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Energy Management Systems for Energy Communities

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Preface

The PhD activity was carried out at the Engineering Department of the University of Palermo (Italy) from November 2022 to November 2025.

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Abstract

The global energy sector is undergoing a profound transformation driven by environmental, economic, and geopolitical pressures associated with conventional energy production. The long-standing reliance on fossil fuels, while historically enabling industrial growth and societal development, has led to significant challenges, including greenhouse gas emissions, climate change, resource depletion, and geopolitical dependencies. Recent estimates indicate that fossil fuel reserves may be exhausted within a few decades, while current global warming trends pose severe risks to ecosystems and human societies. These concerns necessitate a transition toward sustainable, resilient, and decentralized energy paradigms.

In this context, Energy Communities (ECs) have emerged as a promising solution to address both environmental and structural inefficiencies of traditional power systems. The concept of collective energy management is not entirely new; historically, communities have cooperated to harness shared energy resources such as windmills, watermills, and district heating systems. However, modern ECs extend this concept through the integration of distributed energy resources (DERs), advanced communication technologies, and intelligent energy management systems. Formalized within recent European regulatory frameworks, including Renewable Energy Communities (RECs) and Citizen Energy Communities (CECs), ECs enable active participation of consumers (now “prosumers”) in the generation, storage, sharing, and trading of energy.

The transition from fossil-fueled centralized to green decentralized energy systems introduces multiple technical and operational advantages. ECs contribute to reducing transmission losses by promoting local consumption of locally generated energy, thereby minimizing long-distance energy transfer. They enhance grid reliability and resilience through distributed generation and storage, enabling functionalities such as controlled islanding and improved fault tolerance. Furthermore, ECs if coordinated perfectly, can mitigate peak demand pressures, reduce dependence on expensive and polluting peaker plants, and facilitate better integration of renewable energy sources. From a socio-economic perspective, ECs foster user engagement, promote energy awareness, and enable fair distribution of benefits among participants. These characteristics position ECs as key enablers of future smart grids and sustainable energy transitions.

Despite their advantages, several challenges hinder the large-scale deployment of ECs. These include the need for scalable coordination mechanisms, privacy concerns related to user data sharing, computational complexity of centralized optimization approaches, and the

risk of blind behavior preventing collaboration in decentralized decision-making processes. Existing methods often rely on centralized control architectures, which conflict with the decentralized nature of ECs and require extensive data access, raising privacy and scalability issues. Alternatively, fully decentralized approaches may suffer from inefficiencies or lack of convergence guarantees.

This PhD thesis addresses these challenges by proposing a secure, distributed, and scalable energy management framework for Energy Communities. The core contribution of this work lies in the development of a decentralized optimization approach based on game-theoretic principles, where each participant independently optimizes its local energy schedule while interacting with others through aggregated system signals. The method employs a best-response iterative mechanism that converges toward an equilibrium state, ensuring coordinated behavior without requiring full information exchange.

To preserve user privacy, the proposed framework integrates cryptographic techniques, including secure aggregation and partial homomorphic encryption mechanisms, allowing the computation of global variables (such as total load or generation) without revealing individual user profiles. This ensures that sensitive consumption and generation data remain confidential while still enabling system-wide coordination. Additionally, the method is designed to be computationally efficient and does not rely on high-performance computing resources, making it suitable for real-world deployment in large-scale communities.

Another key contribution of this thesis is the formulation of an objective function based on the concept of minimizing mismatch between generation and consumption, effectively maximizing self-consumption and shared energy within the community. The framework incorporates realistic constraints, including appliance scheduling, user comfort, and battery operation. The interaction between users is modeled as a non-cooperative game, and the convergence properties of both simultaneous and sequential decision-making schemes are investigated.

The proposed methodology is extensively validated through multiple simulation scenarios. These include analyses of systems with and without energy storage systems (ESS), sensitivity to battery capacity, scalability with increasing number of users, different load and generation patterns, and the impact of collaboration among participants. The results demonstrate that the proposed approach effectively increases shared energy, reduces grid dependency, and achieves stable convergence under various operating conditions. Furthermore, the study highlights that user participation and willingness play a critical role in the overall performance of ECs, emphasizing the importance of incentive design alongside technical solutions.

The structure of this thesis is organized as follows. Chapter 1 introduces the background, historical evolution, and fundamental concepts of ECs, along with their benefits and challenges. Chapter 2 reviews the state of the art in EC modeling, control architectures, and optimization techniques, identifying key research gaps addressed in this work. Chapter 3 presents the proposed methodology, including regulatory considerations, system modeling, mathematical formulation, secure distributed scheme, and game-theoretic framework. Chapter 4 provides simulation results and detailed discussions, covering multiple case studies related to storage, scalability, convergence behavior, and grid interaction. Finally, Chapter 5 concludes the thesis by summarizing the main findings and outlining potential directions for future research.

In summary, this work contributes to bridging the gap between theoretical models and practical implementation of ECs by offering a privacy-preserving, distributed, and scalable energy management solution. The proposed framework aligns with the evolving regulatory landscape and technological advancements, providing a viable pathway toward efficient, resilient, and user-centric energy systems.

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Chapter 1

Introduction

1.1 The History

Metaphorically speaking, societies and civilizations as bodies necessitate energy as blood for their survival. It has been millennia that different forms of energy have enabled humans to get survived, be civilized, develop, and increase their convenience. Noticing every single milestone in civilizations would reveal the role of energy, from the discovery of fire and resultant crafts and sailing development due to wind energy harness, to the Industrial Revolution, and future forms of energy such as nuclear fusion. In addition to the improvements, energy plays a salient strategic role in the development of nations and massively affects their international geopolitical power and brings them an upper hand in controversies [84]. Due to the mentioned importance, high capital investment, and technological requirements, energy has traditionally been supplied in bulk by governments or large corporations, transmitted through centralized infrastructure, and distributed to end users. Also, this centralized scheme of energy route is mainly consolidated by the essence of fossil fuel resources and the required expensive excavation apparatus. However, there are long-term disadvantages to this scheme. The effects of global warming due to pollution emitted from fossil fuels in recent decades have set the alert that the traditional scheme of energy conversion should be modified, or the most catastrophic event of the century will make the planet inauspicious for living [92]. Also, political dependencies and the rapid depletion of fossil resources intensify the motivation to modify the current trend.

On one hand, thanks to the recent developments in power electronics, materials, and communication technologies, the use and integration of renewable and green resources have been economically justified. Both attractions (from renewable energy resources development) and repulsion (from the cons of fossil resources) reasons have persuaded governments to boost the movement toward a green world in terms of sustainability and resiliency. The following table compares different aspects of traditional resources and renewable distributed resources.

With the emergence of affordable technologies to control, exploit, and integrate such

Parameter	**Traditional Centralized Resources**	**Renewable Distributed Resources**
Types	Electrical, Thermal, Mechanical	Electrical, Thermal, Mechanical
Applicable Size	Medium, Bulk	Small, Medium
Accessibility	Regionally restricted	Geographically widespread
Pollution	High	Low to medium
Energy Carriers	Oil, Gas, Uranium, Coal, Water (gravitational)	Direct solar radiation, indirect radiation (wind, tidal)
Control	Controllable, Dispatchable	Controllable, semi-Dispatchable
Installation Cost	Medium to high	High
Operation Cost	Medium	Low

Table 1.1: Comparison between traditional and distributed renewable resources

distributed resources, the centralized scheme of the energy route is about to lose its monopolistic role. The trait of being distributed, accessible all over the world regardless of a specific region, scalable, and applicable for a wide range of power demands, has led to a paradigm shift in energy provision schemes. Such resources are not in the control of empowered minorities, governments, or a specific country or region (such as oil, gas, coal, uranium, etc.), therefore, each entity, from a person to a government, can benefit from these resources through generation, consumption, or reservation. The mentioned attributes have allowed the users to interact with the utility actively. It has been decades since the end nodes of such systems are equivalent to the term “user”. Users passively consume the power, and the only controllable factor that they enjoy is the amount of consumption and associated time. However, with the advent of energy storage and DERs, the “users” can emulate generation entities. Therefore, the word “user” may be changed to “end nodes” since they are not only consumers but also able to offer a variety of services actively. The aforementioned end nodes in such a scheme may aggregate together or may operate solely to offer their services. Simply speaking, aggregation of these end nodes from a system that is called **"energy communities"** and can include a variety of members from a person to a company.

1.2 Definition and Typologies

According to the EU definition of energy community (EC) in Clean Energy Package (CEP), energy community refers to collective energy actions that foster citizens’ participation across the energy system [19]. Two expansions of the definition are presented in which some differences are visible. The first one, which was introduced in 2018 and accents the renewable resources, describes energy communities as "a legal entity which, in accordance with the applicable national law, is based on open and voluntary participation, is autonomous, and is effectively controlled by shareholders or members that are located in the proximity of the renewable energy projects that are owned and developed by that legal entity; the shareholders or members of which are natural persons, small and Medium-sized Enterprises (SMEs) or local authorities, including municipalities, and the primary purpose of which is to provide environmental, economic or social community benefits for its shareholders or members or for the local areas where it operates, rather than financial profits" [104]. The second definition was proposed by the same organization just a year later, in 2019, in the electricity market directive and is known as Citizen Energy Communities (CEC). This definition is not restricted to renewable energies and does not necessitate geographical adjacency to the resources, which is described as follows: " a legal entity that is based on voluntary and open participation and is effectively controlled by members or shareholders that are natural persons, local authorities, including municipalities, or small enterprises; has for its primary purpose to provide environmental, economic, or social community benefits to its members or shareholders or to the local areas where it operates rather than to generate financial profits; and may engage in generation, including from renewable sources, distribution, supply, consumption, aggregation, energy storage, energy efficiency services or charging services for electric vehicles or provide other energy services to its members or shareholders"[104]. As can be seen, both explanations share common points except for two major factors. The first one is the use of renewables (which requires contiguous beneficiaries), which differs between CEC and Renewable Energy Communities (REC). The other is the size of players, wherein citizen communities contain smaller entities. Regardless of the type of community, both provide benefits for the demand side and users, and the utility side.

1.2.1 Individual benefits

Since the energy communities will be an integral part of smart grids, the conditions for studying the outcomes should be according to smart grid concepts. Some key factors of smart grids are communication and cybersecurity, transparent market dynamic pricing mechanisms, adoption of energy storage systems, pervasiveness of electric vehicles, etc. Once the energy communities are established in a framework of legislated directives, the minimum advantage is awareness of live prices and the load shift to the most economical times of the day [113]. Moreover, with the installation of energy storage devices, citizens will be able to save energy (especially electricity) in low-load hours of the day and sell it back to the utility or neighboring users. Some governments may propose Feed-In-Tariff (FIT) contracts to accelerate investments in renewable resources and use long-term guaranteed payments as financial incentives [95]. With an eye to the future, personal electric vehicles could be considered as moving and dynamic energy storage that may aid the grid by allowing the utility to use the capacity of Electric Vehicle (EV) batteries subjected to predefined conditions. Even in countries that set minimum capacity as a prerequisite condition for participation in the energy market, aggregator companies may be established to accumulate microgeneration from their members, take part in the energy market, bid, and then share the profit between their contributors.

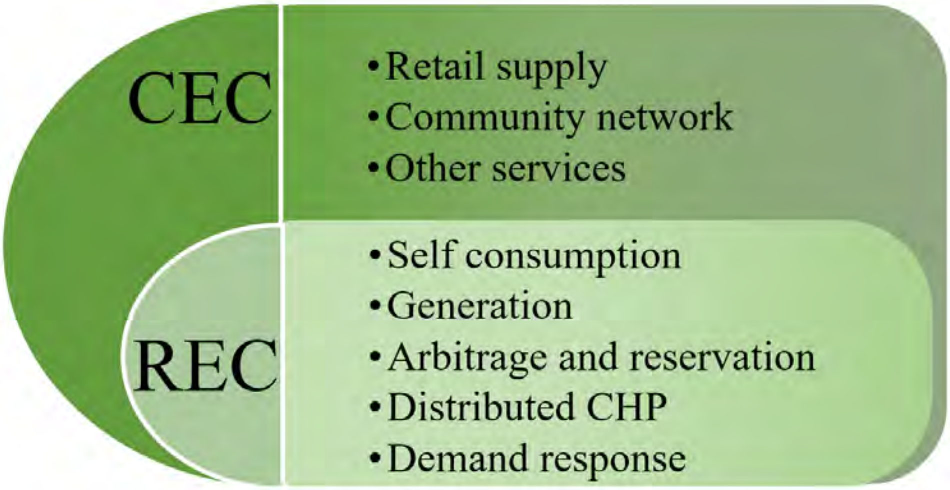

Figure 1.1: CEC and REC services

1.2.2 Utility benefits

In traditional energy flow, there is a unidirectional route of energy from the generation side to the end users, whereas in the distributed scheme of energy communities, there is a bidirectional flow of energy and communication between generation plants, smart houses, small-scale renewable resources, energy storages, etc. Figure 1.2 demonstrates the traditional and distributed energy flow.

