSC (**right**): energy withdrawn from the gird with regard to varying BESS size.

3.2. Activation Cost and Energy Arbitrage

Adjusting the Activation Cost (AC) parameter across various levels results in the computation of diverse optimal BESS schedules. Over a 20-year analysis period, these variations in AC values significantly impact cash flows and BESS lifetimes, consequently influencing the Net Present Value (NPV), which is highly dependent on AC. Simulations encompassing each scenario and BESS size have been conducted with AC values ranging from 5 to 60.

Figure 12 provides a summary of the optimal AC values, maximizing the NPV transformation (NPV*) over 20 years. These simulations focus on scenarios performing EA. Since AC does not influence the gain from CSC (see Figure 2), there is no point in studying its effects in scenarios without EA. The results are presented with confidence intervals, wherein NPV* values differ by less than 1% of the NPV* value. The battery cost, equivalent to the replacement cost at the end of its life, emerges as the most influential parameter. For BESS costs around 200 EUR/kWh, it is advisable to set AC values between 20 and 30 to enhance EA profits, albeit at the expense of accelerating battery consumption with numerous cycles. Conversely, for higher costs, optimal values shift toward 50, indicating fewer cycles but highly profitable ones, ensuring prolonged battery longevity. The graph also illustrates that the battery size and energy price do not significantly influence AC selection.

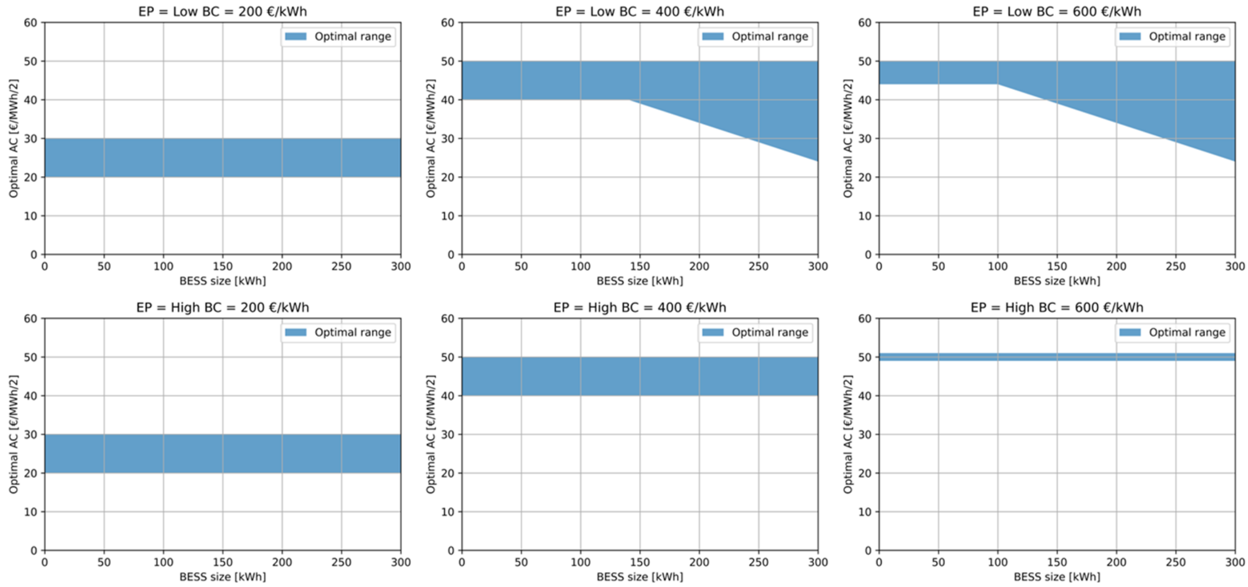

Figure 12. CSC + EA: optimal Activation Cost (AC) values for varying Energy Price (EP), battery cost (BC), and battery size.

Summing up, the importance of optimizing battery scheduling considering the expected replacement cost is evident. One way to achieve this is proposed in this study by optimizing the AC parameter entered as a penalty of the objective function.

3.3. Economic Feasibility

The findings presented in this concluding paragraph exclusively pertain to configurations with optimal Activation Cost (AC) values. Figures 13 and 14 delineate the respective contributions of the two principal cash flows, energy arbitrage (EA) and collective self-consumption (CSC), to the investment's returns.

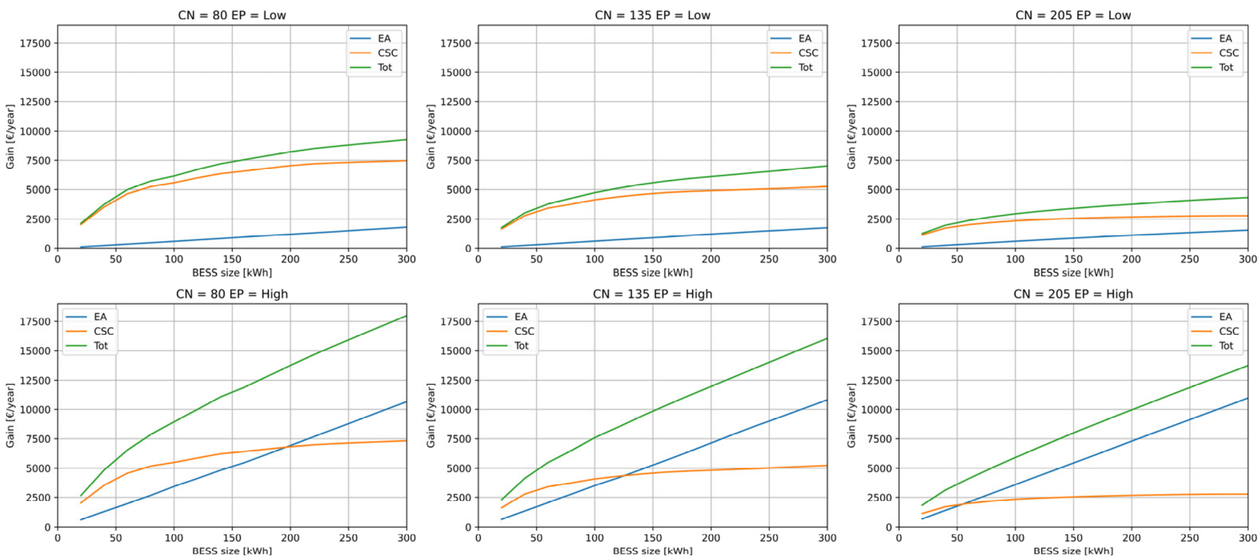

Figure 13. CSC + EA: cash flow for varying number of customers (CN), Energy Price (EP), and BESS size.

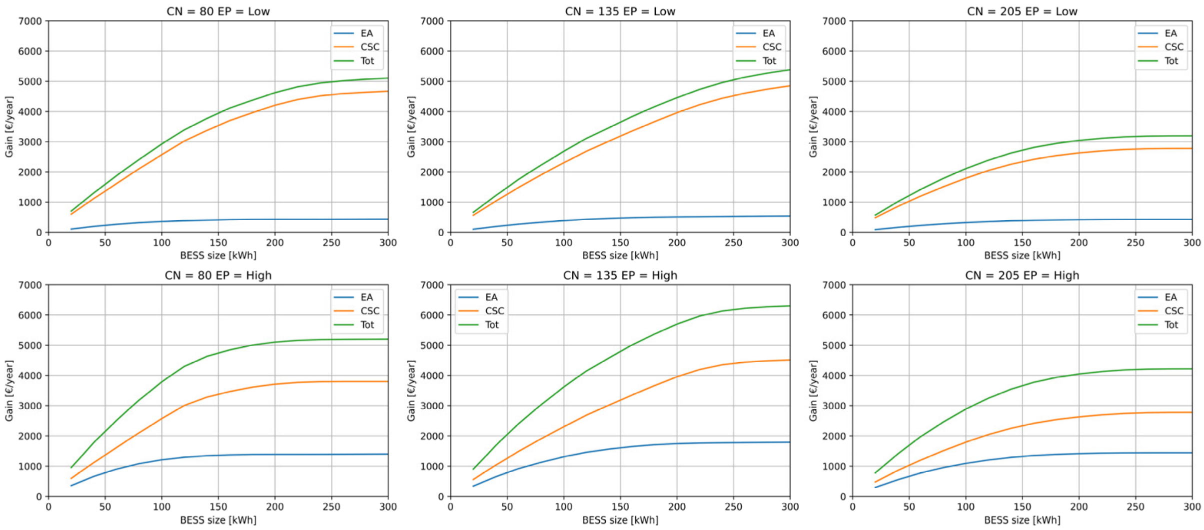

Figure 14. CSC: cash flow for varying number of customers (CN), Energy Price (EP), and BESS size.

The analysis reveals that in scenarios featuring EA (Figure 13) and characterized by low energy prices, the gain derived from CSC significantly surpasses that of EA, exceeding it by approximately fivefold. Consequently, investments in such scenarios are primarily driven by REC incentives and are contingent upon the evolution of customer numbers over time. In other words, it is crucial to match the BESS to a REC with a lot of energy surplus. However, with high energy prices, the profit from EA may indeed outstrip that from CSC.

In scenarios without EA use (Figure 14), the EA gain is only due to the buying and selling of energy at times of surplus and need in the REC and not to an actual EA that exploits electricity market price fluctuations. In these cases, the total cash flow experiences a decline by several thousand EUR per year (see *y*-axis scale), chiefly due to reduced EA profits but also due to lower CSC levels. However, if energy prices are high, EA continues to make an important contribution of about one-third of the total cash flow.

Figures 15 and 16 depict the transformed Net Present Value (NPV*) as it relates to BESS size, offering insights into optimal BESS sizes for each scenario of Table 1.

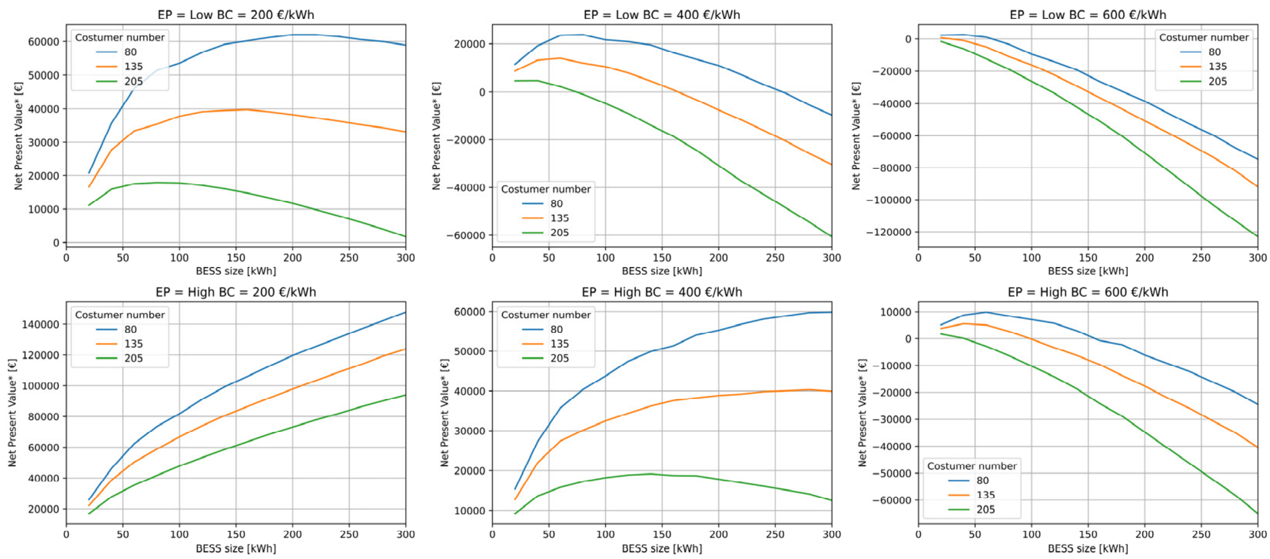

Figure 15. CSC + EA: NPV* varying Energy Price (EP), BESS cost (BC), number of customers, and BESS size.