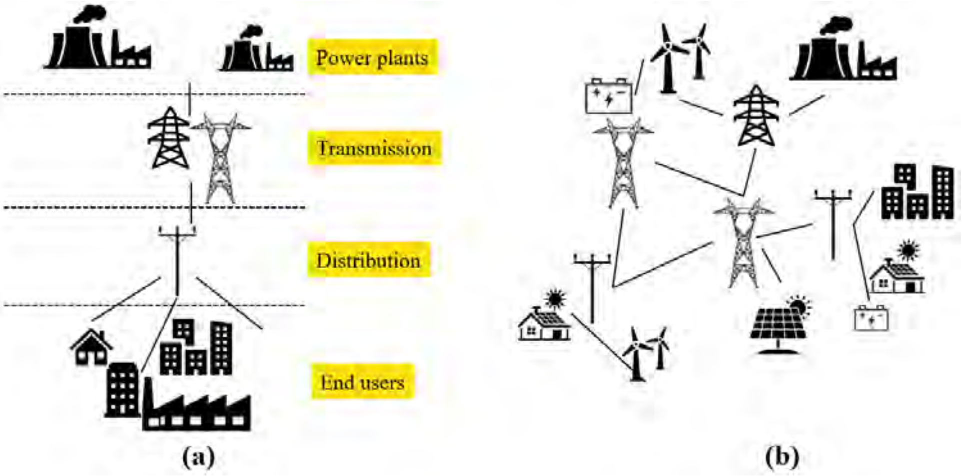

Figure 1.2: Energy route in (a) traditional and (b) EC schemes

As it can be inferred from Figure 1.2, in the traditional scheme, the total length that a unit of energy should traverse to reach the user is much greater than in the distributed one. The distributed resources and providers are able to feed the contiguous loads in the region, meaning that the important transmission lines do not face congestion in load peaks, resulting in a reduced risk of cascaded blackouts [5]. In addition, the amount of energy losses along the transmission line increases with the ratio of load augmentation in the power of two. Considering X the percentage of transmission losses at P megawatt demand, in the peak of loads (assuming $2P$) it reaches to X^2. In other words, the loss factor is equal to the square of the load factor. It's worth noting that in countries with a higher load Peak to Average Ratio (PAR), this issue becomes significantly more pronounced. As it is depicted in Figure 1.3, which is based on the real official data of the Iranian grid during 2011-2012 [70] as an example, the increase in transmission losses is obvious as the load grows.

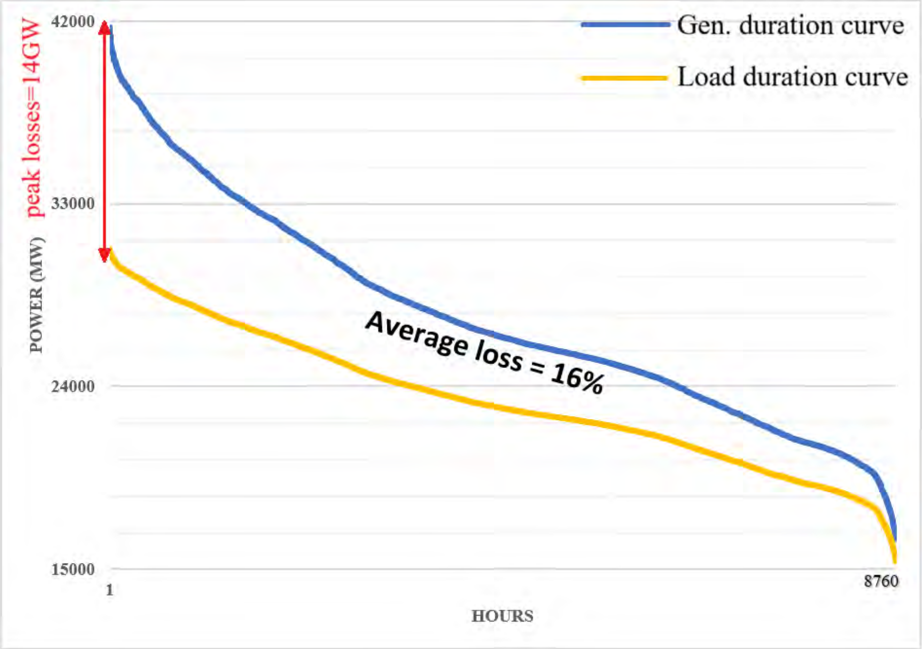

Figure 1.3: Transmission losses in load duration curve

Therefore, the regional supply of demand also decreases the power losses, in which a single percent of sparing brings a large amount of financial savings. Furthermore, in countries with an inappropriate daily/seasonal load factor where the load curve contains remarkable differences between minimum and maximum demand with sharp variations, governments are to install a large capacity of power plants to commit to the maximum demand, which only appears in a few hours of the year. Also, as loads grow up to the maximum level, the most expensive and pollutant peaker plants turn on (Figure 1.4). This additional capacity remains largely underutilized throughout the rest of the year, implying that a considerable capital investment is made for infrastructure that operates infrequently.

By the emergence of energy communities with their local energy provision and energy storage systems, the pressure on old and inefficient units will be mitigated. Enhancement of power quality, reliability, security, and voltage stability are some other technical advantages of distributed energy communities' establishment.

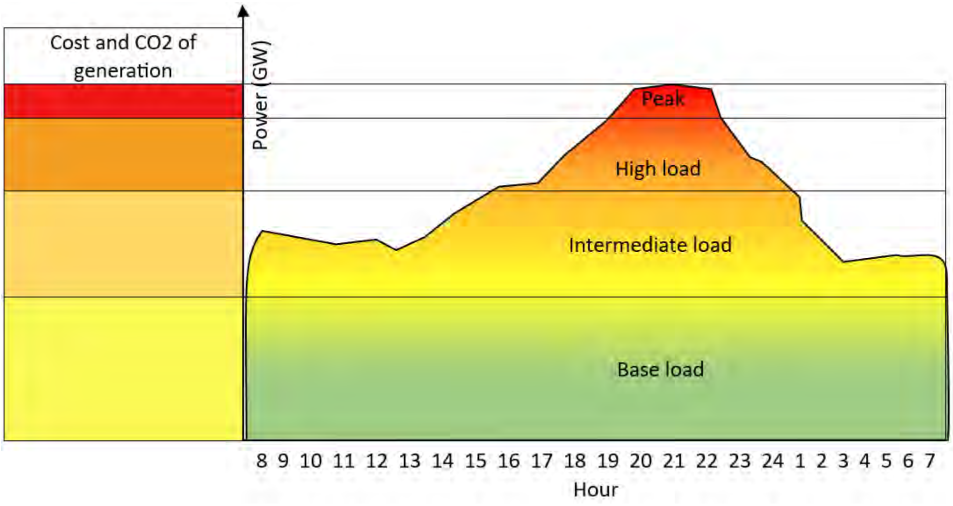

Figure 1.4: Cost of Generation

1.2.3 Global benefits

The contribution of citizens to energy sectors is not restricted to individual benefits or utility improvement. Major outcomes of their participation in energy plans affect the environment, political interactions, ecosystem species, and their daily habits. While fossil fuels are formed over millions of years, we have been exhausting the resources rapidly for a short time. Concerns about the depletion of fossil resources are growing, with estimates suggesting they may be exhausted within the next 54 years [18]. In parallel, the current rate of global warming is projected to melt up to 50% of polar glaciers within this century [72]. These trends require serious and immediate attention. The recent strike in Ukraine also approved the independency in energy supplies. From a strategic perspective, energy communities could be introduced as a Critical Infrastructure Protection (CIP) plan. Since a country with ideal energy communities is made of sub-regional, self-sufficient, and distributed stable microgrids, invasions to vulnerable points of energy routes will not lead to blackouts and paralyzing situations. Furthermore, the self-sufficiency and smartness of communities allow Special Protection Schemes (SPS) such as controlled islanding to be applied during catastrophic events like earthquakes and hurricanes. One of the main global and social benefits of EC is the involvement of the folk in green energy system plans. This will help increase the acceptance of green technologies and responsibilities. With the public taking part, a culture of sustainable and clean energy development will flourish, and this will be reflected in other aspects of consumption and future projects. Moreover, social participation can also start a habit shift in consumers, making them more aware of the impacts of their choices[61].

1.2.4 Potential challenges and threats

As with any other technology, preparing the current system to host energy communities on present infrastructures has its own challenges. The need for low-latency communication channels, new protection coordination, market, payment mechanisms, universally agreed protocols of devices, big data management, acceptance in public beliefs, controversies on access levels, personal data leakage, and privacy flaws are just a few numbers of the potential challenges. As it was stated earlier, energy communities entail smartness, and smartness follows sufficient information obtained through communication. With the penetration of communication technologies (e.g., IoT), the risk of cyberattacks grows significantly. The level of the target could vary from a house to the national Supervisory Control And Data Acquisition (SCADA) system. Also, types of attacks such as Man In The Middle (MITM) or Denial of Service (DoS) can determine the volume of defects. The detailed data of devices and operating time in each house could be tempting information for advertisement companies. With the advent of millions of players and devices joining the energy network and their rate of data production, a system for efficient data selection and big data management seems inevitable. And at last but not least, the platforms and frameworks for a fraudless, transparent, and secure payment are disputable.

1.3 Examples Across the World

The fundamental concept of energy communities is not new. It has been hundreds of years since humans have understood the importance of energy (in all forms). The ownership of windmills or watermills in the past centuries demonstrates the value of energy services in history. Even if the construction of such an energy harvest apparatus was costly, a group of people restricted to a region like a village tried to afford the infrastructure in collaboration. The services were shared among investors or sold to outsiders according to the schedules or priorities. The idea of ancient public baths all around the world is almost the same, while focusing on heat. Popular public baths in the Roman territory [112], China, ancient Greek, and Muslim countries were founded to provide heat-based services (semi-equivalent to modern CHP services), since the infrastructures were technologically complex and financially inaccessible for individuals to construct. Although the traditional public energy harness equipment cannot be considered as an energy community according to the newly defined criteria, it represents an equivalent model to what is expected from energy communities since it includes major attributes of an energy community. Today, ECs may trade energy or schedule their consumption for multi-objective purposes. Based on their activities, the services they provide, and the type and level of payment, some studies have classified them into distinct categories [21]. Although ECs are at the beginning of their journey, there are some pilot models all around the world. To better understand the following report and facilitate a comparison, it is crucial to explain some definitions and categories. One criterion to discriminate EC from each other is the type of services they provide. According to [19], ECs may be engaged in some or all of the following activities.

1.3.1 Types of services

- **Generation**: this activity indicates that the energy community members do not consume the energy provided within community but sell it to a supplier or utility.
- **Supply**: energy supply may differ from energy generation, since it means the sale (and resale) of electricity and gas to customers. It does not entail the energy to be self-produced. They can play the role of retailer as an interface in large communities. They may also be engaged in aggregation activities and trade energy or auction in electricity markets as a proxy of the whole community.
- **Consumption** and sharing: this class of activity resembles a micro-scaled of the traditional grids which it means both generation, consumption, and sharing happen inside the grid. The consumption and generation can be both individual or collective.
- **Distribution**: funding, ownership, or management of distribution networks within a community, such as local electricity grids or small-scale heating and gas pipes.
- **Energy services**: This class of services include a variety of activities tied with energy efficiency or energy savings. Also financial services like energy auditing are considered in this class. Providing flexibility, energy storage installation and smart grid integration, energy monitoring systems and energy management for network operations, etc. could be done as an energy services category.
- **Electro-mobility**: communities try to benefit from green transportation including car sharing, car-pooling or charging stations that serve EVs.
- **Other activities**: these activities are mainly consultation services and mentoring to establish local communities and cooperatives.

However, authors in [19] have proposed three types of EC in their review. main grid supply with no generation within, hybrid supply, and micro-energy supply with no dependence on utility [21]. The overall results show that the major engagement of communities is the generation of activity. Figure 1.5 illustrates the number of communities (within 24 cases) that provide a specific service.

Another feature of communities is their ownership and legal structure. With regard to attributes of communities and their geographical settlement, social backgrounds, upstream directives, and type of activities, various forms of legal entity could be selected for an energy community, which is expressed in paragraphs.

1.3.2 Types of Legal Structure [19, 55]

- **Energy cooperatives:** The swiftest expanding type of energy communities is also the most prevalent. The members primarily benefit from this type of ownership. It

Figure 1.5: Energy Community's activity area

is a commonly accepted practice in nations that have made significant strides in the development of renewable energy sources and community-driven power initiatives.

- **Limited partnerships:** This kind of collaborative alliance has the potential to facilitate the allocation of tasks and the utilization of resources to accrue financial benefits by actively engaging in communal energy initiatives. The governance model often relies on the significance of each partner's shares, which implies that equal voting rights is not adopted.
- **Community trusts and foundations**: Their goal is to create societal benefits and promote growth within the community, rather than solely benefiting individual participants. Profits are utilized for the entire community regardless of the absence of investment shares among certain partners.
- **Housing associations:** Non-profit organizations have the ability to provide benefits to residents living in social housing despite their passive role in decision-making processes. These forms are perfectly suited for tackling the issue of energy poverty.
- **Non-profit customer-owned enterprises:** this legal structures is usually used by communities that engage with the management of independent grid networks. With regard to the type of structure, it is well-suited for the prevalent community with district heating systems found in nations such as Denmark
- **Public-private partnerships:** the option for local authorities to engage in agreements with citizen groups and businesses with the aim of securing energy provisioning, along with other potential benefits for the community, is a viable course of action.
- **Public utility company:** Municipalities oversee and operate public utility corporations, acting on behalf of taxpayers and community members, by financing and administering

these services. Although infrequent, these forms are specifically appropriate for remote or countryside locations.

Comprehensive research by the European Commission [19] studied 24 cases in 9 countries in Europe and compared them from different perspectives. The following paragraphs briefly summarize and aggregate the conducted research and its findings.

Germany

Germany can be considered a forerunner in communities of citizen-led investments in renewables. EWS Schönau in Germany is a cooperative utility company that fits as a distributed energy community operating its own power grid. The company was the local power grid provider for Schönau in the 1990s and was named the first German community to expand its activity to the grid as well as the electricity supply to the local community [31]. Also, in 2009, EWS Schönau extended its services into operating the local gas system and supplying gas. According to reference [19], Germany is estimated to be the pioneer in terms of the number of ECs by 2019, with 1750 Energy Communities [55], thanks to strong traditional communities' ownership in the country and the prevalence of social enterprises. These social roots made the cooperative model the most common legal structure in Germany. The limited partnership is also common in Germany since this model is appropriate for large projects with costly investments such as Sprakebüll which is a community-wind farm pioneered by a group of villagers. Voting rights are proportional to the invested contribution, instead of the democratic one member – one vote cooperative principle [23]. Another incentive in Germany, which is called feed-in-tariff laws was introduced in 1991 and caused remarkable community investments in renewable energy that increased total communities to 1750 and total payments from the Renewable Energy Sources Act to almost 24.5 million euros by 2016 [19]. The role of such government-supported incentives can be understood by noting that a survey by Deutscher Genossenschafts- und Raiffeisenverband, in 2015, demonstrated financial restrictions and tendering rules by the government as the main reason for the 25% decrease in the number of newly founded cooperatives compared to 2014. Although there are some examples of biomass activities by the EWS Schönau or Bioenergiedorf Jühnde in Germany, the most commonly utilized technologies are solar and wind power. As an example, Sprakebüll represents a wind power-based community where affordable solar panels are employed by individuals. A summarized result extracted from [19], which indicates the studied communities in Germany is depicted in Table 1.2.

Japan

Japan is one of the most developed countries in the world in the field of EC. There are samples of successful communities in Japan that have specialized their activity in geothermal energy, residential community, aggregation, or industrial cooperatives. NEXT21 (Osaka, Japan) is an example of a new view of collective housing and urban architecture of $1500m^2$ which is based on the concept of energy sharing among the end-users that can exchange energy with each other. The adopted technology is mainly a 100 kW fuel cell-based CHPs where the

EC	**Elektrizitätswerke (EWS) Schönau**	**Bioenergiedorf Jühnde**	**Sprakebüll Village**
Year	2009	2005	1998
No. of Member	7300	1089	247
Legal Structure	Cooperative Sales Ltd	Cooperative	Ltd company & limited partnership
Activity	Electricity: RE generation, supply, distribution Heat: Supply and distribution Other: Gas supply and distribution; Energy services; Electro-mobility	Electricity: RE generation Heat: Generation, supply –	Electricity: RE generation Heat: Supply renewable heat –
Capacity	–	Electricity: 5 MWh/y; Heat: 4.5 MWh/y	Electricity: 1878.1 MWh/y (wind)
Energy	Multi	Multi	Multi
Contact	`www.ews-schoenau.de`	`www.bioenergiedorf.de`	`www.co2munity.eu`

Table 1.2: Three samples of German energy communities

Direct Current (DC) electricity is provided in common and the heat provided by fuel cells is dispatched among users. In addition, storage batteries are used to increase the reliability of the system and self-consumption and also photovoltaic (PV) panels are located on the rooftop as backup systems [20]. Industrial scales of such EC contribute to a green environment, which can be found in Yahata Higashida area in Kitakyushu. It is a regenerated industrial area that contains commercial, residential, offices and industrial sections. The project was initiated with a hydrogen project in the same area and accomplished to reduce 30% of CO2 emissions. The main engagement of this community is to improve energy load sharing between residential and industrial sectors to smooth peak load curves. A project in Yokohama city covers up almost 80% of its residential consumption by its installed renewable resources. The whole project includes an energy management system (as supervisory management) and a building management system and factory energy management system, with a 27 MW photovoltaic system, 4000 smart houses, and 2000 EVs. Energy Communities may involve more than a few homes and form a smart energy municipality. Waita geothermal community is one of the examples of an energy community and municipality in Japan where the financial benefits of a 20 MW geothermal power plant are returned to the citizens in the form of salaries, and the acquired funds are deposited to be used for the second phase of the project and another geothermal power plant [100].

Italy

One of the incentives for community establishment is the weakness of the grid or the high cost of grid expansion to a remote or less populated area. In this case, the total expense of an independent energy community construction will be economical compared to grid extension to the region. South Tirol in Italy is an exemplary model because in July 2009 the region consumed 236 GWh of electrical energy while it produced more than twice its own requirements (543 GWh) [99]. Leaf Community project in Ancona is honored to be named the first smart energy community in Italy with a total investment of 1 million euros. This project includes 6 apartments, industrial buildings, electric vehicles, and smart schools that are fed by 5 photovoltaic systems, hydroelectric plants, ground source heat pumps, fuel cells, and energy storage systems [20].

Other countries

Various energy communities in the field of type, activity, and ownership are studied in [19] from all over Europe. Although most of them use multiple energy resources to serve the community or bring financial benefit, the prevalence of a specific technology is confined to geographical capacities. Wind energy harvesting dominates the areas with appropriate wind conditions, like Sweden and Denmark. Besides geographical conditions, policies can affect the type of invested plants that solar-based cooperatives are commonplace in countries that have Feed-In-Tariff policy, such as Germany, Netherlands, Belgium, Iran, etc. For instance, a solar park in the north coast of the Netherlands (Ameland), which is co-founded by the municipality, Eneco and Amelande Energie Cooperative, has employed 23000 solar panels, which generates more than the total consumption within the island's houses (more than 1500 houses). There are also a few examples of biofuels (biomass and biogas) in Poland, France, Sweden, Denmark, etc. These communities propose CHP services, and Farmarenergi i Eslöv AB in Sweden is one of the most interesting limited companies in biofuels which involves only 9 farmers, but with a remarkable capacity of a 600 kW boiler and a 495 kW preheater. In addition to producing 2000-2500 MWh per year from the boiler, the community generates 70000 kWh per year from two solar farms. The mentioned research projects also show that hydro schemes are less common while solar-based resources are the most employed technology. Figure 1.6 demonstrates the prevalence of energy resources in 24 studied cases by the European Commission's Joint Research Centre (JRC), and brief information on the mentioned communities is embedded in Table 1.3.

Table 1.3: Studied cases in JRC report [19]

Name	**Country**	**Member**	**Legal form**	**Energy/Tech**
BeauVent	Belgium	>5000	Cooperative Limited Liability	Multi
Courant d'Air	Belgium	>2000	Cooperative Limited Liability	Wind, Solar

Table 1.3: Studied cases in JRC report [19]

Name	Country	Member	Legal form	Energy/Tech
Ecopower	Belgium	56000	Cooperative Limited Liability	Multi
Svalin co-housing	Denmark	20 Houses	Energy collective	Solar, Geo, ESS
Marstal Fjernvarme	Denmark	1600	Non-profit customer owned enterprise	Solar, Bioheat
Enercoop	France	70000	cooperative society of collective interest	Multi
Mobicoop	France	20000	cooperative society of collective interest	Transportation share
SAS SAES	France	180	cooperative society of collective interest	Solar PV
Amelander Energie	Netherlands	286	Cooperative Company	Solar, EV
Duurzaam Ameland	Netherlands	9 Co. partners	Public-Private Partnership	Multi
Żywiecka Energia Przyszłości	Poland	40	Civic law cooperation agreement	Multi
Spółdzielnia Nasza Energia	Poland	300	Cooperative	Biogas, CHP
Słupsk pilot project	Poland	200 Houses	N/A (Project)	Solar PV
Som Energia	Spain	59320	Cooperative	Multi
Som Mobilitat	Spain	1350	Cooperative of Consumers	EV sharing
Bostadsrättsföreningen Lyckansberg	Sweden	85 Houses	Housing association	Solar,Biomass
Farmarenergi i Eslöv	Sweden	9	Corporate Enterprise	Biomass, Solar

Table 1.3: Studied cases in JRC report [19]

Name	Country	Member	Legal form	Energy/Tech
Solbyn Association	Sweden	50 Houses	Housing association	Solar heat
Edinburgh Community	UK	541	Cooperative	Solar
Energy4All	UK	27 cooperative 16978 persons	Private Limited Company	Multi
Isle of Eigg	UK	96 Houses	Private limited Company	Multi

1.3.3 Energy communities' regulations

In general, "regulatory" in the word means control and guidance based on a rule, principle, method, or law. In other words, it is the justification of a mechanism to work accurately. From a legal perspective, a regulation can be defined as a rule written to implement a specific law. It is a form of secondary law enacted by a government minister or regulatory entity in accordance with primary law and intended to be effectively enforced. Therefore, it can be said that the institution or the regulatory entity is formed based on the law to ensure compliance with the legal frameworks and achieve the goals. A regulator can be an independent governmental or non-governmental institution that has the legal authority to enact policies and enjoys supervisory competence that is usually formed based on the law. The energy industry is subject to principles that govern both the physical characteristics of energy and also satisfy the expectations of providers and consumers. The purpose of a regulation is to legalize the service provider companies. In fact, regulation is the law of supervision and control of companies (for example, utility companies), intending to provide public interest. Regulation tries to set a balance between consumers' rights and investors' benefits. On one hand, it seeks to protect users from the market power that may impose monopolies and oligopolies to propose high prices or lower the quality of their goods or services. On the other hand, regulators aim to protect investors from the State, which might act opportunistically by setting supply tariffs and obligations that would preclude recovery of the investment [83].

In this regard, the public interest entails that:

1. providers are obliged to provide their services to customers who are in their service area and can afford to pay for such services, without discrimination and in a safe and reliable manner.

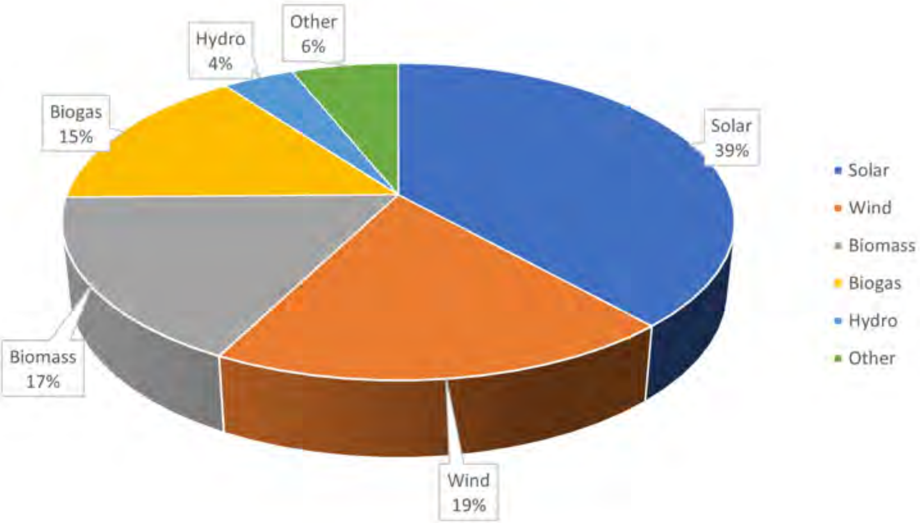

Figure 1.6: Energy Community's renewable resources

2. In case of not providing acceptable services, according to the approved law and regulations, the regulatory institution can penalize the company providing the service and even disqualify it (revoke the company's license).

3. These companies should have acceptable financial health and should not receive more than the real value of the services.

4. It should be assured that costs resulting from improper efficiency, degradation, old technologies, and mismanagement will not be paid by customers.

On the other hand, to protect the investors, the government or the regulatory institution is also committed to calculating the tariffs based on real costs and the right of these companies in a way that includes a reasonable profit for them. If these conditions and prices really do not have economic justification for the private sector, they should convince the organization by presenting documents and negotiating with the regulatory organization. It is obvious that the regulatory organization usually carries out its decisions and determines the tariffs in a way that provides motivation and incentives when it is necessary to invest.

Generally, three institution types of Ministry-governed, regulatory commission and competition authority constitute the body of the regulatory system. In federal systems, these institutions may be established at central and regional levels. In Europe, the European Union, with the Agency for the Cooperation of Energy Regulators (ACER) acts as central regulatory, and regulatory authorities of member states are responsible for regional regulations [83]. Depending on the border drawn between freedom and restrictions, different models of the regulatory institution can be proposed. The models may differ in some aspects, but share common fundamentals according to the definitions. For example, according to directives definitions, different legal forms of energy communities (associations, cooperatives, and others) through a legal entity are allowed. Before getting specified, it is worth mentioning that Belgium enjoys having a central federal regulator named Commission for the Regulation of Electricity and Gas (CREG) and three regional regulators. Details of the Green certificate system mechanism that has been adopted at the federal level are left for each region. In this regard, Flanders has applied the green certificate policy, which entails an initial proposal of the demanded energy to the regulator. Upon acceptance by the regulator, the provider will receive a certificate that indicated the amount of energy (MWh) produced that can be injected into the grid or self-consumed by the producer. Also, this certificate can be sold on the market. The price varies depending on the sources' technology and their date of operation. This mechanism enables flexibility according to the policies where in 2014 it was decided to omit the incentive for residential PV and apply restrictions on the age of the installations [26].

In Wallon region of Belgium, a decree has been published in April 2019 which amends three previous decrees of April 12, 2001 (relating to the organization of the regional electricity market), December 19, 2002 (relating to the organization of the regional gas market), and January 19, 2017 (relating to the applicable tariff methodology to gas and electricity distribution system operators). In this amendment, which clearly emphasizes energy communities, all previous articles, and discussions are modified to adapt and foster the concepts of energy communities[1]. However, the mechanism was already being used in the form of green certificated with different coefficients for each sector (according to policy priorities). The condition for the Brussel region is more motivational, where for residential PV installation, such a certification is not needed. [26] Sweden has no official framework for energy communities, but only self-consumption or collective self-consumption within a building with all its houses belonging to the same grid connection [19]. Poland follows the same status, and the two European Union directives have not yet been considered in Polish law. Although the term "energy clusters" is being focused on by the government, it is limited to a civil law agreement between participants that does not have legal personality. The German government has defined citizen energy companies in Renewable Energy Act (EEG) as a community containing a minimum of ten local natural persons enjoying at least 51% of votes, with no entity taking possession of more than 10% of votes [38]. Estonia shares the regulatory task between its two ministries of economic affairs and communication (responsible for EU direction adoption) and the Ministry of the Environment. The regulatory ends at the central level, and there are no local regulatory entities for energy management but only a legal framework that eases the installation of small-scale electricity plants.