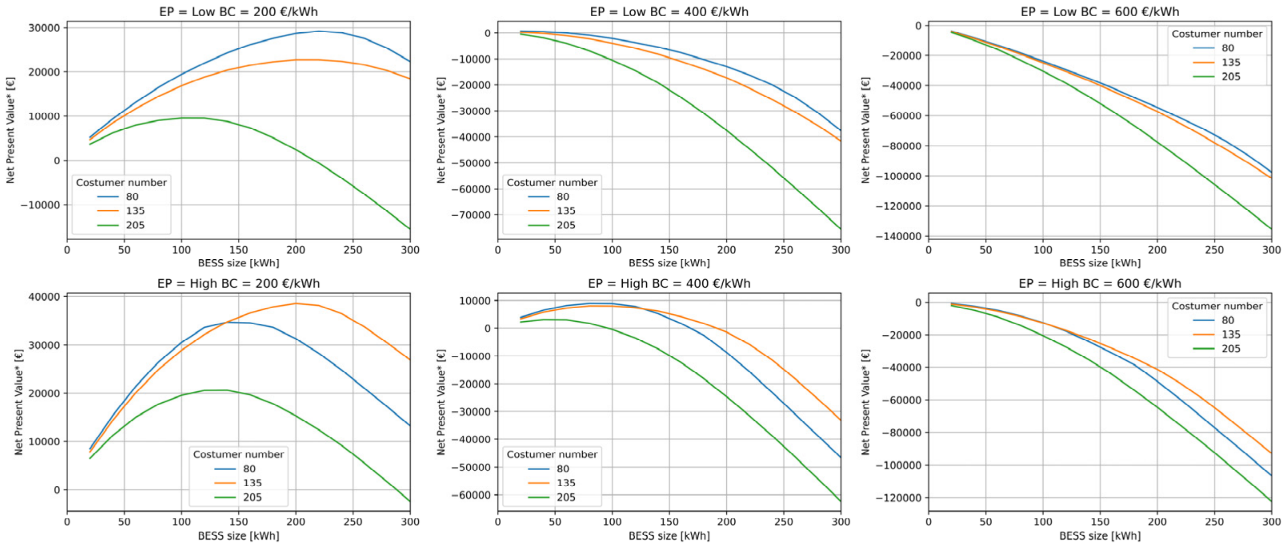

Figure 16. CSC: NPV* varying Energy Price (EP), BESS cost (BC), number of customers, and BESS size.

In scenarios using EA (Figure 15), a BESS cost of 600 EUR/kWh renders BESS installation economically unviable, while 400 EUR/kWh proves attractive, especially in scenarios with high energy prices. A larger BESS size is recommended for setups with a substantial surplus, while scenarios with low energy prices favor smaller BESS units. A cost of 200 EUR/kWh strikes a balance, rendering BESS integration cost-efficient across various scenarios.

Not performing EA (Figure 16) diminishes battery investment attractiveness. At 400 EUR/kWh, only smaller batteries are feasible, while 200 EUR/kWh remains appealing, even if the NPV* values achieved are lower than in the case with EA.

An intriguing observation arises regarding the impact of the customer number on battery investment. In EA scenarios, it becomes apparent that as the number of customers decreases (and REC surplus consequently increases), the NPV* of the investment rises. This trend stems from the augmented income attributed to the withdrawal by the BESS of the REC surplus energy that becomes CSC. However, in instances where EA is not implemented, this assertion holds only partially true. This is because for the BESS to be able to utilize such surplus, there must also be REC energy needs to justify its re-injection later. Consequently, it is implied that batteries should be matched to REC converging toward an equilibrium point between surplus and need, thereby optimizing both collective self-consumption (CSC) and collective self-sufficiency (CSS), i.e., with neither too many nor too few customers (Figure 16, bottom left).

Figures 17 and 18 provide further clarity by illustrating the progression of NPV, focusing on the original NPV rather than the transformed version and considering the optimal BESS size solution for each scenario. These curves offer a comprehensive perspective on investments, encompassing NPV, payback time, and battery lifetime.

In scenarios using EA (Figure 17), a BESS cost of 200 EUR/kWh presents compelling investments, ensuring a 5-year payback period in low-price scenarios and even shorter periods in high-price scenarios. A cost of 400 EUR/kWh also allows for investments with payback times of less than 10 years, albeit with more significant impacts from energy prices and customers. However, 600 EUR/kWh is evidently excessive.

Without EA (Figure 18), investments become less attractive, with payback periods extending by approximately 5 years and optimal battery sizes decreasing alongside NPV. Here, the battery cost must be around 200 EUR/kWh or less for attractiveness.

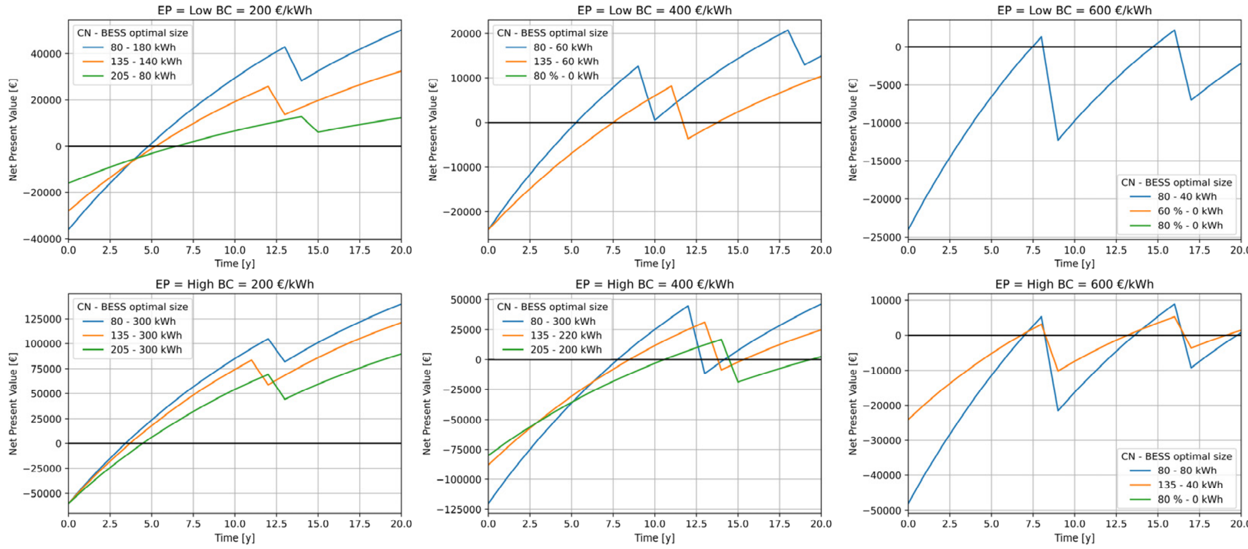

Figure 17. CSC + EA: optimal investments assessment for varying Energy Price (EP), BESS cost (BC), and number of customers (CN).

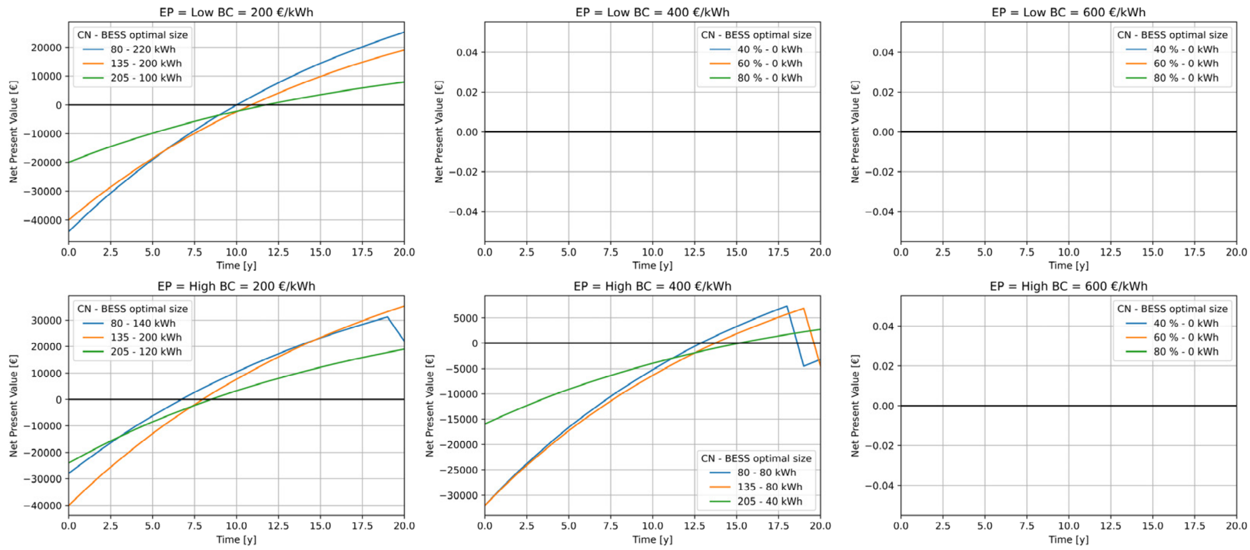

Figure 18. CSC: optimal investments assessment for varying Energy Price (EP), BESS cost (BC), and number of customers (CN).

Battery lifetimes exhibit steps due to replacement costs. Without EA, batteries can last about 20 years or longer; while performing EA, lifetimes vary between 7 and 13 years. Despite reduced lifetimes, the increase in cash flow, payback time, and NPV over 20 years compensates, rendering the investment more attractive overall.

4. Discussion

In a residential renewable energy community (REC) powered by 100 kWp of photovoltaic systems, a comprehensive techno-economic analysis was used to assess the energy and economic impact of integrating a grid-connected Battery Energy Storage System (BESS). Various scenarios were examined, accounting for factors like community size, market prices, battery characteristics, and the choice to engage in energy arbitrage (EA), with the Italian market and regulations serving as a reference.

The analysis focused on two main revenue sources: the increase in collective self-consumption (CSC) incentives resulting from BESS surplus energy withdrawal and EA, involving participation in electricity markets to capitalize on price differentials. A 20-year simulation, considering battery aging and optimized scheduling, revealed the significance of a shared battery in enhancing collective self-consumption and sufficiency. However, scenarios with EA demonstrated higher total energy transactions compared to those without a battery.

Activation costs played a crucial role in EA scenarios, emphasizing the importance of optimizing battery scheduling and considering replacement costs. Economic findings highlighted optimal battery sizes and cost-effectiveness thresholds, with dedicated CSC batteries requiring a maximum cost of 200 EUR/kWh. Conversely, EA enabled viable investments even with costs around 400 EUR/kWh, halving the payback period and emphasizing the market's dependence on incentives.

Interestingly, the most suitable REC for BESS integration featured an intermediate number of customers, balancing surplus and demand levels unless EA was involved. In that case, REC with low customer numbers or high surpluses was preferable.

Battery aging analysis revealed that while a BESS dedicated to CSC could last 20 years, EA halved its lifespan. However, increased cash flow and net present value compensated for this reduction, rendering the investment more attractive overall.

A comparison between energy and economic optimality highlighted discrepancies, indicating the need for further reductions in battery prices, enhanced market incentives, and regulatory reviews concerning the role of grid-connected BESS within RECs.

Future studies could explore BESS potential in RECs beyond CSC and EA, considering additional revenue streams such as ancillary services. Moreover, battery management strategies should integrate real-time control for dispatching and address forecast errors and grid constraints for a comprehensive analysis.

Author Contributions: M.P.: Term, Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Data Curation, Writing—Original Draft, Visualization. L.B.: Term, Conceptualization, Methodology, Validation, Formal Analysis, Writing—Review and Editing. M.B.: Term, Conceptualization, Methodology, Validation, Formal Analysis, Writing—Review and Editing. M.I.: Term, Conceptualization, Methodology, Validation, Formal Analysis, Writing—Review and Editing. F.G.: Resources, Writing—Review and Editing, Supervision, Funding Acquisition. G.F.: Writing—Review and Editing, Supervision. C.C.: Resources, Writing—Review and Editing, Supervision, Project Administration, Funding Acquisition. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All the codes used are publicly available on GitHub [52,54]. Production data are downloaded from PVgis [50], and load profiles are from ARERA [51].

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

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Journal of Energy Storage 114 (2025) 115837

Contents lists available at ScienceDirect

Journal of Energy Storage

journal homepage: www.elsevier.com/locate/est

Research papers

Self-dispatching a renewable energy community by means of battery energy storage systems

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ARTICLE INFO

Keywords:
Renewable energy communities
Battery energy storage systems
Photovoltaic systems
Forecasting
Optimization
Scheduling
Control
Dispatch
Energy arbitrage
Collective self-consumption

ABSTRACT

Renewable energy communities, where citizens, businesses, and institutions produce, consume, store, and share energy, are increasingly pivotal in energy markets. The use of shared community batteries introduces the challenge of adapting control strategies to community needs, which remains an open question in energy management.

This study presents a two-layer optimal control model for managing community Battery Energy Storage Systems in low-voltage networks to self-dispatch, engage in energy arbitrage and maximize collective self-consumption, as well as preserving battery lifespan. The scheduling layer calculates the optimal dispatch plan and battery trajectories to maximize profits based on long-term forecasts. The real-time control layer minimizes dispatch errors based on real-time data and short-term forecasts.

The key contribution of this work is the experimental validation of a novel model that, for the first time in the literature, integrates dispatch, energy arbitrage, and collective self-consumption services. This model is the result of adapting and enhancing an existing framework, which had previously been limited to mathematical formulation and simulation. Here, it is experimentally validated in a real-scale microgrid, demonstrating its applicability and effectiveness in managing these services.

1. Introduction

The EU Directives 2018/2001 [1] and 2019/944 [2] initiated the widespread development of Renewable Energy Communities (RECs) across Europe, providing the framework for national regulations.

RECs are non-profit organizations that unite citizens, companies, and institutions to generate environmental, social, and economic benefits for their local areas. These communities integrate producers, consumers, and prosumers who generate, consume, store, and share energy.

A key feature of RECs is collective self-consumption (CSC), which aggregates the virtual self-consumption of all members and is incentivized across the EU with values around 120 €/MWh, depending on the country [3,4]. These incentives may be redistributed among members or used for shared projects, such as installing community Battery Energy Storage Systems (BESS).

In addition to energy sharing, RECs can act as Balance Responsible Parties (BRP [5]) in electricity markets, buying and selling electricity on behalf of their members. As BRPs, they are responsible for managing grid imbalances, incurring penalties when their purchased or sold energy does not align with actual usage or production. To address this, RECs equipped with shared BESS can:

1. Maximize CSC to earn associated incentives.
2. Perform energy arbitrage (EA), buying energy during low-price periods and selling it at peak prices.
3. Minimize imbalance penalties through real-time control that aligns dispatch with market bids.
4. Potentially offer ancillary services like frequency containment, local flexibility, and peak shaving (not covered in this study).

Effective BESS management requires a combination of scheduling and real-time controls [6,7]. Scheduling optimizes long-term dispatch plans using forecasts, while real-time control minimizes dispatch errors using short-term forecasts and real-time data. Although existing literature on microgrids addresses BESS scheduling and real-time control, critical gaps remain, including experimental validation, forecast uncertainty handling, detailed electrical grid modelling, the integration of

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https://doi.org/10.1016/j.est.2025.115837
Received 1 November 2024; Received in revised form 29 January 2025; Accepted 11 February 2025
Available online 14 February 2025

Nomenclature

A_b	complex power entering the generic branch b of the power grid
a_b	complex power injected/absorbed on the downstream bus of the generic branch b of the power grid
AC	alternative current
ACT	BESS activation penalty
act^{cost}	BESS activation penalty weight parameter inside the objective function
b	branch/bus index
BESS	Battery Energy Storage Systems
BRP	balance responsible party
CoDistFlow	Corrected DistFlow
CSC	collective self-consumption
csc^{inc}	incentive associated to collective self-consumption
csc^{value}	value of collective self-consumption
DIS	dispatchability
dis^{cost}	dispatch ability weight parameter inside the objective function
DER	distributed energy resources
DP	dispatch plan
DSO	distribution system operator
EA	energy arbitrage
EP	energy price
f_b	square of the current in the generic branch b of the power grid
G	power grid adjacency matrix
i_b	current in the generic branch b of the power grid
$i_{b,max}$	ampacity limit of the generic branch b of the power grid
iDist Flow	Improved DistFlow
inc	incentive
Im()	imaginary part function
LF	load flow
LV	low-voltage
N_b	number of branches in the power grid
N_s	number of forecasted scenarios
N_t	number of timesteps
OPF	optimal power flow
P_b	active power entering the generic branch b of the power grid
p_b	active power injected/absorbed on downstream bus of the generic branch b of the power grid
p_b^{bess}	active power injected/absorbed on downstream bus of the generic branch b of the power grid by BESSs
p_b^{pv}	active power injected/absorbed on downstream bus of the generic branch b of the power grid by PVs
p_b^{load}	active power injected/absorbed on downstream bus of the generic branch b of the power grid by loads
$\hat{p}_b^{pv}$	active power injected/absorbed on downstream bus of the generic branch b of the power grid by PVs, forecast.
$\hat{p}_b^{load}$	active power injected/absorbed on downstream bus of the generic branch b of the power grid by loads, forecast.
p_b^{lco}	active power loss in the generic branch b, correction term
p_0	active power injected/absorbed on the grid connection point (bus 0)
$\bar{p}_0$	active power injected/absorbed on the grid connection point (bus 0), realization according to real-time data monitoring
p_0^{DP}	active power bidded to the grid connection point (bus 0) according to the dispatch plan
PV	photovoltaic system
Q_b	reactive power entering the generic branch b
q_b	reactive power injected/absorbed on downstream bus of the generic branch b of the power grid
q_b^{bess}	reactive power injected/absorbed on downstream bus of the generic branch b of the power grid by BESSs
q_b^{pv}	reactive power injected/absorbed on downstream bus of the generic branch b of the power grid by PVs
q_b^{load}	reactive power injected/absorbed on downstream bus of the generic branch b of the power grid by loads
${q_b}^{co}$	reactive power loss in the generic branch b, correction term
r_b	line resistance of the generic branch b of the power grid
r_b^{bess}	battery equivalent resistance
Re()	real part function
rt.	real-time control
s	scenario index
sc	scheduling
SoE	state of energy
t	timestep index
T^{step}	timestep interval
$T^{step,sc}$	timestep interval in the scheduling problem
$T^{step,rt}$	timestep interval in the real-time control problem
v_b	square of the voltage of the downstream bus concerning the generic branch b
$v_{up(b)}$	square of the voltage of the upstream bus concerning the generic branch b
v_b^{ap}	voltage on the downstream bus concerning the generic branch b, approximation term
v_b^{co}	square of the voltage drops between downstream and upstream buses concerning the generic branch b, correction term
v^{max}	square of the voltage of the downstream bus concerning the generic branch b, maximum value
v^{min}	square of the voltage of the downstream bus concerning the generic branch b, minimum value
z_b	line impedance of the generic branch b of the power grid
z_b^*	complex conjugate of the line impedance of the generic branch b of the power grid
x_b	line reactance of the generic branch b of the power grid

multiple services and adaptation of models to the specific context of RECs, i.e., a subset that has been well defined and regulated of the more generic microgrids.

A prior study by the lead author [8] took an initial step in addressing these gaps and this article overcomes the limitations of such first study making an even deeper contribution to the topic. It refines and extends the model proposed in [9] with formulations from [6,7], adapting them for REC-specific needs and validating the framework experimentally for the first time. By testing the model in a real-world microgrid, this study not only advances REC-specific literature but also contributes broadly to literature on the operation of BESS and microgrids, bridging the gap between theoretical models and practical applications.

1.1. *Literature survey*

There is a significant gap in the literature concerning BESS within renewable energy communities (RECs). Although the literature on RECs is growing, it often overlooks the specific role of BESSs within RECs. It especially does not consider fundamental details of BESS management, such as electricity grid modelling, forecasting uncertainties, BESS ageing and the possibility of multiple services. On the other hand, these aspects are instead studied in the literature on grid-connected BESSs and microgrids, and thus only need to be adapted to the RECs specific context.

The literature on RECs primarily focuses on economic aspects. The main research questions pertain to the financial conditions necessary to make a REC competitive and how stakeholders contribute to value creation [10] and receive benefits [11]. Various business models are proposed and examined, each suggesting different schemes for profit redistribution and cost allocation, as well as other approaches to participation in the electricity market [12–17]. Additionally, significant attention is given to the effects of the composition and configuration of the REC itself, in terms of member clustering [18], technologies employed [19], and the type of organizational structure utilized [20,21].

When BESSs are involved in REC literature, the aspect most studied is their sizing and the impact this has on self-consumption, CSC, earnings and distribution network [22–25]. Regarding BESS management, the possibility of controlling a fleet of several BESSs [26], or even several heat pumps [27], with a centralized manager, is being considered. Some articles instead go into the details of scheduling [28,29].

A review highlights the need for community BESS to cater for multiple services and the lack of studies in this regard [30]. The few contributions in this field propose community BESS for EA and peak shaving [31], EA and CSC [8], the participation in capacity and balance market [32,33] or the provision of load flexibility and capacity sharing [34]. Dispatching, EA and CSC at the same time have not yet been considered in the literature.

All the articles cited on the use of community BESSs focus on the economic aspects using simplified management models that never consider all the main elements required for BESS management: considering forecast uncertainty, evaluating ageing, incorporating grid constraints into optimization problems to avoid unfeasible solutions, and developing not only scheduling models but also real-time control. Furthermore, simulations are found in literature but never actual experimental tests.

Accurate and comprehensive models on BESS management can be found in the utility-scale BESS and microgrids literature and can and should therefore be adapted for use in community BESSs.

[9] proposes a scenario-based model for the scheduling of a BESS to provide multiple services and uses it in the problem of providing dispatching, proposing it in simulation without considering the real-time control phase. The paper provides a framework called “CoDistFlow” that accounts for grid and battery losses addressing the non-convexity of the optimal power flow problem. Here, the same framework is used by modifying the objective function to provide EA and CSC in addition to dispatching. Furthermore, the framework is completed by adding to the scheduling phase also the real-time control part. And, even more importantly, the model has been experimentally tested for the first time.

The real-time control formulation added is the one proposed in [6] where it is first formulated in a general way to provide simultaneously multiple grid services. Here, the model is adapted to provide dispatching, CSC and EA, and it is included in the “CoDistFlow” framework.

Additional details and variations about the methodology proposed for the control of a BESS can be found in [7], where a two-level control layer to avoid BESS saturation is proposed, or in [35] where the provision of AS is also added to the problem’s formulation.

To provide further points of comparison to the proposed model, a brief literature search on microgrids follows.

Huynh et al. apply metaheuristic methods, to minimize generation costs in islanded microgrids, highlighting scalability and adaptability challenges adaptability [36]. Xiaodong et al. focus on coordinated optimization for grid-connected microgrids, integrating RES and electric vehicles but with limited real-time responsiveness [37]. These studies emphasize cost efficiency but provide limited network dynamics modelling.

To address renewable generation and load demand uncertainties, robust, stochastic, and predictive strategies are widely used. Lin et al. propose a Tube Model Predictive Control method for enhanced robustness and computational efficiency [38]. Zhou et al. integrate scenario-based methods within a multistage robust scheduling framework, explicitly modelling network constraints [39]. Kaheni et al. introduce a rule-based predictive framework that dynamically adjusts BESS operations [40]. However, many of these models lack experimental validation or detailed power grid constraint modelling.

Multi-energy microgrid systems expand BESS applications by integrating electricity, heat, and gas. Lin et al. use predictive scheduling to balance multi-domain energy flows domains [41], while Zheng et al. emphasize frequency constraints for islanded microgrid stability [42].

These studies neglect regulatory and community-specific frameworks essential for RECs by focusing, instead, on generic microgrid operational aspects that may have limited real applications. Additionally, thorough electrical network modelling and experimental validation are often missing. This paper aims to bridge these gaps by proposing a specialized model for RECs that integrates economic incentives, network modelling, and experimental validation, offering a novel contribution to the field.

1.2. Paper novelty

This study advances REC literature by presenting a comprehensive methodology for using community BESS to simultaneously perform dispatching, energy arbitrage (EA), and collective self-consumption (CSC)—a combination never previously explored in microgrid research.

The proposed methodology integrates forecast uncertainty, electrical grid modelling, BESS ageing, and real-time control to follow dispatch plans generated during scheduling. This level of detail and completeness in BESS management surpasses prior REC studies, paralleling the sophistication typically found in utility-scale BESS and microgrid literature.

Building on the CoDistFlow model, the study adapts and enhances it for REC-specific applications, adding a real-time control phase and conducting its first experimental validation. Tested in a real-world microgrid, this framework demonstrates its feasibility for practical deployment, marking the first experimental demonstration of a community BESS managing these three services. The methodology is now ready for implementation in operational energy communities.

2. Methodology

This chapter starts by clarifying the problem statement, then gives details about the grid and BESS models and finally goes into the formulation of the scheduling and real-time control optimization problems.

2.1. Problem statement

A REC operating on a radial low-voltage (LV) power distribution network is considered, integrating heterogeneous distributed energy resources (DERs). These include uncontrollable assets, such as photovoltaic (PV) systems and loads, and controllable resources, limited to grid-connected BESSs.

The REC is assumed to receive incentives for CSC [3,4] and also functions as a BRP, representing its members in day-ahead and intraday electricity markets. As a BRP, the REC manages grid imbalances, incurring penalties when energy transactions deviate from the actual energy fed into or withdrawn from the grid connection point (GCP) [5].

To minimize imbalance penalties, the REC uses real-time BESS control to align with dispatch plans optimized for economic performance. These plans are computed through a scenario-based scheduling approach, chosen for their ability to handle forecast uncertainties in renewables, loads, and grid constraints without rendering the optimization problem excessively complex. The objective is to maximize gains from CSC and energy arbitrage (EA) while minimizing imbalance costs and mitigating BESS ageing.

Scheduling occurs hourly, leveraging long-term forecasts (e.g., 24 h ahead), and dispatch plans can be updated up to 1 h before delivery. Within the hour, real-time control adjusts BESS set points every 30 s based on short-term forecasts and real-time data to minimize dispatch errors.

Both scheduling and real-time control are formulated as alternative current optimal power flow (AC-OPF) problems that incorporate grid modelling and constraints.

2.2. Grid model

The exact AC Optimal Power Flow (AC-OPF) problem is inherently non-convex and computationally challenging due to the non-linear power flow equations. To address this, the study employs the CoDistFlow scheme [43], an iterative method tailored for solving scenario-based AC-OPF problems in radial networks with stochastic resources and controllable BESSs, accounting for both grid and BESS losses.

The CoDistFlow scheme relies on the branch-flow model (Fig. 2) and combines two sequentially executed modules until convergence (Fig. 4). The first, Improved DistFlow (iDF) [44], uses relaxations and approximations to maintain convexity in power flow equations while estimating grid losses and nodal voltages. The second module performs a full, non-approximated Load Flow (LF) analysis to update correction and approximation terms based on the BESS power outputs from the previous iteration.