In the Netherlands, the Dutch framework utilizes a regulatory sandbox that persuades initiative projects through regulatory exemptions for small-scale renewables generation. Article 7a of the Dutch Electricity Act introduces a regulatory sandbox for types of energy associations and cooperatives [26], which allows them to operate a local microgrid for households. As an incentive, these communities will enjoy exemption from the supply license requirement and grid tariff structures for a period of a maximum of 10 years. Only projects operated by cooperatives and associations of owners are permitted. Also, community energy associations and cooperatives are allowed to share their energy with their own self-defined tariffs for internal supply. Spain proposes a similar definition of local energy communities as mentioned in EU directives and emphasizes on "the main social objective is to offer energy benefits to its members or to the community where the activity is carried out, rather than generating financial profitability." Spain engages different governmental institutions in its energy regulatory task, but the most relative institution dealing with local energy communities is the Institute for the Diversification and Saving of Energy (IDEA). The agency which is the main energy-related agency of the national government has prepared a guide and instructions concerning the possibility of financing pilot projects. While the regulations are supposed to ease communities' access to the market, in Spain, the regulations themselves preclude new renewables cooperatives for participating in the market due to required financial guarantees and complicated procedures. Therefore, it is required to exclude new citizen-based cooperatives from some official requirements to let the energy communities flourish.

In Italy, the Italian Regulatory Authority for Energy, Networks and Environment (ARERA) and the Ministry of Economic Development (MISE) are responsible for most of the regulatory activities. Despite directives concerning energy communities not yet being implemented, small-scale collective self-consumption of renewable energy plants below 200 kW for customers linked to distribution sub-grid is considered as an experimental and transitory regulation and pilot according to associated directives and articles [26]. Thanks to the nationalization of the electricity grid, energy cooperatives enjoy a special legal status that allows them to preserve their local grid dominance. Many energy cooperatives can be found in the Trentino and South Tyrol regions. They have consolidated over the years from the beginning of the twentieth century and grown into large economic companies that sell energy to thousands of their customers. In Italy, energy communities are regulated by Law No. 83 of 2019 “Provisions for the promotion of energy from renewable sources and for energy efficiency”, which transposes the provisions of Directive 2018/2001/EU on the promotion of the use of energy from renewable sources. It defines energy communities as legal entities established by natural people, small and medium-sized enterprises, or local authorities to generate, consume, and manage energy from renewable sources. Indeed, energy communities can operate in various forms, such as cooperatives, consortia, and associations. Moreover, the Law establishes a regulatory framework for the creation and operation of energy communities, including their registration, governance, and management. In particular, the law provides:

- The possibility for energy communities to access the electricity market, both as producers and consumers.
- The possibility for energy communities to use the electricity distribution networks to exchange energy with each other and with the rest of the electricity system.
- The possibility for energy communities to receive compensation for excess energy

generated.

- Access to tax incentives and subsidies provided for renewable sources and energy efficiency.
- Access to financing and technical support.

In summary, regulators have understood that moving away from a traditional model is a need, and the existing rules are lagging behind new concepts. From a general perspective, it can be said that the movement toward well-organized and clear legal instruction has been initiated. Reforming the regulatory framework to address regulatory concerns associated with energy communities' concepts becomes crucial. Designing a regulatory framework that ensures the safety of users and the public whilst facilitating the commercial use, consumer enjoyment, and global environmental benefits of energy communities has its own challenges. Fortunately, the presence of energy communities around the world provides reliable data, and the data of these communities is readily available to facilitate accurate legislation. These data can be utilized to help regulators consider legal requirements and mechanisms. Also, the availability of existing successful models of energy communities, their governing instructions, and their embodiment allows legislators to safely examine and study appropriate decisions in the sandbox regulatory model [39] and import the advantages of each model into the regulation articles.

1.3.4 Software tools and platforms adopted

Since energy communities are operating based on smart grid concepts, it covers the whole chain of generation, transmission and distribution, and consumption. The integration and aggregation of such operations within an area (varying from a home to a city), entails effective management and control systems. Each level requires its own considerations, criteria, goals, tools, decision parameters, and depth of penetration and interference. It makes it more sophisticated by considering that an entity, like a house, may take its part in different levels from generation to consumption. Also, trading aspects of energy sharing should be foreseen and an appropriate platform must be implemented. Another challenge is public involvement who find it difficult to grasp technical concepts of energy and trading [107]. With the emergence of promising solutions by IoT technology, the level of access has grown into home appliance devices. In this situation, even the fundamental properties of energy communities (like demand response) require computational assistance. In addition, the profit gained from ensemble activities within a community is shared between the residents of the community and, if they find it sophisticated, questions are raised about how energy sharing and benefits work. Here, effective and user-friendly software that guarantees a simple representation of technical concepts is needed at the end nodes level. Before implementing any software, people should be trained and aware of the general fundamentals of smart grids and energy communities. Besides governmental incentives and media, some companies have designed simulators and games to educate folks (for a variety of audiences) with concepts of Demand Response (DR), energy communities, and trading on the blockchain network [79]. A few of them are available for download and almost all follow the green world energy target. As an example, a promising game is Social MPower, which tries to provide community members with a brief perception of DR and energy sharing. With consideration of a medium between the game and real-life measurements, as the Sharebuddy software did, the games will be able to reflect back the consequences of consumers' behavior through prizes and gift cards [79].

The proposed software is supposed to be able to implement Demand Side Management (DSM) strategies and local functionalities that are specified for the house level such as micro generation control, battery management systems and electric vehicle charge manager, house energy management, home appliances, and smart metering [62]. The motivation or incentive within a single house is almost the level of comfort and price. Imagine a hierarchical decision-making system; once the end nodes gather to form a community, the targets and criteria defined at the community level move to the upper stages of the pyramid and alter to more general goals. The aforementioned objectives of energy communities (such as CO2 reduction, cost reduction, zero-net energy, etc.) intend to be introduced at this level. A local energy market within a community can also be established and trade energy or services inside the community or outside. As with every single house, the presence of an energy management system within a community is essential. This system interacts with both the utility side and individual houses as an interpreter. The general goals are dictated from a plan by the government, the goals are translated to objectives in DSM and passed to the community energy management system, and then the management system defines the direction for houses in the way that their ensemble behavior results in desirable achievements. Since there are different levels of management and coordination, we categorize the existing software and platforms into two classes of end-node (users) side and the community management side. The users' software should be user-friendly, equipped with trading properties, and offer an easy perspective of technical concepts. The associated platforms may vary from a smartphone to a separate building management device. The platform, which includes both hardware and software, is fed with a variety of upstream and local (from house) signals. DSM policies, incentives, and pricing signals are provided for each house as an upstream signal. In addition, the user side management is provided with local feedbacks like the state of charge of batteries, EV's charge status, real-time PV generation curve, real-time consumption (KW), cumulative energy consumption (KWh), etc.

On the other hand, management systems in community and upper levels, as described in [94] entail higher memory, computational resources, and connection to other systems like Geographic Information System (GIS), meteorological system, Consumer Information System (CIS), and Distribution Management System (DiMS). Since these accessibilities require their own authority, expense, and infrastructures, they are settled in higher levels of a smart grid. The following paragraphs introduce a few examples of software and platforms at the end-nodes side with the property of energy trading.

1.3.5 Examples of platforms

As mentioned earlier, at this level the objective is maximizing users' comfort while minimizing the costs (by DR or energy selling), considering the dictated constraints and incentives. In an ideal case, accessibility is provided to control and monitor almost all devices and systems through IoT, and the trading apparatus is expected to be adopted. The BloRin project is an Italian software that aims to create a trading platform based on the blockchain for renewable energies and the management of energy exchanges. This platform helps individuals to constitute a solar community and will be able to foster interactions between providers and consumers, manage electric vehicle recharging infrastructures, and coordinate exchanges with the electric energy distributor. Blockchain technology is used to manage energy exchanges between prosumers. The BloRin platform is developing and tested at the Engineering Department of the University of Palermo and will subsequently be tested in the field on two Sicilian islands, with the contribution of the distributors. A micro-grid will be tested in Lampedusa, which will involve a mix of photovoltaic plants and storage systems with the possibility also of managing the demand profile of various users, thanks to DR-enabled property [2]. Exodus is a smartphone application in the UK that enables P2P trading within local communities. It allows homeowners inside communities to monitor energy production, consumption, and storage. If the users also generate electricity, they can exchange their excess energy as well as transfer it into the utility via ExodusHOME trading platform. P2P-SmartTest is a transactive energy model based on smart grid concepts that investigates and displays smarter electricity control benefiting from the regional markets, innovative business models, and advanced ICT. The DERs inside a community will operate at optimum case using this model, leading to maximum profit [78]. In Denmark, Alborg University has introduced Energy Collective project that gives consumers priority, allowing them to easily produce, trade, and consume. Also, this platform is enriched with P2P market designs based on blockchain [32]. Blockchain technology of Power Ledger in Australia, caused many projects to flourish within the region, where most projects are now using Power Ledger platform for energy trading. However, Power Ledger is not restricted to Australia, and its cooperation with BCPG, a Thai renewable energy company, has enabled users to trade electricity with the option to sell extra electricity back into the system. Also, in the same collaboration with Thailand, Power Ledger is developing a blockchain-based digital energy company that will allow P2P energy trading. A comprehensive research [78] provides a brief view of existing platforms and software for energy trading in all continents. However, as it is expressed in [98], these software are almost trading platforms, and integration of such platforms with micro/mini grid management systems that emphasize other technical aspects would be challenging. The ideal software should propose a well-organized architecture that considers both the utility side as well as users side, Advanced Metering Infrastructures (AMI), Smart Meters (SM) at homes, optimization signals from the utility, security of data, big data management, etc. and such platform (at any scale and version) should be scalable and compatible with other utilized software in other levels of systems, or it will require an overwhelming amount of work to design a comprehensive mega-software for each level of system and the required property. Also, coordination between the platform and distribution infrastructures should be considered.

The proposed method, which is described in detail in the following sections, is designed to address these requirements in a practical and effective manner. It is fully compatible with the objectives of energy management software platforms, enabling seamless integration within existing frameworks. The approach is computationally efficient and does not require high-performance computing resources, making it suitable for real-world deployment even in systems with limited processing capabilities. In addition, the method is inherently scalable, allowing it to accommodate an increasing number of users without a significant rise in computational complexity. Importantly, it also incorporates privacy-preserving mechanisms, ensuring that individual user data remain protected throughout the optimization process while still enabling coordinated decision-making at the community level.

Chapter 2

Literature Review

2.1 System Descriptions

Each energy community, including microgrids in a broader context, comprises various categories of components and facets. Some are indispensable for the grid's functionality, while others are contingent on specific cases. These include communications infrastructure, market participation capabilities, physical elements (such as loads, resources, and storage facilities), and a control and supervision algorithm that functions as the grid's central intelligence. Modeling the mentioned components is crucial for establishing an optimized community that operates with minimal CO2 emissions and maximized benefits. These models essentially translate the function, responsibilities, and impacts of each component into a unified mathematical formula that accounts for constraints and represents the associated costs. Depending on the defined objectives, referred to as "objective functions," the models may vary. The modeling and design of an energy system for energy communities can be approached as an optimization problem, or through the simulation of multiple scenarios. Modeling of energy communities involves using various tools, techniques, and methodologies to analyze and optimize the generation, consumption, and distribution of energy within these community-based systems. This field is crucial for achieving sustainable and efficient energy use in local communities. Based on objectives and uses, the model varies in detail, allowed approximations, hypotheses, level of consideration, etc. For example, when a model is supposed to study management or economical aspects of a community, some details like Pulse Wide Modulation (PWM) controllers or the dynamics of the system can be ignored. Here are some key aspects of modeling energy communities that can be studied in further research review:

1. **Renewable Energy Integration:**
   Many energy communities focus on utilizing renewable energy sources like solar, wind, and hydroelectric power. Modeling helps in determining the optimal placement of renewable energy systems, estimating their potential generation capacity, and designing systems that can efficiently harness and distribute this energy.

2. **Demand-Side Management:**
   as the on of main modeling in this thesis, this modeling considers the patterns of energy consumption within the community. This involves understanding when and how much energy is used, and then finding ways to optimize consumption patterns through measures like energy efficiency improvements and load shifting.

3. **Storage Solutions:**
   Energy storage technologies, such as batteries, are crucial for balancing energy supply and demand, especially in renewable energy systems with intermittent generation. Modeling helps in sizing and placing energy storage systems to ensure a reliable energy supply.

4. **Grid Interaction and Microgrids:**
   Some energy communities are connected to the larger electrical grid, while others operate as microgrids, which are self-contained systems that can operate independently. Modeling helps in determining the best configuration and management strategy for grid-connected or isolated systems.

5. **Economic and Financial Analysis:**
   This involves assessing the costs and benefits of different energy technologies and strategies. It includes considerations like capital costs, operational expenses, potential revenue streams (e.g., feed-in tariffs, energy sales), and the overall return on investment.

6. **Environmental Impact Assessment:**
   Modeling can help evaluate the environmental benefits of community-based energy systems, including reductions in greenhouse gas emissions, air pollution, and other environmental impacts.

7. **Resilience and Reliability:**
   Energy communities often aim to enhance resilience against power outages and other disruptions. Modeling helps in designing systems that can continue to operate during adverse conditions and in identifying backup solutions.

8. **Regulatory and Policy Considerations:**
   The regulatory environment can significantly impact the feasibility and operation of energy communities. Modeling considers factors such as local energy policies, incentives, and regulations to ensure compliance and optimize for financial benefits.