This approach is universally applicable to radial networks, which are typical in low-voltage RECs due to safety and protection requirements. However, its practical implementation requires detailed knowledge of the network topology, often necessitating close collaboration with Distribution System Operators (DSOs). As RECs evolve, such partnerships are expected to enable access to the required network data, facilitating the application of this methodology [45,46].

For networks where topology and grid model are unavailable, parameter inference techniques using metering infrastructures provide an alternative [47–49]. For example, methods like those in [50] may be capable to directly estimate the admittance matrix from synchronized measurements, eliminating the need for prior network model knowledge (although information of specific data like branch ampacity limits is still necessary).

2.2.1. Branch-flow model notation

Since the aim is to model a REC with resources interfaced via a LV grid, the corresponding branch model of the grid lines can be represented using only longitudinal impedances, allowing us to neglect the presence of the lines' shunt capacitances that, as known, make some constraints of the problem non-convex [51]. Each branch $b \in B = [0, \ldots, N_b]$ of the distribution grid is modelled according to the branch-flow model (Fig. 2) where: $A_b = P_b + iQ_b$ is the complex power entering the branch, with P_b being the active and Q_b the reactive power respectively; f_b is the square of the current circulating along the longitudinal equivalent impedance of the branch; z_b is the impedance of the branch, r_b is its resistance and x_b its reactance. $v_{up(b)}$ and v_b are the square of voltage magnitudes respectively of the up(stream) and down(stream) bus concerning the branch, where up(stream) means closest to grid connection point (GCP). $a_b = p_b + iq_b$ is the complex power injected/absorbed in each bus, where $p_b = p_b^{bess} + p_b^{pv} + p_b^{load}$ and $q_b = q_b^{bess} + q_b^{pv} + q_b^{load}$ are the active and reactive power injected/absorbed in each bus by BESSs, PVs and loads. The sign of absorbed powers is assumed to be positive while the sign of generated powers is negative (i.e., loads convention).

$G_{b,k}$ is the standard adjacency matrix of the graph of the grid, characterized by $G_{b,k} = 1$ for two buses $k, b \neq 0$, if $k = up(b)$, otherwise $G_{b,k} = 0$.

2.2.2. Battery equivalent losses model

As detailed in [43], all BESS losses, whether from cells, converters, or transformers, are approximated using a single equivalent resistance, as these losses generally scale with the square of the current flowing between the BESS and the grid (Fig. 3). This simplification unifies all AC interfaces into one resistance, allowing the BESS to be modelled as an ideal storage system with unitary efficiency. The active power is represented as being absorbed or injected at a virtual node connected to the grid via the equivalent resistance, while the reactive power, fully managed by the converter, is assumed to be injected or absorbed at the upstream node of the equivalent resistive branch.

This modelling approach enables seamless integration of the equivalent resistance into the power grid's admittance matrix without affecting the problem's convexity. For multiple BESSs, additional virtual branches and ideal batteries can be added as needed. The equivalent resistance value can be determined experimentally, ensuring the model's accuracy and applicability.

2.2.3. iDistFlow equations

According to the branch flow and the BESS equivalent resistance models, let us consider $b \in B = [0, \ldots, N_b]$ the branch/bus index with N_b being the total number of branches in the grid (i.e., including also the BESSs equivalent resistance branches); $t \in T = [0, \ldots, N_t]$ the time index where N_t is the number of considered timestep (e.g. 24 h in the scheduling problem), and $s \in S = [0, \ldots, N_s]$ the scenario index where N_s is the number of scenarios assumed to sample the probability density functions of renewables production and load forecasts. The equations defining the constraints and variables of the iDistFlow optimization problem are as follows $\forall b \in B, \forall t \in T, \forall s \in S$:

$$P_{b,t,s} = p_{b,t,s} + \sum\nolimits_{k:G_{b,k}=1} P_{k,t,s} + p^{co}_{b,t,s} \tag{1.1}$$

$$Q_{b,t,s} = q_{b,t,s} + \sum\nolimits_{k:G_{b,k}=1} Q_{k,t,s} + q^{co}_{b,t,s} \tag{1.2}$$

$$v_{b,t,s} = v_{up(b),t,s} - 2Re\left(z_b^{*} \cdot A_{b,t,s}\right) + v^{co}_{b,t,s} \tag{1.3}$$

$$Re\left(i_{b,t,s}\right) = P_{b,t,s} \Big/ v^{ap}_{up(b),t,s} \tag{1.4}$$

$$Im\left(i_{b,t,s}\right) = Q_{b,t,s} \Big/ v^{ap}_{up(b),t,s} \tag{1.5}$$

$$v^{min} \geq v_{b,s,t} \leq v^{max} \tag{1.6}$$

$$Re\left(i_{b,t,s}\right)^2 + Im\left(i_{b,t,s}\right)^2 \leq i^2_{max,b} \tag{1.7}$$

$$v_{0,t,s} = 1 \tag{1.8}$$

$$cos(\varnothing)_{0,t,s,} > 0.9 \tag{1.9}$$

$$SoE_{b',t+1,s} = SoE_{b',t,s} + T^{step} \cdot p^{bess}_{b',t,s} \tag{1.10}$$

$$SoE_{min} \leq SoE_{b,t,s} \leq SoE_{max} \tag{1.11}$$

$$p^{bess,min} \leq p^{bess}_{b,t,s} \leq p^{bess,max} \tag{1.12}$$

$$q^{bess,min} \leq q^{bess}_{b,t,s} \leq q^{bess,max} \tag{1.13}$$

Eqs. (1.1)–(1.5) are derivations of Kirchhoff's and Ohm's laws applied to the generic branch model shown in Fig. 2. The active power entering the branch (Eq. (1.1), $P_{b,t,s}$) is the sum between the active power injected/absorbed on the downstream bus $(p_{b,t,s})$, the power entering the adjacent downstream branches $(\sum_{k:G_{b,k}=1} P_{k,t,s})$ and the active power losses ($p^{co}_{b,t,s}$). The same relationship applies to reactive power (Eq. (1.2)). Eq. (1.3) represents the voltage drop between bus up and bus down of a branch based on the power entering and voltage losses ($v^{co}_{b,t,s}$), z_b^{*} is the complex conjugate of the impedance. Eqs. (1.4) and (1.5) represent the current ($i_{b,t,s}$) voltage ($v^{ap}_{up(b),t,s}$) ratio.

Eqs. (1.6) and (1.7) represent nodal voltage constraints and branches ampacity limits, respectively. Eq. (1.8) assumes that the nodal voltage at the GCP (bus 0) is constant and equal to 1 pu, which is necessary for OPF convergence and plausible since it is imposed by the external network. Eq. (1.9) is the limit on the ratio between active and reactive power at GCP imposed by the power grid operator and can be linearized as in.

Eqs. (1.10)–(1.11) define the State-of-Energy (SoE)[1] of the BESSs and their limits, and Eqs. (1.12)–(1.13) define the limits of active and reactive power produced by the BESS converters. T^{step} is the time step considered.

Eqs. (1.1)–(1.13) define the constraints and variables of the iDistFlow optimization problem that is solved to both scheduling and real-time control to optimize the respective objective functions (as they are defined in the following paragraphs by Eqs. (4) and (5)). In both problems, the variables to be optimized are the active and reactive powers setpoints of the BESSs (p^{bess}_b *and* q^{bess}_b) in each future timestep and scenarios considered. By solving the iDistFlow, the optimal active and reactive power setpoints of the BESS are obtained but due to relaxation and approximation terms in the equations of the iDistFlow, necessary to make them convex, the set points obtained must be corrected using the iterative loop scheme described in the next paragraph.

2.2.4. CoDistFlow scheme and load flow equations

In Eqs. (1.1)–(1.5) the terms $p^{co}_{b,t,s}$, $q^{co}_{b,t,s}$, $v^{co}_{b,t,s}$ and $v^{ap}_{up(b),t,s}$ are relaxations and approximations for losses and nodal voltage, used as in [43] to render the problem convex by replacing the following non-linear terms presented in the original AC OPF problem:

$$p^{co}_{b,t,s} = r_b \cdot f_{b,t,s} \tag{2.1}$$

$$q^{co}_{b,t,s} = x_b \cdot f_{b,t,s} \tag{2.2}$$

$$v^{co}_{b,t,s} = \|z_b\|^2 \cdot f_{b,t,s} \tag{2.3}$$

$$v^{ap}_{up(b),t,s} = \sqrt{v_{up(b),t,s}} \tag{2.4}$$

By using correction and approximation parameters for losses and voltage these values will be inaccurate, it is necessary, for each scenario and for each timestep, to solve a Load Flow problem (Eqs. (3.1)–(3.4)) using as input the BESSs' power values obtained to calculate the real losses and voltage and update, by means of Eqs. (2.1)–(2.4) the correction and approximation parameters. The iDistFlow is then recomputed with the updated parameters and in a few iterations (depending on the characteristics of the network and how large the losses are) the scheme in Fig. 4 converges. This feature is important because it allows the hourly scheduling problem to converge in about 30 s and the real-time control problem, used every 30 s, to converge within approximately 1 s.

The system of Eqs. (3.2)–(3.4) is the well-known load flow problem that can be solved for each scenario and timestep to correctly estimate the grid state and consequently losses and voltage.

$$P_{b,t,s} = p_{b,t,s} + \sum\nolimits_{k:G_{b,k}=1} P_{k,t,s} + r_b \cdot f_{b,t,s} \tag{3.1}$$

$$Q_{b,t,s} = q_{b,t,s} + \sum\nolimits_{k:G_{b,k}=1} Q_{k,t,s} + x_b \cdot f_{b,t,s} \tag{3.2}$$

$$f_{b,t,s} = \|A_{b,t,s}\|^2 \Big/ v_{up(b),t,s} \tag{3.3}$$

$$v_{b,t,s} = v_{up(b),t,s} - 2R\left(z^*_b C_{b,t,s}\right) + \|z_b\|^2 \cdot f_{b,t,s} \tag{3.4}$$

2.3. Scheduling

The scenario-based scheduling optimization problem consists of a CoDistFlow scheme in which the iDistFlow model is composed by the Eqs. (1.1)–(1.13) defining variables $\forall b \in B, \forall t \in T^{sc}, \forall s \in S$ and Eq. (4) defining the objective function to be maximised.

The controllable variables to be optimized are $p^{bess}_{b,t,s}$ and $q^{bess}_{b,t,s}$, i.e. active and reactive powers of BESSs in each node, timestep and scenario, as well as the dispatch plan $p^{DP}_{0,t}$ that is the active power bidded at the grid connection point for the following hours.

$$f_{obj,sc} = \sum\nolimits_{t=H+1}^{N^{sc}_t} \sum\nolimits_{s=1}^{N^{sc}_s} \left(EA_{t,s} + CSC_{t,s} - DIS_{t,s} - ACT_{t,s}\right) \tag{4}$$

$$EA_{t,s} = T^{step,sc} \cdot EP_{t,s} \cdot p^{DP}_{0,t} \tag{4.1}$$

$$CSC_{t,s} = T^{step,sc} \cdot csc^{inc} \cdot csc^{value}_{t,s} \tag{4.2}$$

$$csc^{value}_{t,s} = min\left\{ \sum\nolimits_{b=0}^{B} \widehat{p}^{pv}_{b,t,s}, - \sum\nolimits_{b=0}^{B} \left[\widehat{p}^{load}_{b,t,s} + max\left(0, p^{bess}_{b,t,s}\right) \right] \right\} \tag{4.2.1}$$

$$DIS_{t,s} = T^{step,sc} \cdot dis^{cost} \cdot \left| p^{DP}_{0,t} - p_{0,t,s} \right| \tag{4.3}$$

$$ACT_{t,s} = T^{step,sc} \cdot \sum\nolimits_{b=0}^{B} act^{cost}_b \Big/ 2 \cdot \left| p^{bess}_{b,t,s} \right| \tag{4.4}$$

The scheduling objective function (4) is the sum over N^{sc}_t future time intervals (e.g. 24 h) and N^{sc}_s forecast scenarios considered, of four economic terms:

- Gain from EA, i.e. the buying and selling of electricity at GCP that exploits price fluctuations to buy cheaply and resell at higher prices.
- Gain from the amount of incentive collected from a REC CSC.
- Penalty related to the dispatchability (DIS) of the dispatch plan and thus to the charges to be paid in case of imbalances.
- Penalty related to the activation cost (ACT), a parameter needed to preserve the battery's life.

$T^{step,sc}$ is the time step used in the scheduling problem, typically equal to 1 h or 15 min, depending on the market. $EP_{t,s}$ is the energy price and csc^{inc} is the value of the incentive for the CSC of a REC. In EU countries an indicative value of the incentive is around 120 €/MWh but may change from state to state depending on regulations. csc^{value} is the REC CSC that is the self-consumption of the aggregate of all community members: producers, prosumers and consumers together. It can therefore be calculated with Eq. (4.2.1) as the minimum on an hourly (or quarterly) basis between the energy fed into the grid and the energy withdrawn by all the members of a REC. In the calculation of total withdrawals, the energy withdrawn from BESSs also counts. Energy input from storage systems does not contribute to the CSC. This detail may also vary from state to state, but basically, the energy withdrawn from a grid-connected BESS for subsequent feed-in must only be counted for CSC once, either in withdrawal or in feed-in.