9. **Social and Behavioral Aspects:**
   Understanding the preferences and behaviors of community members is crucial for successful energy community projects. Modeling can incorporate social data to anticipate energy usage patterns and to design programs that incentivize participation.

10. **Scenario Analysis and Sensitivity Studies:**
    Modeling allows for the exploration of various scenarios, such as changes in energy demand, fluctuations in renewable energy generation, or shifts in policy and regulatory frameworks. Sensitivity studies help in understanding how different parameters impact the overall performance of the community energy system.

Overall, modeling energy communities is a multidisciplinary endeavor that involves aspects of engineering, economics, environmental science, social sciences, and policy analysis. It helps in designing and optimizing community-based energy systems to meet the energy needs of local residents while promoting sustainability and resilience. In addition to the aforementioned aspects of modeling, objectives, variables, constraints, components, and optimization techniques are tuned based on goals. Physically, modeling can cover energy sources which include renewable sources like solar, wind, hydro, and biomass, as well as non-renewable sources like fossil fuels. Also, it covers energy demand that considers the energy requirements of individual households, businesses, and other entities within the community. The other important subject that is studied in modeling is storage and grid integration, in which models often account for energy storage solutions like batteries and their optimum sizing, charging periods, and optimum arbitrage as well as the integration with the larger electrical grid.

2.1.1 Elements in EC

A typical EC is a self-sustained microgrid consisting of loads, distributed generation, and an energy storage system. The integrated energy system, positioned near the end-user, encompasses multiple energy carriers such as cold, heat, electricity, and gas. It incorporates micro sources, loads, energy storage, as well as associated control, monitoring, protection devices, and energy management systems. This system operates as a singular, manageable micro-energy network capable of optimizing internal, network, load, and storage elements within a specific region. Contemporary systems have grown notably intricate, particularly power supply systems [44].

2.1.1.1 Energy Sources (Generation and Storage)

Energy resource modeling plays a pivotal role in understanding, predicting, and optimizing the utilization of various sources of energy. It encompasses a wide range of techniques and tools that aid in simulating and analyzing the behavior of energy systems, from conventional fossil fuels to renewable and sustainable alternatives. By employing mathematical models and computational simulations, energy resource modeling allows us to assess factors such as availability, costs, environmental impacts, and system integration. Although the scope of this work does not include a detailed analysis of energy generation and storage technologies, these technologies are briefly introduced to provide contextual background and facilitate a clearer understanding of their role when deployed within EC. we explore the significance of energy resource modeling in shaping the future of energy community resources, and delve into its applications in achieving a more sustainable and efficient energy landscape. Stable ECs utilize a diverse array of energy resources to generate electricity, ensuring a reliable and sustainable power supply for communities, buildings, or specific facilities. Here is a brief list of some of the different types of resources commonly used in ECs:

1. **Solar Photovoltaic Panels:**
   These panels convert sunlight directly into electricity. Solar PV is a popular choice for microgrids due to its scalability and ability to generate clean energy.

2. **Wind Turbine:**
   Wind energy is harnessed through turbines that convert the kinetic energy of wind into electrical power. Wind turbines can be deployed in microgrids, especially in areas with consistent and adequate wind resources.

3. **Hydroelectric:**
   Small-scale hydroelectric systems can be incorporated into microgrids, utilizing flowing water to generate or store electricity. These can include run-of-the-river systems or small dams.

4. **Biomass and Biogas:**
   Organic materials like wood, agricultural residues, and organic waste can be converted into energy through processes like combustion, gasification, or anaerobic digestion. Biogas, produced from organic matter, can also be used for electricity generation.

5. **Geothermal Energy:**
   This resource taps into the Earth's natural heat to generate electricity. It involves using hot water or steam from the Earth's crust, typically found near tectonic plate boundaries. Although this resource is considered renewable, it needs infrastructure and may not be applicable to small

6. **Fuel Cells:**
   These electrochemical devices convert chemical energy directly into electricity, typically using hydrogen as a fuel source. Fuel cells are highly efficient and can operate with low emissions.

7. **Diesel or Natural Gas Generators:**
   While not renewable, these traditional generators can be integrated into the community for backup power or to complement renewable resources, providing stability and reliability.

8. **Battery Energy Storage Systems (BESS):**
   BESS stores excess electricity generated during periods of low demand and releases it during high-demand periods or when renewable resources are not producing. This helps

to balance supply and demand. Batteries represent dual aspects, playing a resource role when discharging and being considered as a load when charging.

9. **Combined Heat and Power (CHP) Systems:**
   Also known as cogeneration, CHP systems simultaneously produce electricity and useful heat from the same energy source, often using natural gas or biomass.

Although technologies such as ultracapacitors and flywheels have been explored in Energy Community studies, their use is far less prevalent compared to conventional solutions. The selection of resources for a specific community depends on factors like geographical location, available resources, energy demand profile, budget, and environmental considerations. Many communities employ a mix of these resources to create a balanced and reliable energy system. To facilitate a straightforward comparison among different resources economically, the Levelized Cost Of Energy (LCOE) metric can be utilized. This metric signifies the average earnings per unit of electricity generated necessary to cover the expenses of constructing and running a power plant over an assumed financial lifespan and operational cycle. LCOE incorporates factors like capital costs, decommissioning, fuel expenses, fixed and variable operational and maintenance outlays, financing charges, and an assumed utilization rate [106].

2.1.1.2 Loads

In an EC, loads are not just passive elements that consume electricity; they are central to how the whole system is judged and operated. The extent to which the EC is able to reliably supply these loads, and the quality of service it guarantees (in terms of continuity, comfort, and meeting users' needs), directly reflects how well generation, operation, and management are coordinated. In practice, an energy community that appropriately manages its loads, by planning around them and respecting their operational requirements, is more likely to be effectively designed and well managed

Loads can be described and grouped in several ways, depending on what aspect of the system we want to highlight. From a sectoral point of view, they may be residential, commercial, industrial, or related to public services. From a temporal point of view, they can be baseline or must-run loads, peak loads, or more generally time-varying loads that follow daily, weekly, or seasonal patterns. Another important dimension is their flexibility: some loads are essentially non-flexible or critical, some are shiftable within a certain time window (e.g., dishwashers or washing machines), and others are controllable or adjustable in terms of power level (e.g., certain HVAC or industrial processes), as long as comfort or process constraints are respected. Finally, loads can also be categorized by their electrical behavior, such as constant-power versus impedance-type loads. These views are not exclusive; the same device can belong to multiple categories at once, and each classification captures a different facet of how the load interacts with the EC.

In the literature on energy communities and demand-side management, many of these classifications appear, and different works emphasize different aspects depending on the problem under study. In this thesis, however, we focus on the operational management of ECs under the Italian regulatory framework. For this purpose, the most meaningful and practical criterion is load flexibility, because it directly links users' behavior and technical constraints to the EC's ability to shift or reshape demand.

1. **Critical loads:**
   Critical loads are end-uses that must be supplied at all times and cannot be curtailed or shifted without unacceptable consequences. They usually correspond to essential services usually associated with base loads of the houses (lights, refrigerator, etc.) or, if overlapped with sectoral load types, can be referred to (e.g., hospitals, emergency systems, key communication infrastructure, etc.) and are treated as non-flexible in scheduling and DR models.

2. **Shiftable Loads:**
   Shiftable loads are end-uses whose total energy demand is fixed but whose execution can be deferred in time within a specified window, without changing the service delivered (e.g., washing cycles, dishwashing, some EV charging). Their consumption pattern can be moved from one time slot to another, subject to user-defined constraints such as earliest start time, latest finish time, and minimum uninterrupted operating duration.

3. **Controllable/Adjustable Loads:**
   Adjustable (or controllable) loads are end-uses whose instantaneous power level can be modulated—continuously or in discrete steps—while the service is maintained within acceptable comfort or process limits (typical examples: HVAC systems, thermostatically controlled loads, and some industrial processes). Their flexibility lies in changing power, not necessarily shifting the entire operation to a different time.

The modeling and mathematical formulation of these loads will be examined in more detail in the methodology section.

2.1.2 Supervision and Managment

As the number of nodes within a community grows and renewable resources see higher utilization, the complexity of energy management schemes rises dramatically. Hence, a robust, dependable, and intelligent energy management strategy becomes essential to tackle this challenge. Securing the energy sustainability of a power system involves addressing a multifaceted challenge with multiple constraints. The energy system must possess the ability to swiftly and effectively determine how electrical power generated by various resources should be distributed. This control process for the components of the energy community is referred to as Energy Management, and the unit that carries out this duty is called Energy Management System (EMS). In general, the optimization tasks in EMS of communities are classified into major types as follows [101]:

Forecasting:

The forecasting objective usually covers the use of machine learning, AI techniques, and regression to predict the futuristic load/generation profiles

Economic/Environmental Dispatch:

IT focuses on techniques that work towards improving the use of renewable resources to increase the environmental/economic benefit. Market modeling, economic optimizations, environmental optimization, and probable acts from multiplayer are studied categories.

Unit Commitment:

The unit commitment targets coordinating the different resources to completely feed the demand at the lowest possible cost and increase the revenue returns.

Demand Management:

The demand management objective mainly targets the effective utilization of the load and scheduling of the usage patterns to increase the financial benefit.

2.1.2.1 Schema and Architecture of Management

Choosing the correct scheme of control and supervision is paramount in the effective operation of a microgrid of a community. Additionally, the choice of control and supervision scheme directly impacts the microgrid's resilience and reliability. The community, comprising Distributed Energy Resources (DERs) and loads, may operate as an independent entity or in coordination with the main grid most of the time. The control and supervision scheme determines how these components interact and respond to changing conditions. Also, it represents the data flow and command flow of components (whether physical or virtual) associated with ECs. A centralized control scheme may be ideal for communities with a limited number of DERs, where a single control center can efficiently manage operations. On the other hand, decentralized control is crucial for larger communities with numerous DERs and loads as it enables localized decision-making, reducing the burden on a single central authority. This flexibility allows for quicker responses to local conditions and better accommodate fluctuations in renewable energy generation. However, in a decentralized scheme, it might be difficult to give authority to every single player to access the most high-level data in the decision-making pyramid. In addition, in a decentralized system, decision-making can become more complex, particularly if there are many units with varying levels of autonomy. This can lead to slower decision cycles. Another option, which is hierarchical control, provides a structured approach that ensures clear lines of communication and well-defined roles for each component. This is crucial for critical infrastructure and essential services that require a high level of predictability and reliability. Decentralized schemes, on the other hand, enhance the microgrid's robustness by allowing for more autonomous decision-making in individual zones or clusters. In case of faults or disruptions, these localized units can continue to operate independently, enhancing the overall resiliency of the microgrid. Therefore, the correct choice of control and supervision scheme not only optimizes the efficiency of energy distribution but also bolsters the communities' ability to withstand and recover from unforeseen challenges. A brief explanation of available schemes with their pros and cons is as follows.

2.1.2.2 Decentralized Scheme

The effectiveness of a decentralized control schema depends on the specific context and objectives of the system or organization. When implemented correctly, decentralized control can lead to increased flexibility, adaptability, and resilience. However, it requires careful planning and coordination to ensure that the benefits outweigh the challenges. Figure 2.1 illustrates a sample of decentralized control in a microgrid.

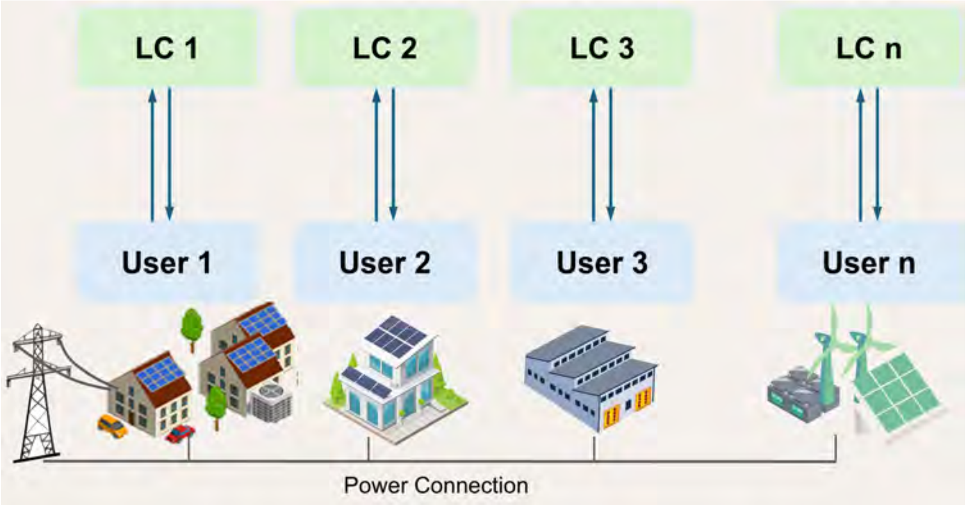

Figure 2.1: Decentralized architecture of EC

However, decentralized approaches are sometimes incorrectly labeled as distributed. In the following, we clarify the distinction between these two control paradigms to avoid confusion when reviewing the relevant literature.

Pros of a decentralized control scheme: Flexibility and Adaptability: Decentralized control allows for quick decision-making and adaptation to changing conditions. Each local unit or node has the autonomy to respond to its specific circumstances, so the flexibility and adaptability of this design are pretty high. Also, decentralization reduces the reliance on a single central authority for decision-making. This can lead to more efficient operations, especially in large and complex systems. Since the control and supervision in this architecture does not depend on the higher level of signals, it can also improve the resiliency from a Critical Infrastructure Protection (CIP) point of view. Decentralized systems can be more resilient to failures or disruptions. If one part of the system experiences a problem (whether cyberattacks like what happened in Ukraine [65, 109], or physical attacks on centers), other parts can continue to function independently. Moreover, Local units often possess specialized knowledge about their specific areas. Decentralization allows this expertise to be leveraged for better decision-making. One of the momentous attributes of ECs, which is scalability, is enabled by this scheme. Decentralized systems can be more easily expanded or modified to accommodate growth or changes in requirements. New nodes can be added without significantly impacting the existing structure.

Cons of decentralized control scheme: Decentralization can lead to coordination difficulties, especially in larger and more complex systems. Ensuring that all units are working towards a common goal requires careful planning and communication. Since there is no central supervision, each local unit may optimize for its own specific objectives, potentially leading to sub-optimal overall performance. Balancing local and global goals can be challenging. Without a centralized authority overseeing operations, there is a risk of inconsistencies or conflicts arising between different units or nodes. In a decentralized system, decision-making can become more complex, particularly if there are many units with varying levels of autonomy. This can lead to slower decision cycles. In addition, decentralization can make it more difficult to allocate resources efficiently across the system. Without a centralized authority, resource allocation decisions may be less coordinated.

2.1.2.3 Centralized Scheme

Centralized control is a management approach where decision-making authority and control over various aspects of an organization or system are concentrated in a single central authority or entity. This central authority holds the power to make critical decisions and oversee the operations of the entire entity. In centralized systems, key decisions, policies, and directives are typically issued from the top down, and lower-level units or departments are expected to follow these directives. This hierarchical structure establishes a clear chain of command, with well-defined reporting lines. This approach is commonly found in traditional structures, where a central unit or a single person at the top of the hierarchy has the ultimate decision-making power. It's often utilized in environments where uniformity, standardization, and efficiency are valued. However, a centralized scheme also has its drawbacks. For instance, it may be less adaptable to rapid changes or local conditions, potentially leading to slower responses in dynamic environments. Additionally, there is a risk of delayed feedback and a potential lack of independence if decision-making authority becomes overly concentrated.

In centralized architecture, the central control center holds the ultimate decision-making power for the community. It determines when and how different energy sources (such as solar panels, wind turbines, batteries, and generators) are utilized to meet the demand. Also, the central control center is tasked with optimizing the performance of the EC. This involves coordinating the output of various energy sources to ensure a reliable and efficient supply of electricity to meet the demand. However, several types of duties are usually entrusted to the central authority, such as enforcing policies related to energy management, such as demand response programs, time-of-use pricing, and renewable energy integration.

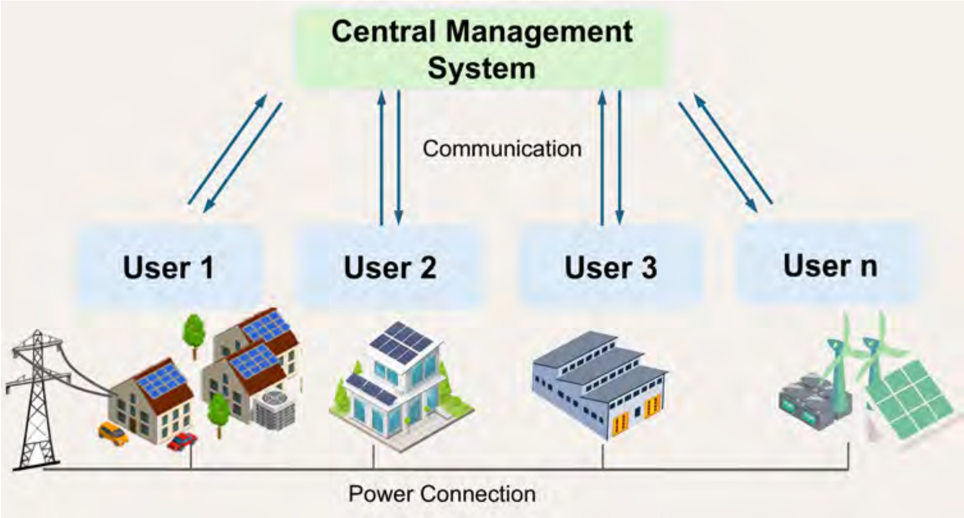

Figure 2.2: Centralized architecture of EC

Pros of the centralized scheme: Centralized supervision allows for optimal allocation of energy resources based on real-time demand and availability. This ensures that energy generation matches the load requirements, leading to efficient resource utilization. Since it provides unified oversight, it leads to a stable and reliable power supply, which is critical for sensitive applications like hospitals, data centers, and industrial processes. With a central control center, the manager or authorized entity has comprehensive visibility into the community's performance. This allows for timely identification of issues, reducing downtime and enhancing overall reliability.

Due to more concentrated information about the grid, a centralized scheme enables smooth interaction with the main grid, which allows for energy exchange, enabling services like frequency regulation, voltage support, and participation in grid balancing programs and demand response, where energy consumption can be adjusted in response to grid conditions or price signals. With theeconomicl justification of using high-power computational resources, centralized control enables the implementation of sophisticated algorithms for energy management and optimization, and can easily integrate with advanced technologies like artificial intelligence, machine learning, and advanced analytics for more sophisticated control strategies and optimization.

Cons of the decentralized scheme: Since communities may grow, scalability might be a challenge for centralized architecture. As a microgrid of a community expands in size and complexity, a centralized control system may struggle to effectively manage a large number of DERs and loads. This can lead to inefficiencies and difficulties in coordination. Also from CIP point of view, aggregation of data and decision-makers in one place makes the system vulnerable to cyber threats. A central control center represents a potential single point of failure and is susceptible to cyber attacks. Ensuring robust cybersecurity measures becomes crucial to safeguard a set of communities in one region. A successful cyber attack could have severe consequences on the grid's operation and security. Also, if the centralized control system experiences a failure or malfunction, it can have widespread and serious consequences for the entire community. This emphasizes the importance of backup systems and redundancy in a centralized control setup. Centralized supervision may limit the autonomy of individual components or zones within the community. This can be a drawback in situations where local decision-making and control is important, such as in the case of critical loads or specialized applications, since locals are usually more expert in their usage and customized profile, and it will be challenging for central EMS to consider individual preferences and heterogeneity. Setting up and maintaining a centralized control system can be complex and costly for small-scale communities. The infrastructure and technology required for a central control center can be economically prohibitive for some applications. Moreover, in some cases, there may be communication delays between the central control center and remote components within the EC. This delay can affect real-time decision-making, especially in situations where immediate responses are critical. Although centralized systems ease integration under one banner on one hand, on the other hand, integrating various types of energy resources, storage systems, and loads under a centralized control system can be challenging. Different components may have different communication protocols or requirements, which need to be seamlessly integrated. In addition, the privacy of users and their load profile might be violated by providing their data to a central authority. It's important to note that while centralized control has its drawbacks, it also has significant advantages. The choice between centralized and decentralized control should be based on the specific context, objectives, and requirements of the system. In many cases, a hybrid approach, combining elements of both centralized and decentralized control, may be employed to strike a balance between efficiency and resilience.

2.1.2.4 Distributed Scheme

In a distributed scheme, which is superficially similar to a decentralized one, local controllers (or local EMSs) collaborate to manage the overall system. The key difference is that, in a distributed architecture, these units actively exchange information with one another over a communication network, rather than operating in complete isolation. Typically, the aim of a distributed scheme is to achieve a global objective (e.g., minimizing total operating cost, maximizing social welfare, or ensuring network-wide security), rather than merely improving local performance. Local controllers therefore act cooperatively, explicitly sharing and updating information (such as marginal costs, Lagrange multipliers, or power set-points) to approximate or converge to a coordinated global control or optimization solution. Nevertheless, even within this cooperative framework, each EMS retains its own local state, constraints, and preferences. The distributed algorithm must therefore reconcile these local considerations with the overarching system-level objective, ensuring that the final operating point is both globally consistent and locally feasible.

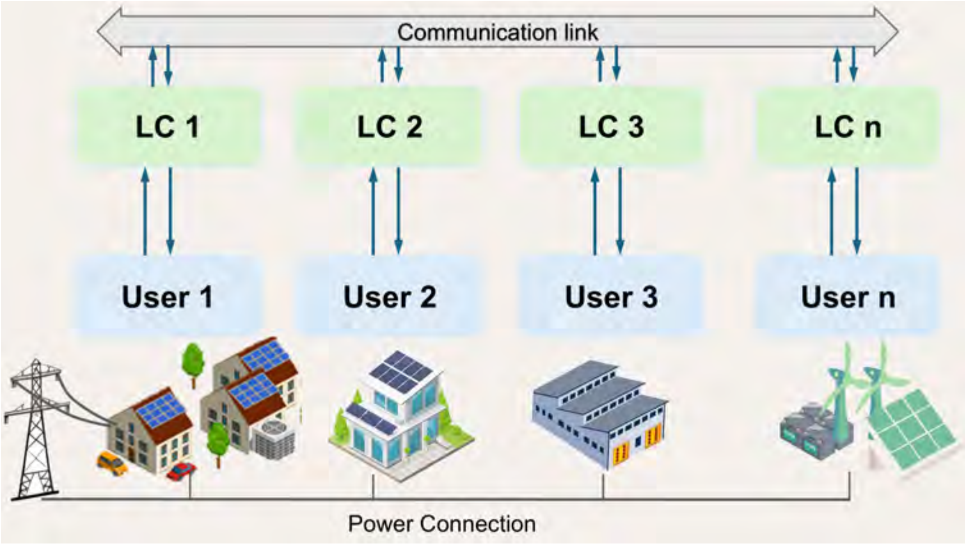

Figure 2.3: Distributed architecture of EC

Pros of a distributed scheme Distributed control offers several important advantages compared to purely centralized architectures. By spreading decision-making across multiple local controllers or agents, it eliminates the single point of failure associated with a central supervisor and generally improves system reliability and fault tolerance. Because each agent solves a local problem and exchanges only limited information with its neighbors, distributed schemes also scale better with the number of DERs and prosumers and naturally support modular, plug-and-play expansion of microgrids and energy communities. At the same time, consensus-based or decomposition-based algorithms allow these agents to approximate the same global objectives as a centralized optimizer (for example, minimum system cost or losses), but without requiring full system information at a single location. An additional advantage, particularly relevant for ECs, is that detailed consumption data and user preferences remain local; only aggregate variables or price signals are exchanged, which reduces data centralization and mitigates some privacy and cyber-security concerns.

Cons of Distributed Scheme These benefits, however, come at the price of higher complexity and infrastructure requirements. Distributed control schemes rely on iterative cooperative algorithms whose convergence and stability must be guaranteed under realistic conditions, making their design and analysis more challenging than for simple centralized or purely decentralized solutions. Their performance is strongly dependent on the quality of the communication network. Delays, packet losses, link failures, or cyber-attacks can degrade convergence or even damage stability, so a careful design of communication is required. Moreover, the deployment of distributed control presupposes an advanced ICT infrastructure and intelligent field devices with local computation and communication capabilities, implying a non-negligible upfront investment and integration effort. Finally, in highly dynamic environments the convergence time of distributed algorithms may be comparable to, or slower than, the rate at which operating conditions change, which can lead to sub-optimal operating points or oscillatory behavior in practice.

2.1.2.5 Hybrid Scheme (Hierarchical)

Hybrid approach combines elements of both centralized and decentralized control strategies. It leverages the strengths of each approach to optimize the operation of the community. In this hybrid framework, a central supervisory system provides high-level directives and oversees the operation of the system, ensuring adherence to global objectives and constraints, and also provides global coordination, sets overall objectives, and ensures system-wide efficiency. Concurrently, localized controllers are distributed throughout the system, each responsible for managing specific components or subsystems. These local controllers possess a degree of autonomy, allowing them to make decisions based on local conditions and real-time data. This decentralized aspect enables rapid responses to immediate conditions within their respective domains. The central supervisory system coordinates and integrates the decisions made by the local controllers, ensuring that the entire system operates efficiently and effectively. This approach strikes a balance between the need for high-level oversight and the importance of decentralized decision-making, ultimately enhancing the reliability, efficiency, and adaptability of the managed system. Between the mentioned centralized and decentralized supervision and control schemes, the hierarchical design has more capability to adapt the EC management system. Since there are high-level decision variables on one hand, and the need for a quick response with a high degree of liberty and autonomy on the other hand, the devised solution should cover both advantages of centralized and decentralized schemes. The hybrid architecture of the system is an approach to meet the requirements of the EC management and control system. In this design, management and control tasks can be split into categories based on their priority in a hierarchical pyramid.

Having established the fundamental concepts, structural elements, and operating principles of the energy community, we are now in a position to situate the proposed work within the existing state of the art. In the next section, we therefore review the relevant background and literature, with the dual aim of outlining the main methodological approaches in the field and identifying the specific research gaps that motivate the contributions of this thesis.

2.2 State of Art

Energy production has typically followed a centralized model for many years, where electricity is generated at large plants, transmitted, and then distributed to consumers. Centralized schemes can also be used for renewable energies, but as the location of such large plants is not load dependent, but rather nature dependent, it happens that large load centers are far from large renewable generation plants [67]. With the emergence of affordable technologies to

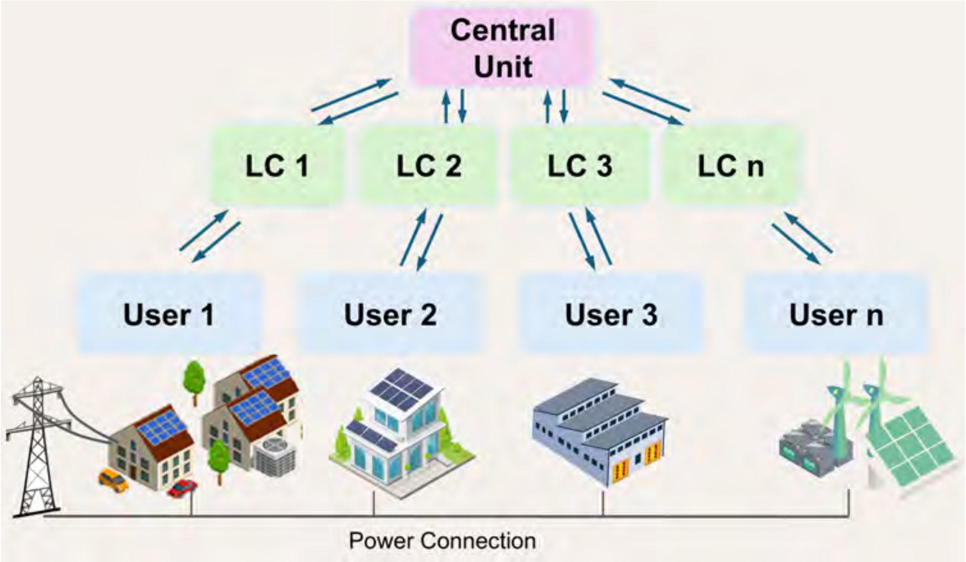

Figure 2.4: Hybrid architecture of EC

manufacture, control, exploit, and integrate such distributed renewable resources on-site, the idea of self-consumption and self-sufficient groups of users has been highlighted [41]. The aforementioned users aggregated to perform collective actions of production and consumption, are called Energy Communities as the EU has defined them in the Clean Energy Package (CEP) [104, 105].