$\widehat{p}^{pv}_{b,t,s}$ and $\widehat{p}^{load}_{b,t,s}$ are the PV production and load forecasts.

$DIS_{t,s}$ (Eq. (4.3)) is a penalty related to the dispatchability of the dispatch plan at time t concerning the realization of the scenario s, which is calculated as a dispatchability cost dis^{cost} for the absolute value of the imbalance $\left|p^{DP}_{0,t} - p_{0,t,s}\right|$, i.e. the difference between the active power realized at the GCP in a certain scenario at a certain time step and the power bidded according to the dispatch plan. It is important to highlight that dis^{cost} corresponds neither to the imbalance price nor the difference

[1] The term SoE refers to the amount of energy stored in the BESS that is the quantity explicitly constrained via Eq. (1.11). The usage of the term state-of-charge (SoC) is intentionally avoided, as this is typically used to indicate the amount of charge stored in a battery.

between the imbalance price and the energy price, dis^{cost} is merely a weight for the dispatchability of the dispatch plan. Considering such prices within the scheduling problem would require that these, as the sign of zonal imbalance, can be forecast with sufficient accuracy. Unfortunately, such forecasts are not currently possible given the current lags with which the transmission system operator usually reports data.

Eq. (4.4) defines the cost of using BESSs necessary to preserve their lifespan, as it was proposed and studied in [52]. The higher the activation cost parameter, the fewer cycles the BESSs will undergo and the longer their life will be. With lower values, the BESSs will be used more frequently, in particular, to take advantage of small price fluctuations on the markets, thus increasing earnings but shortening their lifetime. An optimum value can be found for each context of use.

At the end of every hour, the CoDistFlow scheduling problem calculates and updates the dispatch plan for the following hours (e.g. 24 h). Assuming intraday market participation, at the end of each hour H the dispatch plan for hour H + 2 is bidded on the market (see Fig. 1).

The scheduling optimisation problem, as the control one explained in the next paragraph, is solved with the Branch and Bound method available in the Gourbi solver [53]. In any case, every other solving method for constrained optimization problems should be suitable. The computation time of the scheduling problem is in the order of few minutes, depending on the size of the network considered. For the specific case study discussed in Section 3, by using a 32 GB RAM machine equipped with an Intel Core i7 processor, it is about 40 s. This time appears compatible with a scheduling to be repeated once every hour.

2.4. Real-time control

Within the hour, based on short-term forecasts until the end of the hour and realizations since the beginning of the hour, a real-time control optimization problem decides the BESSs set points every real-time control timestep $T^{step,rt}$ (in our case every 30 s), to minimize the hourly dispatch error (see Fig. 1).

The real-time control optimization problem consists of a CoDistFlow scheme in which the iDistFlow model is composed of Eqs. (1.1)–(1.13) defining variables and constraints $\forall b \in B, \forall t \in T^{rt}$ and Eq. (5) defining the objective function to be minimized. The decision variables are $p_{b,t}^{bess}$ and $q_{b,t}^{bess}$, in each node and timestep until the end of the hour H.

$$f_{obj,rt} = T^{step,rt} \cdot N_t^{rt} \cdot p_{0,t=H}^{DP} - T^{step,rt} \cdot \left(\sum_{t=H}^{\bar{t}} \bar{p}_{0,t} + \sum_{t=\bar{t}}^{H+1} p_{0,t} \right) \tag{5}$$

Eq. (5) and Fig. 5 define and explain the objective function of the real-time control: it is defined as the hourly imbalance, i.e. the difference between the energy bidded according to the dispatch plan (first addend of the equation and orange area) and the energy absorbed at the GCP (second addend of the equation). The second addend is the sum of the energy already realized from the beginning of the hour to the present time $\bar{t}$ (red area), and the energy expected to be realized from $\bar{t}$ to the end of the hour (green area). The latter depends on the short-term forecast of PV and load ($\hat{p}_{b,t}^{pv}$, $\hat{q}_{b,t}^{pv}$, $\hat{p}_{b,t}^{load}$ and $\hat{q}_{b,t}^{load}$) and from the variable to be optimized $p_{b,t}^{bess}$ and $q_{b,t}^{bess}$. $p_{0,t}$ depends on the variables just mentioned, i.e. the state of the network, which is resolved via the Eqs. (1.1)–(1.13).

The control can be defined with a shrinking horizon as the size of the variable to be optimized decreases as it approaches the end of the hour.

$T^{step,rt}$ and N_t^{rt} are respectively the size of the time interval (30 s) and the number of intervals (120, the number of 30 s interval in 1 h). They are needed within Eq. (5) to calculate the energy values by multiplying the power values.

The first values of $p_{b,t}^{bess}$ and $q_{b,t}^{bess}$, i.e. $p_{b,0}^{bess}$ and $q_{b,0}^{bess}$ are used as BESS set points and updated by a new real-time control optimization every real-time control step. It is fair to note that in Fig. 5 $p_{b,t}^{bess}$ is constant until the end of the hour, as the short-term forecasts used in this study are also constant. But by using more accurate short-term forecasts, the real-time control problem formulated as explained in this paper could calculate a BESS set point that varies from $\bar{t}$ until the end of the hour, and in this case, the set point to be sent to the inverter would only be the first one ($p_{b,0}^{bess}$).

The proposed control framework always guarantees convergence. Indeed, as formally demonstrated in [5], the coDisFlow scheme always converges to the global optimum point after only a few iterations. The objective function added to the scheme by this study provides penalties but no additional constraints to the original scheme, which allows convergence to always be achieved, albeit with additional costs in terms of, for example, dispatchability. In addition to this feature, the optimization algorithm is also solved quite rapidly: in fact, convergence time for the considered grid (see Section 3) is on the order of a tenth of a second on a 32 GB RAM machine equipped with an Intel Core i7 processor.

3. Study case simulation and experimental results

The scheduling and control models were evaluated through both simulations and experiments to test the feasibility of a small Renewable Energy Community (REC) self-dispatching using a collective battery. While the experiment involved a single BESS, the methodology is designed to accommodate multiple batteries.

This section details the case study and experimental setup, describes the forecasting methods employed, presents the results from simulations and a 24-hour experiment with real-time control executed every 30 s. At the end of the section, a further simulation of the grid adopted for the experiment is carried out to compare the effectiveness of the proposed method versus one that does not consider the grid model and associated constraints.

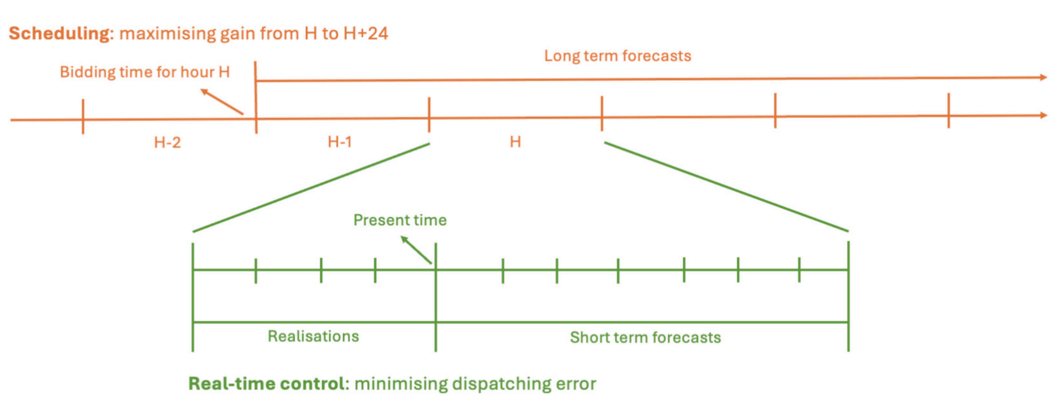


Fig. 1. Scheduling and real-time control scheme.

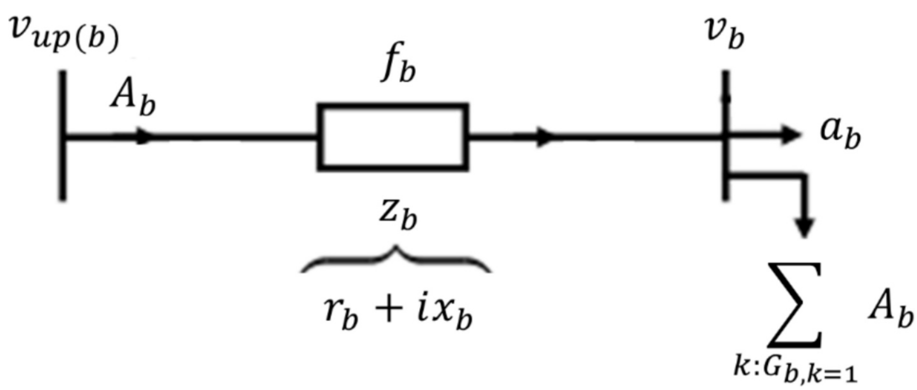


Fig. 2. Branch-flow model (adapted from [43]).

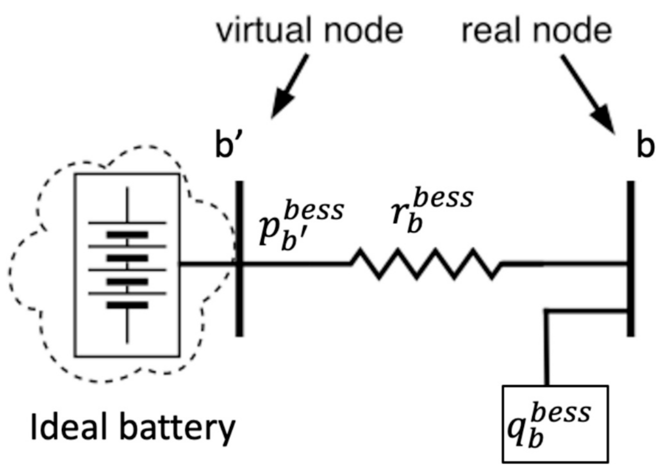


Fig. 3. Battery equivalent resistance model. Adapted from [43].

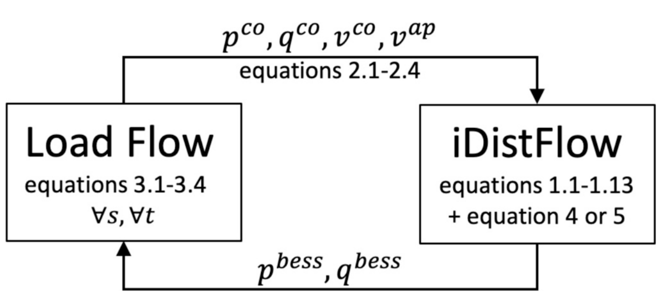


Fig. 4. CoDistFlow iterative scheme. Adapted from [43].

3.1. Study case and experiment setup

The study case (Fig. 6) focuses on a portion of the microgrid at the Distributed Electrical Systems Laboratory (DESL) of École Polytechnique Fédérale de Lausanne (EPFL), modelled on the CIGRE microgrid benchmark system [54]. This radial low-voltage (LV) grid includes seven lines and eight buses, hosting a 20 kWp Zenone virtual load generator, a 60 kWh/20 kWp lithium-ion battery, and two PV systems: 16 kWp on the roof and 14 kWp on a vertical façade, for a total PV capacity of 30 kWp.

Time-synchronized measurements are collected at the grid connection point (GCP, Bus B0) and other asset-connected buses via Phasor Measurement Units (PMUs) capable of 50 frames per second, as described in [55,56]. The BESS uses a National Instruments CRIO 9068 real-time microcontroller to handle tasks such as State of Energy (SoE) measurement, feasible set-point implementation, and communication with the upper-level real-time controller. These functions are implemented in LabView. To investigate further into the literature on methods for estimating the SoE of Lithium-based batteries, we recommend starting with [57].

Communication within the microgrid is managed over a secure IPv4 network using a multicast security protocol [58], while data exchange and storage leverage a centralized time-series database based on InfluxDB.

The resistances, impedances, and ampacities of the lines are known (see table in Fig. 6).

The setup replicates the aggregate demand profile of 10 residential households, each with a typical consumption of 2700 kWh/year, 6 kWh of storage, and 3 kWp of PV capacity. Load curves are generated using ARERA profiles [59], enhanced with randomness modelled through a Weibull distribution (shape parameter = 1.4, scale parameter = 0.5) derived from Pecan Street residential data [60]. These values are adjusted hourly to align with ARERA averages, and load values are extracted every 5 min for aggregation in the Zenone load generator.

The PV systems comprise 200 W modules in three strings for the 14 kWp façade system, connected to a Solis-3P12K-4G inverter with two MPPTs. The 16 kWp rooftop system includes 255 Wp modules in four strings, connected to two Solarmax inverters with two MPPTs each. An additional 13 kWp inverter on the roof was kept offline during the experiments.

3.2. Forecasts

Long-term scenario forecasts for production, load, and energy prices are essential for scheduling, while short-term forecasts (up to the end of the hour) are required for real-time control. This study does not focus on the forecasting of stochastic generation, allowing the interested modeler to use their preferred method. In this work, simple and reproducible techniques were employed, emphasizing the robustness of the experimental validation, as performance is expected to improve with more precise forecasting models. More specifically, 40 scenarios of hourly global horizontal irradiance (GHI) were obtained from a meteorological service [61], updated every 6 h with three-day forecasts (only the next 24 h were used due to service limitations). Historical data and two empirical models were used to convert GHI into active power output for the PV systems. For each PV scenario, a corresponding load scenario was generated using the distributions described earlier, resulting in 40 combined scenarios. To balance computational costs, the number of load scenarios was limited to 40, aligning with the GHI scenarios. One scenario was randomly selected as a realization for the load generator.

Unlike production and consumption, the hourly energy prices on the intra-day market are considered deterministically. That is, these prices are assumed to be known. This assumption is quite close to reality considering that the energy prices on the intra-day market are not very different from the prices on the day-ahead market, which are already

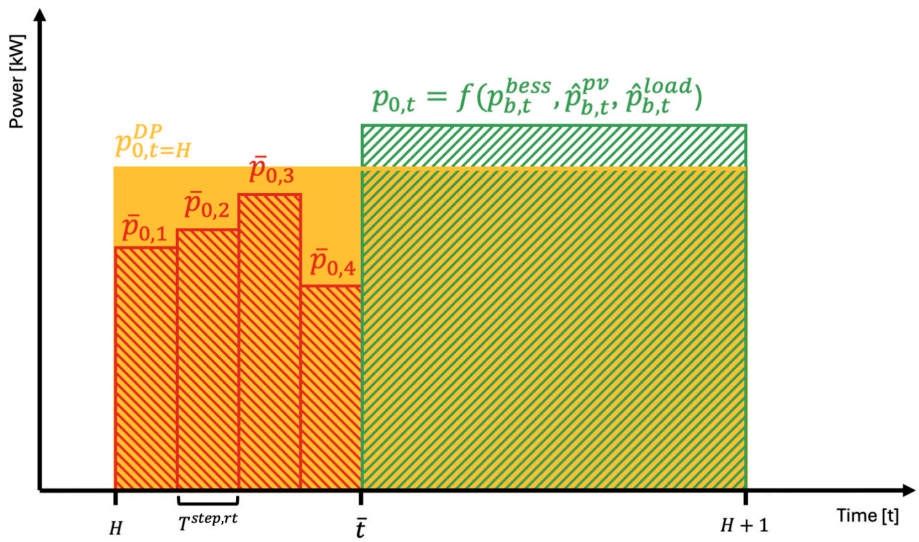
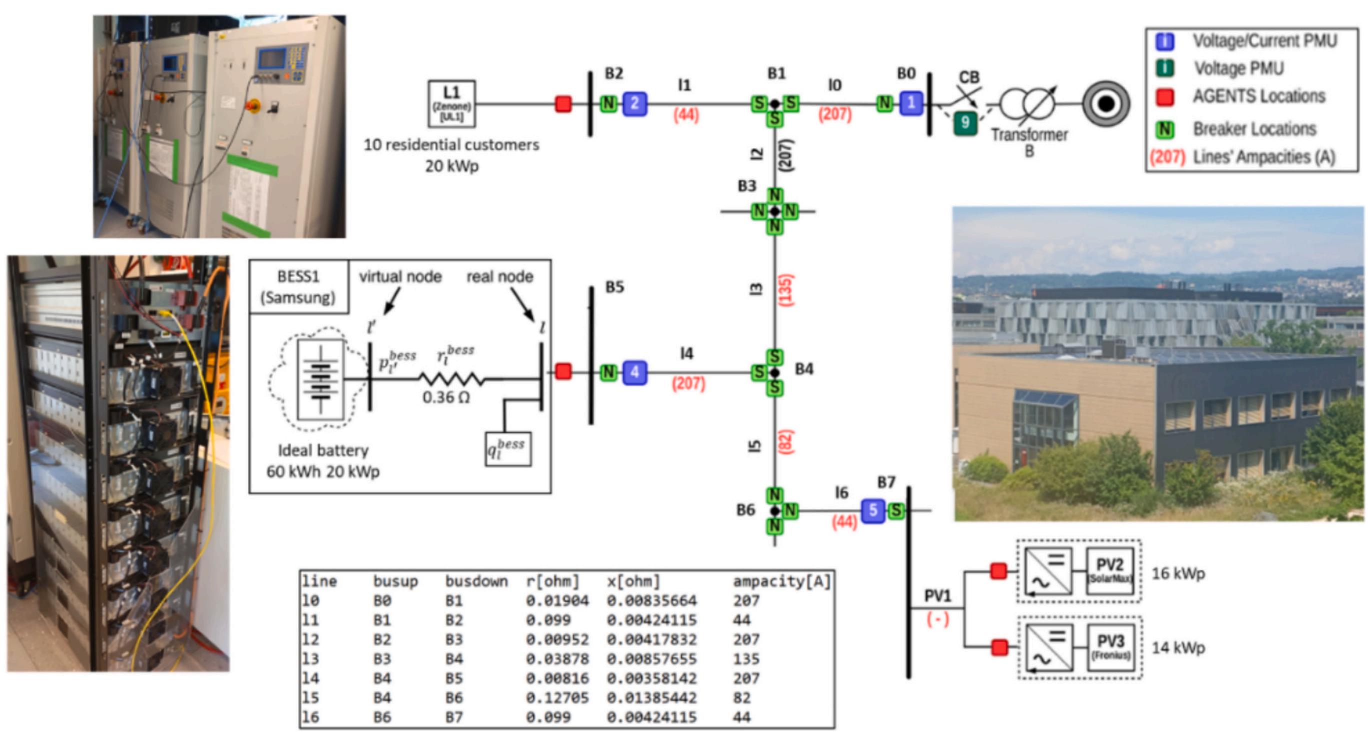


Fig. 5. Real-time control objective function explanation figure.



line	busup	busdown	r[ohm]	x[ohm]	ampacity[A]
l0	B0	B1	0.01904	0.00835664	207
l1	B1	B2	0.099	0.00424115	44
l2	B2	B3	0.00952	0.00417832	207
l3	B3	B4	0.03878	0.00857655	135
l4	B4	B5	0.00816	0.00358142	207
l5	B4	B6	0.12705	0.01385442	82
l6	B6	B7	0.099	0.00424115	44

Fig. 6. Case study: the microgrid!

known at scheduling time. The hourly price variations are based on factors like season, time of day, and electricity usage patterns (e.g., business hours, residential heating/cooling needs). Historical data on Italian electricity market prices are openly available for reference [62].

In real-time control, short-term forecasts for PV production and loads were derived using simple moving averages, updated every 30 s based on the preceding 5 min of data.

3.3. Simulations

This section presents simulations to evaluate the impact of key parameters on scheduling: weather forecasts, the dispatchability weight parameter in the scheduling objective function (Eq. (4.3)), and network line ampacity constraints (Eq. (1.7)). Simulations of BESS activation penalties (Eq. (4.4)) are excluded, as they have been extensively analysed in a previous study by the author [8]. Subsequent sections discuss the results of a real-time experiment and a comparative simulation using a non-grid-aware method.

Fig. 7 illustrates the scheduling process starting at 00:00 for the following 24 h under three weather conditions: variable, sunny and cloudy. The figure comprises six key rows:

1. PV Hourly Production Scenarios: Forty scenarios generated from meteorological irradiance forecasts.
2. Residential Load Scenarios: Forty scenarios derived from Italian residential profiles and Weibull distributions.

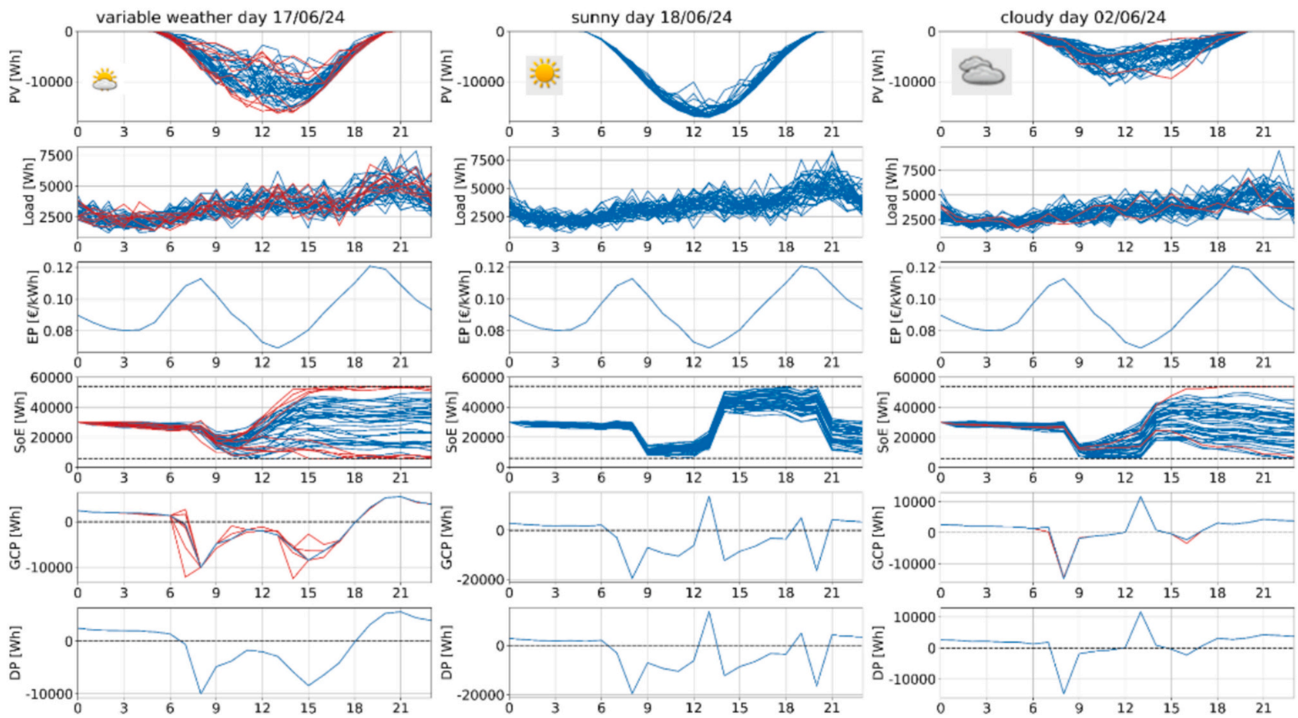


Fig. 7. Scheduling and dispatchability dependence on weather forecast.

3. Energy Price Forecast: A single scenario assuming day-ahead prices, representing the average Italian price over the past year for comparability.
4. BESS State of Energy (SoE): BESS usage trajectories optimized for scheduling objectives across all scenarios.
5. The active power at the GCP in each scenario. The more the powers in each scenario coincide, the more dispatchable the dispatch plan is. The dispatchability penalty increases the more different the scenarios are and is zero if they are all coincidences, i.e., if thanks to the BESS it is possible to cope with all the uncertainty due to production and load forecasts.
6. Dispatch Plan: The optimized plan minimizing deviations across all scenarios at GCP.

Red scenarios are those that involve dispatch errors due to high uncertainty in forecasts and resulting in the activation of the battery SoE limiting constraints.

Fig. 7 shows the following results under three different weather conditions:

- Variable Weather: High forecast uncertainty leads to seven scenarios over forty with dispatch errors due to extreme irradiance variations. The BESS may fully charge or discharge, limiting its ability to manage errors in real time. Under these conditions, the priority on dispatch (via high dispatchability cost weights dis^{cost}) reduces the ability to leverage EA or CSC.
- Sunny Weather: Reliable forecasts enable effective dispatch with no errors. The scheduling plan optimizes EA and CSC by discharging the BESS during price peaks (e.g., 8 a.m. and 7 p.m.) and charging during low-price periods (e.g., 1 p.m.).
- Cloudy Weather: Moderate uncertainty is manageable by the BESS, resulting in only two scenarios with minor dispatch errors. While EA and CSC are achievable, they are less effective than under sunny conditions.

These simulations highlight the critical role of forecast accuracy, BESS capacity, and dispatchability prioritization in optimizing REC performance under varying weather scenarios.

As shown in the graphs in Fig. 7, priority is given to dispatchability, meaning the dispatchability cost parameter dis^{cost} is high compared to energy prices and activation costs. Fig. 8 illustrates the variation in scheduling based on the value of dis^{cost}. If it decreases, less importance is given to dispatch ability, thus allowing for dispatch errors, that is, scenarios even very different from the GCP, in favour of gains from EA and CSC obtained by using the BESS up to its limits.

To demonstrate the scheduling model's ability to account for grid constraints, a simulation (Fig. 9) reduces the ampacity of Line 0 (connecting the GCP as the upstream bus). This forces the model to optimize within the ampacity limit, resulting in a lower maximum current for the line. Consequently, the dispatch plan and battery active power are adjusted, distributing the same energy over longer periods. While this approach ensures grid compliance, it limits the ability to fully exploit peak and off-peak energy price differences.