Renewable ECs (REC) which owe their existence to the distributed characteristics of Renewable Energy Sources (RES), offer multiple benefits to both end-users and utilities while addressing the global concerns too. Besides, involving the public users in green energy initiatives creates a positive culture of sustainable and clean energy development, boosting the overall energy transition. When users participate in such plans, it sparks a change in consumers' behavior making them more aware of how their habits about energy consumption impact the world. As the social benefits are closely tied to financial gains RECs can drive social innovation through financial incentives. In community contexts, these benefits translate into energy savings, profits from energy production, and employment opportunities. In this case, users may gain other monetary benefits if there are other national incentives for RECs, or, isolated and rural communities may experience even greater advantages [113].

On a broader scale, RECs contribute to decentralized and sustainable electricity management, as, by promoting local production the amount of transmission energy losses can be avoided. Enhancement of power quality, reliability, security, voltage stability, and minimizing the gap between maximum and minimum daily consumption are some other technical advantages of RECs' establishment [9]. As proved through previous research [27], RECs including passive and active users contribute to energy security and more resilient grids, economic returns, and climate change mitigation. To operate the community in the most beneficial way (aiming for economic, social, or environmental benefits), it's crucial to have an efficient EMS. Given that an ideal EC operates as a small-scale, intelligent replica of the national grid, similarly it can be analyzed from several aspects, including cybersecurity and communication [93], economical and optimum dispatch and optimization techniques [101], energy markets and trading systems [21], and control and supervision architecture [115], etc. However, in this thesis, we will focus on the optimum operation of a REC. In this regard, various rule-based, optimization-based, game theory-based, and a combination of these, methods are proposed in the literature. Mainly, these methods fit into the mentioned groups of architectures, each with specific benefits and drawbacks [71, 52].

Despite the drawbacks, central methods are effective enough to be used widely in energy communities. As an example, [8] tries to make a balance through RTP and a reduced price of energy as incentive to set up a demand response where the operator computes how much load is shifted/consumed per time slot. A central EMS then solves a scheduling/price assignment problem with a heuristic genetic algorithm to keep load under an upper limit while improving "social welfare". The optimization is run centrally (a single solver deciding schedules and prices). Simulation results reported in the paper indicate the GA converges fast and that participating users obtain tangible incentives through load shifting.

In some central methods, such as [91], uncertainty is also considered. In this work, the authors propose a centralized energy management system for a grid-tied microgrid where all components are controlled by a central controller to dispatch PV, wind turbine, fuel cell, microturbine, and grid exchange under uncertainty. Their workflow proposes a two-stage process. In the first one, a price-based demand response stage curtails or shifts residential demand under time-of-use (ToU) tariffs, where the microgrid operator is allowed to manage participating users' appliances by grouping them into critical, deferrable (shifted to off-peak), and interruptible (turned off above a price threshold) loads. The aim of this stage is to reduces the load request before it reaches the microgrid scheduling problem. Second, the microgrid operator performs day-ahead scheduling and unit commitment and uses a metaheuristic optimizer to purchase/dispatch power from available resources at minimum operating cost. Uncertainty is handled by forecasting next-day load and renewable generation using an LSTM-RNN.

In [28], the proposed method is effectively a centralized (community-level) optimization. Even though assets are physically distributed across apartments, the model centrally coordinates all apartments' AC and batteries to maximize a community-level incentive objective, explicitly introducing the "consumager" idea (users absorbing energy when the community needs it) and describing batteries as "centrally coordinated" toward that collective goal to tackle a very specific gap to the question: "if an energy community owns a shared renewable asset (they use community-owned PV), how to distribute that energy without turning it into paid peer-to-peer trading, and still keep it "fair" in a way that rewards members who actively help the community balance consumption and generation through demand response", [51] has proposed a cooperative game. in this game, each member's contribution is tied to their DR participation, and the Shapley value is computed to quantify each member's marginal contribution across all coalitions. Only members with positive contributions receive a share of the community-owned renewable energy, and the allocated renewable energy is normalized by the total positive Shapley contributions, so the distributed amount stays within what is available. Shapley-value computation and allocation are performed as a community-level calculation using monitored data and forecasts. GA has been used as core optimizer in [73] where the authors aim to address individual and community household participation in DR programs and RES sharing while considering constraints imposed on the operation schedule of appliances through load shifting optimization. For that, the GA takes into account dynamic pricing, distributed generation, and household community energy sharing.

Although central methods usually overlook users' preferences and individual freedom, some research tried to address this concern, as done in [6, 117]. Authors in [6] propose a P2P energy trading and scheduling model for energy communities built around a holacracy governance idea, meaning that the community is treated as a self-organizing system rather than a classic top-down manager–follower hierarchy. Instead of optimizing only cost or profit, it defines a new objective called a Community Convenience Index that explicitly embeds prosumers' preferences and energy community managers' preferences. On the other hand, in [117], a user-dominated demand side response is adopted where users are free to send flexible DR bids to the community EMS, specifying allowable start and end times and response durations that respect comfort constraints for electric heating, EV charging, and other household appliances, thereby giving participants high autonomy. The multi-objective problem then is reformulated as a single-objective optimization that maximizes total response while penalizing imbalance over the DR period, which reduces computational burden. The EMS relays DR events and coordinates dispatch actions, acting as a mediator between the network operator and end-users. But this strategy is only relevant if the network operator starts a DR event. Another work published in [37] tried to address individuals' preferences through a central model of GA and proposed the term "willingness-to-pay" to consider users' preferences. The authors argued that a one-size-fits-all DR fails because residents differ in appliance mix and in how much cost they tolerate for comfort. Their approach is a centralized algorithm that first turns resident heterogeneity into a single, time-varying "willingness to pay", and then uses that number inside a Nash equilibrium-based equilibrium price scheduling mechanism to decide each resident's optimal consumption.

A two-stage central approach is proposed in [75] where the authors' key move is to split community management into two decoupled stages: first, it decides the physical operation of assets (the EMS), and only later it determines how the community PV generation is contractually allocated to members for billing. Both rule-based and optimization-based approaches for the first stage are fully centralized. Although the paper studies various scenarios for both the energy management strategies and the "keys of repartition" among users, the final decision about individual energy allocation and contributions is still made by a centralized EMS, which may restrict individualization and endanger user privacy, especially in the case of conflicts of interest among users. To reduce the privacy, scalability, and coordination problems that come with fully centralized community-wide optimization, [13] proposes a Digital Twin (DT) where scheduling is split across two levels. First, as an individual assistant (iEMS) running at each member and a community assistant (eEMS) running for the whole EC, so coordination is achieved without putting every appliance and preference into one monolithic central optimizer. Although it runs a day-ahead optimization locally at each member to minimize that member's daily cost, the management of EC and day-ahead optimization is still done centrally. It's worth mentioning that this approach can be labeled hybrid/hierarchical from an architectural viewpoint (since part of the decisions are computed at the member level and part at the community level). However, if we judge it from the standpoint of optimizing the overall EC operation, it still behaves essentially as a central method. Even with local scheduling at users' premises, the performance-driven optimization logic remains centered around a single coordinating decision layer, making it effectively centralized in the EC-optimization sense.

Although centralized systems provide advantages such as smooth integration with current market models, coordinated control and global optimization, superior economic efficiency, and fairness [46], they are also not without drawbacks. These concerns include computational burden on central EMS, where the central unit bears the entire processing load, which poses difficulties for real-time operation and scalability as the number of participants grows. Furthermore, such systems are susceptible to a single point of failure and often require complete system knowledge. As the diversity of users increases, this leads to scalability issues and heightened privacy concerns due to access to sensitive data. In addition, they may not adequately satisfy individual user preferences, therefore reducing involvement and satisfaction[114, 16].

Hybrid (hierarchical) methods are often introduced to address practical concerns that arise in fully centralized community optimization, especially privacy leakage (a central optimizer needing detailed appliance states and user preferences), scalability, and computation burden as the community grows, SPOF, and communication dependence when all decisions must pass through one controller. The central layer typically handles only system-wide coordination tasks that naturally require a shared view (e.g., setting community signals, enforcing network constraints, or clearing a shared interaction mechanism), while local agents handle user-specific scheduling and control using their own private states and preferences. This division cuts the amount of sensitive information that must be shared, reduces the computational and communication load on the central unit, improves resilience when connectivity is imperfect, and still maintains coordinated community behavior because the central layer provides the coupling signals that align individual decisions with collective objectives. As an example, hybrid methods such as [111] have been adopted to solve these deficiencies. In this work, real-time energy sharing and management in a community market is split into two coupled layers, including scheduling household appliances and setting the internal trading price. To handle these tasks, the authors introduce a hierarchical deep reinforcement learning framework for multi-household energy trading with a two-stage learning structure. In the inner layer, a multi-agent deep reinforcement learning method learns real-time appliance scheduling policies in a decentralized manner, using only each household's local observations together with the announced internal electricity price. In the outer layer, a deep learning-based pricing agent updates the real-time internal prices using participants' historical net power information and the external supplier's electricity prices, without needing households' detailed states or their scheduling policies. Similar to this work, artificial intelligence and machine learning methods are one of the widely used methods in the central and upper layer of hybrid approaches (due to the presence of strong and effective computational cores).

Another hybrid method has been studied in [40], where a bi-level optimization model that combines centralized storage with a Stackelberg game framework in which consumers try to reduce expenses and maximize comfort, while the central storage operator, who has complete knowledge of the user profiles and preferences, acts as a leader and establishes dynamic pricing in this arrangement. In the first framework, a single optimization maximizes the combined revenues of consumers and the central storage entity by deciding how much energy each consumer buys from the grid, peers, and the battery. The second framework is a bi-level Stackelberg game. The central ESS entity is the leader and maximizes its revenue at the upper level; consumers are followers and maximize their utility at the lower level, where utility reflects preferences (weights) for buying renewable energy from peers vs central storage, comfort, and total purchase cost.

As the definition of EC mentions, energy carriers are not restricted to electricity. In this regard, [30] builds an operational (day-ahead) mathematical framework that, instead of optimizing everything in one place, it connects them to a Smart Multi-Carrier Energy Network through a two-stage, risk-based scheduling structure. In the first stage, each community has its own EC Manager that solves a scenario-based MILP to maximize the community's profit and determine the slack/surplus energy exchanged with the network. Then, in the second layer, the multi-carrier network's operator takes the aggregated exchange information from all EC managers and solves its own optimization to maximize the network's profit subject to multi-carrier network constraints (including DC power flow and capacity limits) while explicitly modeling uncertainty and the operator's risk attitude.

Another bi-level management system, which has been proposed in [85] can not be labeled as fully centralized, despite of the fact that coordination and key decisions remain centralized at the EC aggregator . The aggregator sets the penalty signal, aggregates information, and optimizes the community battery dispatch and net supply. At the customer level, each active home schedules a mix of loads and generations to minimize a multi-objective problem. At the aggregator level, the aggregator controls its own community PV and a large battery and aims to minimize the community's supply-side cost. To connect the two levels, they cast the interaction as a non-cooperative Stackelberg game where the community aggregator is the leader deciding its battery dispatch, and homes are followers responding by updating their demand schedules. Since the lower-level problem is nonconvex and mixed-integer with complex comfort indicators, they solve both the customer and aggregator problems using Genetic Algorithms, embedded inside an iterative exchange loop that updates schedules until convergence to the Stackelberg equilibrium.

On the other hand, decentralized and distributed strategies split the decision-making process between local agents or smart nodes, and each user can maximize its own energy consumption while working with the others if required (in a distributed scheme). The key advantage of decentralized methods is scalability, as communities can grow without limitations, not overloading a central unit [12]. Privacy preservation, robustness, and user-side flexibility, which allow for the reflection of personal preferences and dynamic behavior, are further properties of decentralized approaches. The authors in [116] have implemented a reinforcement learning method for managing households' ESS, where users can buy energy from their community pool or sell their excess energy to the pool in a peer-to-peer (P2P) scheme. This work aims to manage a smart residential energy community that supports P2P trading while coordinating household energy storage, with the goal of reducing users' electricity bills and improving the utilization of local renewable energy. Decision-making is performed by a smart-home agent that controls a household battery subject to SOC dynamics and charge/discharge limits. The trading and storage process is modeled as a Markov Decision Process with three state variables of state of charge, retail price, and community price—updated every 30 minutes. Because SOC and prices are continuous, the authors use Fuzzy Q-learning, where trapezoidal fuzzy sets map these variables into 27 fuzzy rule combinations, enabling Q-learning to operate in a continuous setting.