In the studied case, network constraints were not naturally activated due to the low power levels relative to line ampacities. However, including such constraints in the model is crucial for scalability and adaptability. The proposed framework can handle any radial low-voltage (LV) network and can be extended to medium-voltage networks by incorporating shunt elements into the branch-flow model, accommodating both controllable BESSs and uncontrollable resources.

3.4. Experimental results

To validate the scheduling and real-time control models, a 24-hour experiment was conducted in the microgrid to test the ability to follow the dispatch plan updated hourly. Every hour, 3 min before the end, the scheduling model recalculated the dispatch plan. Real-time control adjusted the BESS set points every 30 s to minimize hourly dispatch errors.

The experiment began at 7:57:00 AM on June 26. To challenge the proposed model, a partially cloudy day with high forecast uncertainty has been deliberately chosen. The left side of Fig. 10 illustrates the initial scheduling, showing consistency between GCP power and the dispatch plan across scenarios, despite variations in BESS behaviour. Two EA

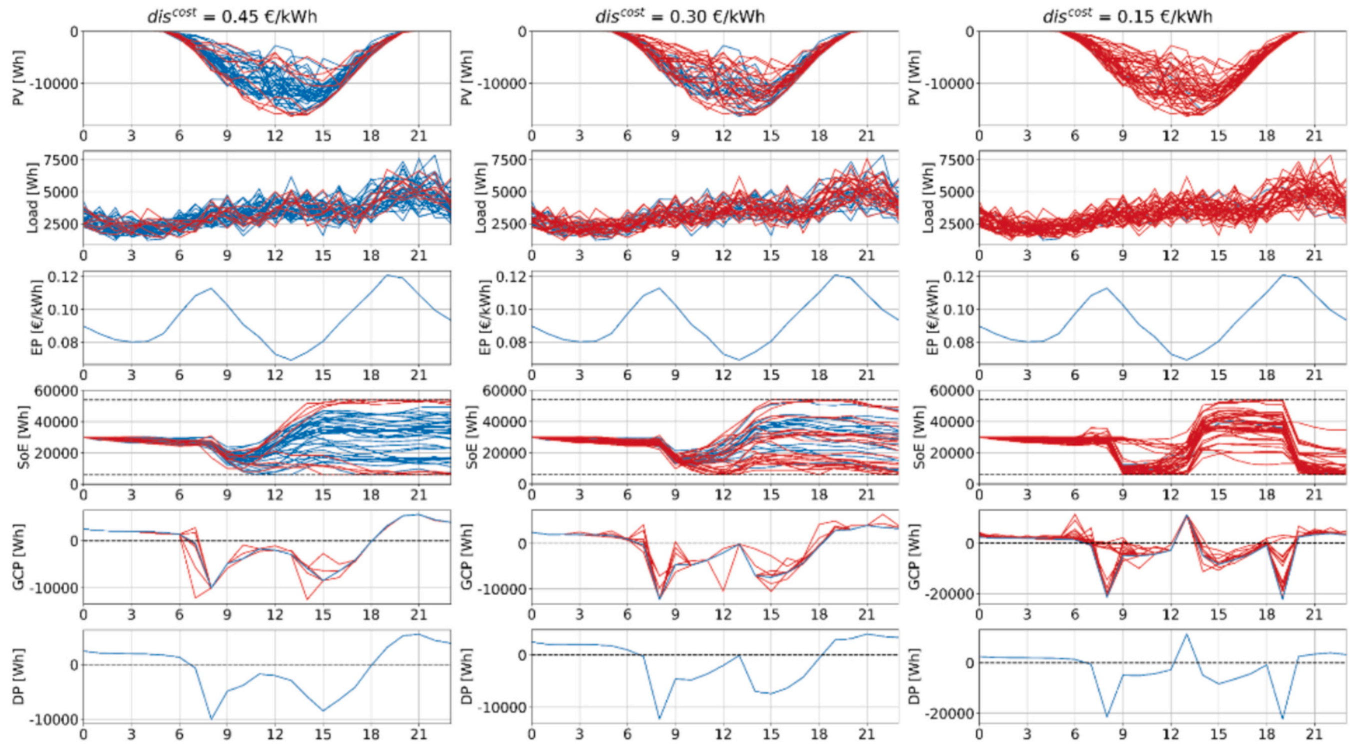


Fig. 8. Scheduling and dispatchability dependence on dispatching cost parameter.

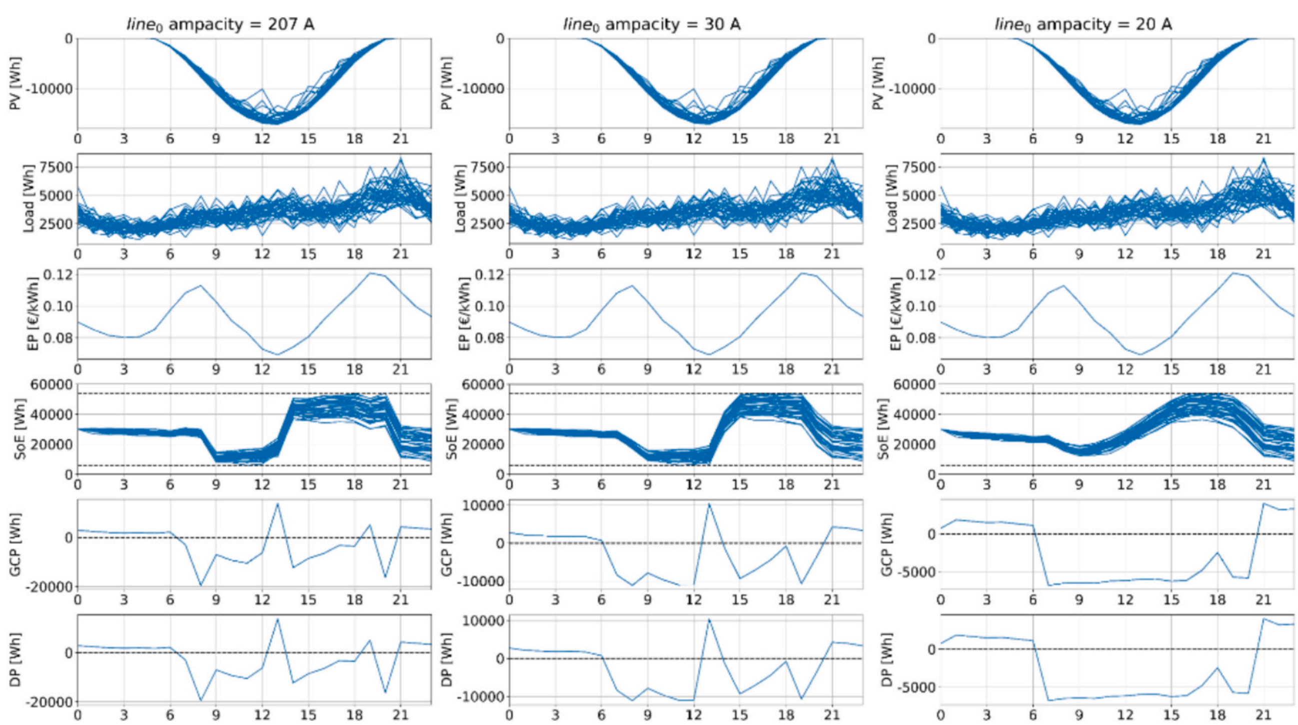


Fig. 9. Scheduling dependence on grid constraints.

main actions were scheduled: charging at low prices (1 PM) and discharging at peak prices (8 PM).

Real-time control began at 8:00:30 AM and ran continuously. The measurement data are real, read directly from the signals sent by the PMUs every 50 milliseconds and integrated every 30 s.

In the morning, solar production matched higher forecast scenarios, allowing the BESS to charge as planned. However, at 1 PM, an unexpected black cloud halted PV production until 4 PM, causing the BESS to discharge to meet the dispatch plan. Despite this unpredicted scenario, recalculating the dispatch plan hourly based on the BESS SoE avoided full depletion and adjusted expectations dynamically (Fig. 11). For example, the 5 PM dispatch plan omitted evening discharging due to insufficient energy.

The results showed the dispatch plan was closely followed, with

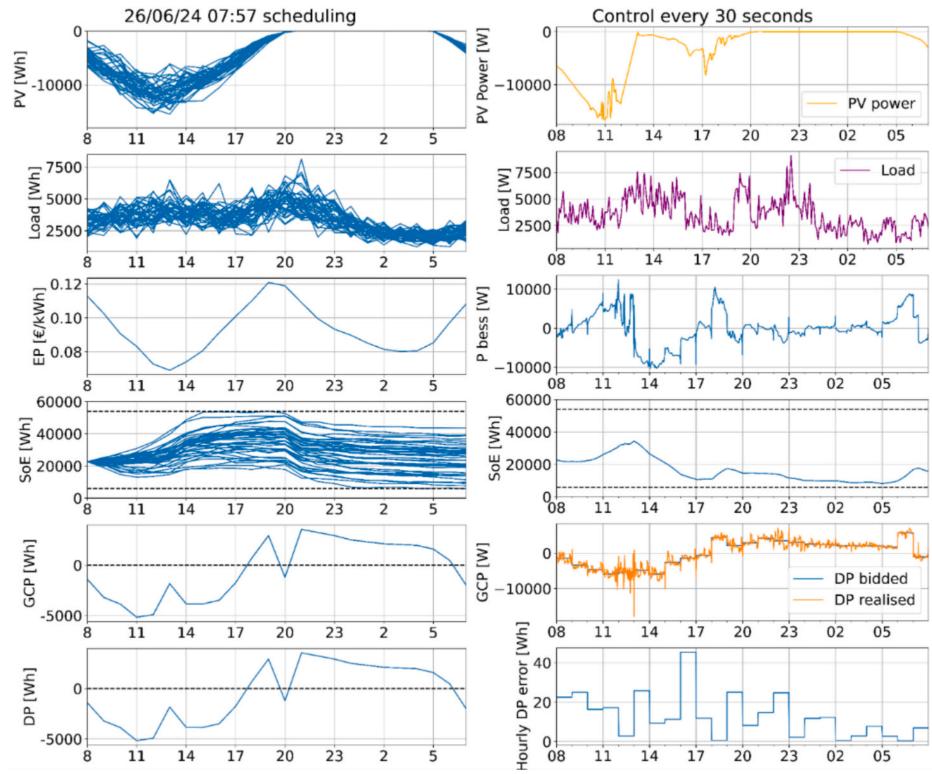


Fig. 10. Results of a 24-hour experiment.

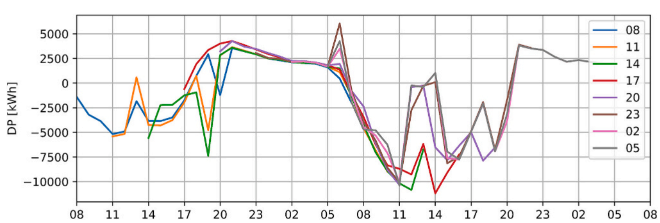


Fig. 11. Evolution of the dispatch plan hour after hour.

hourly errors limited to 307 kWh/24 h. Power peaks were observed at the end of each hour, as real-time control corrected deviations caused by last-minute load and production oscillations.

In conclusion, the real-time control system effectively managed significant forecast errors by recalculating the dispatch plan hourly. Future improvements include enhanced short-term forecasts, potentially through roof-mounted cameras to track cloud movements for more accurate predictions.

3.5. Comparison between the proposed method and a non-grid-aware method

To emphasize the importance of grid modelling in scheduling and control algorithms, a simulation of the same experiment described in the previous sub-section is performed by removing grid constraints and losses from the optimisation problem. The results, shown in Fig. 12, underscore the critical role of grid-aware modelling. Without it, scheduling and real-time control processes are significantly less effective.

Indeed, the absence of grid constraints leads to substantial dispatch errors and inefficiencies. Scheduling is altered compared to Fig. 10, but the most critical issues arise during real-time control. Large power spikes occur at the end of each hour as the system struggles to correct dispatch errors in the final minutes. This is caused by the fact that the model is unaware of the system losses and, at the end of each dispatching period, the energy associated to these losses is accumulating and seen by the controller as a non-negligible disturbance. By 2 PM, the battery is fully discharged, rendering it unable to compensate for subsequent dispatch errors. Additionally, the lack of grid-aware signals prevents proper scheduling for recharging, exacerbating errors throughout the day.

This highlights the necessity of including grid modelling in both scheduling and control processes, as many models in the literature neglect these aspects. The experiment confirms that such omissions can only be identified and addressed through practical validation.

While incorporating grid modelling increases computational costs, the trade-off is justified. Table 1 compares the performance metrics of the grid-aware and non-grid-aware approaches. Without grid modelling, scheduling and control converge faster (15 s and 0.02 s, respectively) but result in a total dispatch error of 77’309 kWh/24 h. By contrast, the grid-aware method, despite requiring 83 s for scheduling and 0.1 s for real-time control, reduces the error to just 307 kWh/24 h. These findings validate the superior performance of grid-aware scheduling and control algorithms and reinforce the necessity of detailed grid modelling for effective BESS management in RECs.

4. Conclusions

This study introduces a novel and comprehensive framework for managing Battery Energy Storage Systems (BESSs) in Renewable Energy Communities (RECs). As the first example in the literature, the proposed approach incorporates into a single optimization framework three key services for REC: dispatching, energy arbitrage and collective self-consumption. This framework incorporates forecast uncertainties handling and a detailed electrical grid model.

An experimental validation carried out on a real microgrid demonstrates the effectiveness of the proposed framework, confirming its applicability in real-world scenarios and its ability to address the unique challenges of REC operations.

In a 24-hour real-world test, dispatch errors were minimized to just 307 kWh/24 h, even under conditions of high forecast uncertainty. The

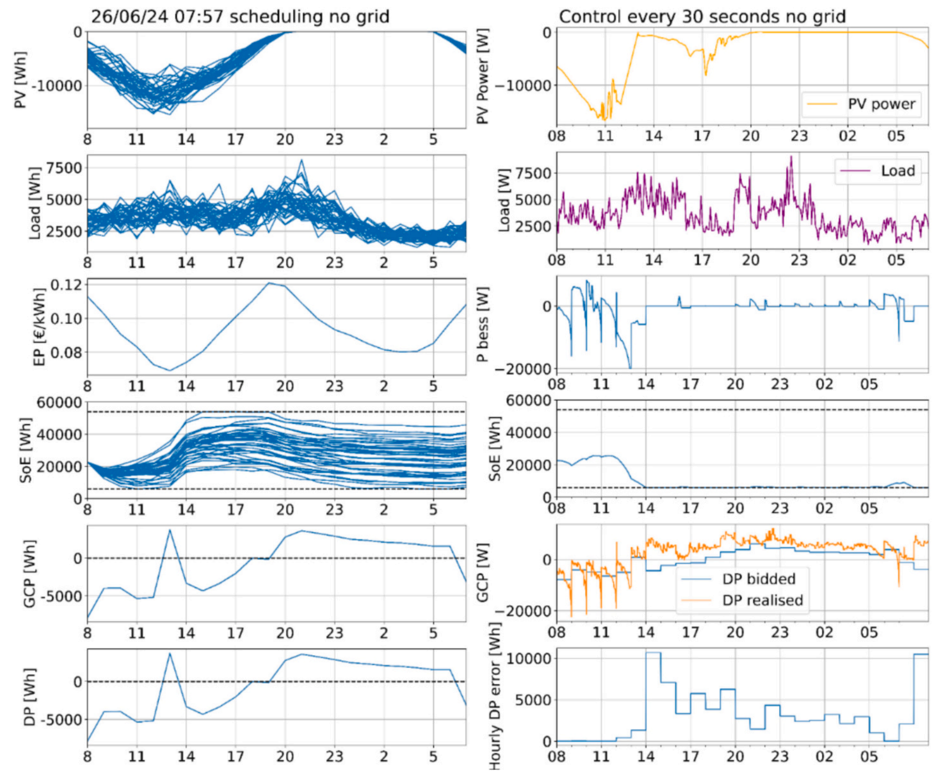


Fig. 12. Re-simulation of the experiment discussed in Section 3.4 with a non-grid-aware method (i.e., without the grid model and its constraints).

Table 1
Comparison indexes methods.

Method	Scheduling time [s]	Control time [s]	Dispatch error [kWh/24 h]
Gird-aware	83	0.1	307
Non-grid-aware	15	0.02	77'309

real-time control effectively corrected for sudden deviations, such as those caused by unexpected weather changes, ensuring the dispatch plan was closely followed throughout the day. The scheduling model demonstrated flexibility in adapting to variable scenarios while maintaining operational feasibility.

Compared to a non-grid-aware approach, the proposed method offers a drastic improvement in containing dispatch tracking errors. Dispatch errors were reduced from 77,309 kWh/24 h to 307 kWh/24 h, demonstrating the importance of grid modelling. Although computational times slightly increased (83 s for scheduling and 0.1 s for real-time control, against 15 and 0.02 of the non-grid-aware approach), these remain well within practical limits for hourly or sub-hourly operations.

The sensitivity analyses conducted on key parameters revealed that forecast accuracy, the dispatchability cost parameter, and grid constraints are critical for optimizing performance and the simultaneous provision of the three services.

Future work will focus on expanding the experimental validation to larger systems with multiple BESS units and incorporating additional services, such as ancillary services and provision of other local flexibilities. Moreover, improving forecasting tools for short- and long-term predictions is expected to further enhance the framework's effectiveness. These developments aim to solidify the role of RECs as key players in sustainable energy markets and ensure their competitiveness in an increasingly decentralized energy landscape.

The methodology and results are made available through an open-source repository [53], offering a resource for interested researchers and practical implementations.

CRediT authorship contribution statement

Mattia Pasqui: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Francesco Gerini:** Validation, Data curation. **Matthieu Jacobs:** Validation, Data curation. **Carlo Carcasci:** Supervision, Resources. **Mario Paolone:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, 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.

Acknowledgements

Thanks to all the buddies of Distributed Electrical Systems Laboratory for welcoming me during my stay in Lausanne.

Data availability

Data will be made available on request.

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3 CONCLUSIONS

The transition to a decarbonised and decentralised energy system represents one of the most pressing challenges of the twenty-first century. In this evolving landscape, RECs have emerged across Europe not merely as a regulatory novelty, but as the crucial organisational and technical model to empower citizens, placing them at the centre of the energy transition. While European directives have successfully paved the way for the proliferation of RECs by formally recognising their social value and empowering them to participate in energy and flexibility markets, a critical operational gap remained: the effective integration and management of energy storage systems. Batteries and thermal energy storage are essential to unlock the flexibility required for managing distributed renewable generation, yet the literature lacked robust, realistic, and validated methodologies tailored to the technical specificities and regulatory constraints of RECs. Existing works often focused on simplified storage scheduling under idealised conditions, neglecting the harsh reality of forecasting uncertainty, grid constraints, and battery ageing. This thesis addressed these limitations by developing, simulating, and experimentally validating a comprehensive suite of strategies for managing electrical and thermal storage within RECs. The research journey described in these pages was not a mere collection of isolated studies, but a coherent evolution driven by the need to solve progressively complex barriers, ranging from economic viability and forecast uncertainty to grid integration, providing a concrete pathway for RECs to evolve from passive consumers to active market players.

The investigation began by challenging the standard approach of managing distributed resources. In the first phase, detailed in [P1] and [P2], we adopted a paradigm shift from the individual prosumer viewpoint to a community-centric perspective. We introduced a centralised, rule-based management strategy for a fleet of distributed batteries owned by REC members. Tested on a real-world Italian case study, and utilizing the novel LoBi profile generation method to ensure realism in the absence of granular data. This approach demonstrated in [P1] a significant increase in CSC of over 35% compared to uncoordinated operation. This result proved that simple coordination can unlock substantial energy value without penalising individual users. This logic was successfully extended to thermal energy storage coupled with HPs in [P2], enabling load shifting strategies that yielded a further 5% to 8% increase in CSC. However, this analysis also highlighted critical technical trade-offs, specifically the reduction in average coefficients of performance (COP) and increased thermal losses due to higher storage temperatures, proving that thermal management requires careful balancing between energy shifting benefits and efficiency penalties.

Despite the technical achievements in increasing CSC, these initial studies revealed three critical limitations that served as the turning point for the entire thesis. First, the economic analysis in [P1] proved that individual residential batteries currently suffer from prohibitively high specific costs, demonstrating that under current market conditions, the distributed investment model is often financially unsustainable. Second, the study highlighted that the economic gains derived solely from optimizing CSC are too marginal to justify the investment; while the rule-based logic successfully raise the shared energy incentive, the resulting revenue stream was insufficient to cover the investment costs for distributed batteries and generate a positive return on investment for the prosumers. Third, the comparison performed against an optimization-based benchmark (MILP) revealed the inherent limits of rule-based strategies. While robust and simple, the rule-based approach proved structurally unable to match the performance of an optimizer, particularly when tasked with managing complex, multi-objective scenarios. It became evident that to reach economic viability, the system needed to stack additional high-value services, specifically EA, which a simple rule-based logic cannot effectively handle. This negative finding was pivotal, as it motivated the strategic shift of the entire thesis towards aggregated, shared assets to exploit economies of scale.

Responding to these challenges, the research pivoted in [P3] towards a Shared Community Battery model. Here, the methodology evolved from simple rule-based logic to advanced LP optimization. This transition was necessary not only to improve the system efficiency but, above all, to unlock the capability of performing EA. This transition revealed that simply maximising CSC is insufficient to ensure profitability. Through extensive sensitivity analyses on BC and market price scenarios, the study demonstrated that a community battery must be a multi-service asset. The results showed that by combining CSC with EA, it is possible to halve the payback period, making the investment viable even with higher BC. Crucially, the study identified a specific saturation effect where maximizing the number of members is not always the optimal strategy; if the aggregate demand of consumers is too high, it absorbs the entire PV production instantly, rendering the battery redundant for CSC purposes. However, under optimal sizing conditions, a clear trade-off emerged: utilizing the battery solely for CSC is the best choice for grid independence but lacks economic appeal, whereas enabling EA allows the REC to exploit price volatility, transforming the battery from a cost centre into a revenue generator. Furthermore, the study integrated a degradation-aware cost function, proving that optimizing considering battery ageing is essential to prevent aggressive cycling that would otherwise erode the asset lifetime value.

Yet, theoretical profitability is meaningless without market access. Since arbitrage revenues are only attainable if the REC acts as a market player, the final and most significant leap of this thesis was bridging the gap between simulation and reality. In [P4], we addressed the operational risks of acting as a BRP. Recognising that deterministic models were insufficient to handle real-world uncertainty, we developed a robust two-layer control framework, combining stochastic scheduling with real-time control. This system integrates grid modelling via the CoDistFlow convexified AC-OPF model, forecast uncertainty, and battery ageing. Crucially, by experimentally minimising dispatch errors on a physical microgrid, this study validated the REC capability to operate as a reliable BRP providing CSC EA and self-dispatch simultaneously. This result is the keystone of the work: it confirms that the economic potential identified in previous steps is attainable in real-world markets without being eroded by imbalance penalties.

Looking back, the methodological progression from rule-based controls to optimisation-based scheduling, and finally to real-time control, provides a coherent roadmap for the development of RECs. It shows how communities can evolve from basic strategies, suitable for early-stage clusters, to advanced services necessary for mature, market-integrated actors. Naturally, this work also clarifies the boundaries of current knowledge and delineates the specific roadmap for future research, grounded in the operational evidence gathered. While the stochastic optimization successfully managed uncertainty, the reliance on standard forecasting inputs highlighted that prediction accuracy remains the primary bottleneck; thus, future research must focus on integrating high-precision forecasting systems, such as "Hawk Eye" sky imagers combined with AI, to provide ultra-short-term irradiance data essential for reducing real-time dispatch errors to zero.

Additionally, while the experimental validation was conducted on a centralized community battery, many RECs will consist of distributed assets owned by individuals. Consequently, the advanced control architectures developed here must be adapted for Virtual Aggregation, solving the hierarchical optimization challenge of prioritizing the individual owner’s bill savings before aggregating the remaining flexibility for community-level services. Furthermore, to fully decarbonize the local energy mix, future strategies must aim for Hybrid Multi-Energy Optimization, coupling the load-shifting capabilities of HPs with the fast response of batteries. Finally, the natural next step identified is the evolution of the REC from a simple BRP minimizing internal imbalance to a BSP. Future research must extend the control framework to enable RECs to actively bid flexibility into the AS Market and Local Flexibility Markets, providing grid services to TSOs and DSOs, a technological frontier for which this thesis has laid the solid foundation.
In conclusion, this thesis delivers a concrete, validated toolbox for the future of RECs. We have provided tools to accurately simulate economic scenarios, proving that EA is not speculative but essential for covering infrastructure costs. We have proven that under current market conditions, uncoordinated individual investments in residential batteries are financially unsustainable. This finding highlights a critical policy insight: if the widespread deployment of distributed storage is a regulatory goal, stronger dedicated incentives are required to bridge the gap between high CAPEX and limited returns. Without such support, the only economically viable path for RECs currently lies in aggregated, shared assets managed via advanced optimization. Most importantly, we have shown that RECs have the technical maturity to evolve from passive incentive receivers to active grid protagonists. This technical evolution is not an end in itself but a means to a social end: by maximizing revenues through advanced optimization and arbitrage, RECs can generate additional CF. These resources can be reinvested to fight energy poverty, support local development, and fund new renewable projects, ensuring that the community delivers on its promise of environmental and social sustainability.
Finally, the research presented in this thesis has already moved beyond the academic domain. The author has personally established a REC and is currently applying the models and strategies developed in this thesis for the optimised management of its battery fleets. This stands as the ultimate validation of the work: a bridge crossed from theory to tangible reality. The reader is invited to contact him to find out more [123].

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