One of the appropriate methods that can be implemented on decentralized or distributed approaches is Game Theory (GT). GT fits decentralized control when the structure of the problem matches how decentralized systems actually work with many self-interested agents, each with private information and local control, coupled only through a shared environment (prices, network constraints, aggregate demand). In this context, A P2P energy trading through a non-cooperative game has been studied in [24]. In this paper, after illustrating the existence of the game equilibrium, the authors present a distributed algorithm to seek the equilibrium with several optimization techniques. The central premise is that each building acts in its own interest and will join the scheme only when it benefits financially. Accordingly, the coordination problem is formulated as a noncooperative game constrained by community-wide conditions, namely, in every time interval the net amount of energy exchanged within the community must balance to zero, and likewise the monetary transfers must clear so that total payments across all buildings sum to zero. In simulation cases, the benefits of a P2P shared energy management, such as more comfortable indoor temperatures and higher economic benefits, have been demonstrated. However, this solution, which is similar to the proposed approach in [25], needs a sharing and trade platform between users of the community.

The research [15] introduced an AI-powered energy community management framework benefiting from multi-agent decision-making that optimizes energy exchange and appliance scheduling in smart homes, enhancing self-consumption and cost-effectiveness by maximizing local PV generation, battery storage, and EVs utilization. For the optimizer, they formulate the household decision process as a Markov decision process and solve it using reinforcement learning. They describe fuzzy Q-learning and also an RL/ANN structure, and they report a comparison against MILP in the evaluation section.

2.2.1 Research Gaps

Centralized formulations are typically attractive because they can coordinate community-level objectives with a single optimization layer. However, the same centralization that enables global coordination also makes the approach structurally dependent on comprehensive information acquisition and accurate modeling of heterogeneous households. In the residential DR scheduling study, the authors explicitly note that conventional centralized DR requires access to residents' appliance information. As community size increases, the communication burden grows accordingly, and privacy concerns intensify because a large amount of resident load information becomes available to the aggregator. In addition, it should be highlighted that heterogeneity is not an edge case but a dominant property of EC differences in appliance characteristics and in affordability and comfort preferences. These features complicate system scheduling and introduce subjective elements that can reduce modeling accuracy in real deployments.

The scalability issue has been explicitly studied in [51], where the model relies on Shapley value computation, and reports that execution time becomes unacceptable beyond relatively small community sizes (e.g., exceeding one day for more than fifteen members). Taken together, the centralized literature implies a recurring limitation. The global optimization is feasible in principle, although it often presupposes:

- extensive private information disclosure and communication,
- reliable user heterogeneity modeling
- computational tractability that may not hold beyond small or medium communities

These limitations and other characteristics of central method cause:

1. risk of privacy violation. Centralized approaches typically require a central operator to access specific information of users, such as detailed load curves, device parameters, operational constraints, and sometimes occupancy or comfort settings, to construct and solve the global optimization problem. Even when the communication channel is encrypted, encryption mainly protects data in transit, but it does not remove the need for the central manager to receive, store, and process sensitive information. Consequently, participants must authorize the central entity to access private data from their premises, which raises concerns about data governance, secondary use, profiling, and increased exposure in case of misuse or cybersecurity breaches

2. overlooking users' preferences. Although some studies introduce tailored mechanisms to apply individual preferences (e.g., preference-weighted objectives, comfort constraints, user-specific utility functions, or learning-based preference estimation), centralized formulations still tend to do DR through a uniform set of rules and parameters. In practice, this translates into applying the same scheduling logic, flexibility assumptions, and incentive/penalty structure across heterogeneous users, regardless of their implicit interests, habits, or willingness to participate. As a result, the estimated "optimal" solution may be efficient at the aggregate level but misaligned with individual priorities, leading to unfair burden allocation, reduced acceptance, and lower long-term participation when users differ substantially in comfort sensitivity, appliance usage patterns, and privacy attitudes

3. Scalability limits. In centralized formulations, a single optimizer must acquire data from all participants (loads, DER/ESS states, constraints, forecasts, and preferences) and solve one large, tightly coupled problem over the full horizon. As the community grows, the number of decision variables and constraints increases rapidly (often proportional to users × devices × time steps and computational complexity, plus network/market coupling constraints). This increase memory usage and solution time, and can turn a set of tractable problems into one that is computationally heavy, especially when uncertainty modeling is included. Scalability is not only computational. The communication burden also expands because the central unit must continuously collect high-resolution measurements and updates and then broadcast setpoints or schedules back to all users. With many agents, this creates congestion and latency. In practice, these scaling effects often push centralized approaches toward hierarchical or decomposed architectures or motivate distributed optimization, where computation and data remain closer to the edge.

Hybrid and hierarchical approaches emerge in these works primarily as pragmatic responses to the scaling and information constraints of pure centralization. Some mentioned models propose a clustering-based hierarchical computation, first at the group level and then within groups, to reduce complexity and extend applicability to larger communities. Upper-level problems usually rely on simplified surrogate models of lower-level behavior (linearized flexibility, convex approximations). If local realities differ (discrete appliances, nonconvex comfort constraints), the upper layer's decisions can be systematically biased. Complex implementation and maintenance are a structural drawback of hybrid and hierarchical schemes because they replace a single optimization block with a multi-layer control stack (device controllers, HEMS/BEMS, a community coordinator or aggregator, and often a market/DSO interface). This layering increases integration effort where heterogeneous devices and vendors must interoperate through compatible protocols, shared data models, time synchronization, and reliable middleware. Operationally, multiple controllers run at different horizons and update rates, so debugging and monitoring become harder, and failures may emerge indirectly, and small inconsistencies at the edge can propagate upward and destabilize coordination.

Decentralized approaches are commonly motivated by privacy, autonomy, and reduced reliance on a single coordinating entity. However, the reviews make clear that decentralization often replaces optimization and information obstacles with behavioral and market-design dependencies. Decentralized/P2P designs often assume people actively tune bids/preferences. In real local market trials cited in [46], <5% of users stayed active after day one; most "set and forget," so the model of continuous rational bidding becomes fragile. Game-theoretic decentralized interaction can oscillate or fail to settle where no Nash equilibrium exists, and the system flips between excess demand and excess production unless agents behave "non-rationally." That's a clean theoretical warning about decentralized self-interest dynamics. in addition, lack of a central unit to optimize the load and generation schedule may cause sub-optimal answers as no "unit with a comprehensive view on the system" is doing the optimization. Usually, in these methods golabl optimum is sacrificed to obtain an acceptabletable answer which approximately falls in the optimum answer for all users. In addition, the absence of a central unit that jointly optimizes generation and demand schedules can lead to systematically sub-optimal outcomes, because no single entity has a comprehensive view of the entire system and all coupling constraints. When decisions are made locally or through limited coordination signals, each participant optimizes with partial information (e.g., local forecasts, local constraints, and an imperfect representation of others' actions), so the collective solution may fail to exploit community-wide complementarities such as diversity in demand profiles, shared flexibility, or optimal use of common assets (e.g., shared storage). Consequently, these methods typically trade global optimality for practicality. Instead of solving one integrated problem, they rely on decomposition, iterative coordination, or consensus mechanisms that deliver a feasible and commonly accepted schedule. The resulting solution is often near-optimal from an individual perspective and acceptable for the community as a whole, but it may still deviate from the true centralized optimum, especially under strong couplings (network limits, peak constraints, collective market bids) or when participants exhibit heterogeneous preferences and flexibility.

While the mentioned methods are mature, in most of them it is assumed that the generation devices and batteries are owned by the aggregator, demoting individual members to the role of mere consumers, which departs from our expectations within the context of energy communities. Furthermore, in a central and hierarchical system, a supervisory aggregator is essential for the collection of consumption data from users and for providing them with the community's load schedule. Another notable study, closely aligned with our work, that illustrates preferences of a distributed and uncoordinated approach over a central one, focuses solely on scheduling the ESS and does not enable energy sharing among EC members. In that approach, all trading activities for individual users are limited to interactions with the main grid [**?**].

This thesis is motivated by the fact that the most of the above-mentioned methods can not be applied as a practical method when:

- The generation resources and ESS are generally not owned by the community or the aggregator.

- There is no market or platform for P2P energy-money flow between REC users.
- Instead of real-time prices and demand response requested from the network operator as motivation for end users [117], there are predefined instructions and incentives for collective energy self-consumption (as a key practical barrier in real deployments in some countries such as Italy).
- Data of REC members are needed to reach an optimum collaborative load profile, while users may hesitate to share their load profile or appliance schedules. Therefore, it is needed to devise a method that not only leads to collaborative arrangements but also guarantees the privacy of users.

Despite the maturity of decentralized and game-theoretic energy management approaches for RECs, existing methods fail to simultaneously address user privacy preservation, compatibility with current REC regulatory frameworks, and the minimization or removal of reliance on energy storage systems, while avoiding the need for a central coordinator.

To address the previously mentioned issues regarding the incompatibility of different proposed methods with some REC architectures (i.e., in Italy), we tried to develop a secure decentralized and distributed optimization framework based on Game Theory, aimed at maximizing collective self-consumption while accounting for individual advantages. In this thesis, we seek to set a trade-off between paradigms, privacy, and knowledge sharing, allowing all members to make optimized decisions at an equilibrium point without disclosing their consumption data.

Based on the identified research gap, the objectives of this study are:

- design a fully decentralized energy management framework for RECs that operates without a central coordinator.
- align individual user preferences with collective self-consumption goals under practical and already-existing regulatory constraints.
- preserve user privacy while enabling collaborative optimization.
- reduce reliance on energy storage systems while maintaining near-optimal performance.

The following contributions are provided to meet the aforementioned objectives:

- A formulation allowing each user to act as an autonomous agent, with iterative best-response dynamics driving the system toward a Nash equilibrium.
- A fully distributed computational structure is adopted, where the scheduling problem is solved locally at the user side and can be executed on low-cost HEMS hardware with limited processing and memory resources. The approach avoids a monolithic

community optimizer and instead relies on lightweight local computations and limited coordination signals, so the computational and communication burden does not grow gracefully as the number of participants increases, supporting scalability in larger energy communities. Despite this decentralization, the formulation is designed to preserve near-optimal system behavior by explicitly capturing the key coupling effects among users, enabling convergence to stable collective operation without requiring full data. Importantly, the method remains effective even when no ESS is available, maintaining acceptable coordination and performance through demand flexibility and strategic scheduling rather than depending on storage to absorb mismatches between local generation and consumption.

- One contribution of this work is to mitigate the reliance on ESS in achieving acceptable scheduling and self-consumption performance. This is strategically important because ESS deployment is not only a techno-economic choice, but also a supply-chain and geopolitical risk. Key battery materials and parts of the manufacturing pipeline may be concentrated in a limited number of countries, and even modest political tensions, trade restrictions, or export and import controls and tariffs can disrupt availability and price stability. In such conditions, power grids and energy communities that over-depend on ESS become more exposed to cost shocks, procurement delays, and long-term replacement uncertainty, which can undermine planning reliability and the resilience of future operations. By reducing the extent to which system-level objectives hinge on ESS, the proposed approach improves robustness against supply-side disruptions while maintaining operational feasibility under realistic constraints.
- Direct compatibility with the Italian REC regulatory framework is ensured by explicitly modeling the operational and settlement logic required for incentive eligibility, rather than treating incentives as an abstract revenue term. In particular, the formulation aligns with the hourly structure of energy sharing used for GSE incentive calculations, so shared energy, imports/exports, and community balances are evaluated on an hour-by-hour basis consistent with how remuneration is determined in practice. By embedding these regulatory elements into the optimization (instead of adding them as an ex-post accounting step), the resulting schedules are immediately interpretable under Italian rules and can be deployed without redesigning the model for compliance. This regulatory grounding demonstrates that the method is not only theoretically efficient but also implementable within real policy constraints, where incentive design, metering granularity, and settlement procedures materially shape prosumer behavior and feasible community operation. Moreover, this thesis is intentionally positioned beyond a purely academic exercise: it is deployment-oriented and industrially relevant, built around real on-ground regulatory requirements and practical operational problems that determine whether an REC solution can function outside simulations.

Chapter 3

Methodology

3.1 Regulation

Electricity market is unlike most other markets because it is intrinsically complex. The flow of energy and the associated transactions are coordinated through tightly structured procedures designed to achieve two goals at the same time: keeping the system open and competitive while also guaranteeing secure operation and uninterrupted supply. To steer the grid toward the intended objectives, it may sometimes be necessary to impose policies whose implementation, while preserving these two operational features, requires considerable care and thorough analysis. For this reason, the market is organized into a sequence of clearly separated stages, and each stage has its own objective and set of participants. A wide range of actors operate across these stages, each with a distinct function in the overall ecosystem. Broadly, the main roles include prosumers, aggregators, the energy market manager, the Transmission System Operator (TSO), the Distribution System Operator (DSO), and Energy Retailers. Given the breadth and complexity of the electricity market, this thesis does not attempt to cover all market segments and actors. Instead, it focuses on the specific market pathway enabled by REC and CEC configurations, i.e., the regulatory and operational chain through which prosumers and consumers coordinate local generation and demand, quantify shared energy, and access the associated settlement and incentive mechanisms. This scoped perspective allows the analysis to remain aligned with the actors, data flows, financial flows, and decision processes that directly determine REC/CEC feasibility and performance in practice.

3.1.1 EU

Renewable Energy Communities and Citizen Energy Communities were created in EU law as part of the “Clean Energy for All Europeans” legislative package to formalize a citizen and community-centered layer of the energy transition, enabling collective ownership, local benefit-sharing, and active participation in energy markets rather than a purely centralized producer–consumer model. At EU level, RECs are defined in Directive (EU) 2018/2001 (RED

II) as local, proximity-based legal entities centered on renewable projects and community benefit rather than profit, supported by a mandatory "enabling framework" obligation on Member States (Article 22). The EU framework has materially evolved twice since the 2019 "Clean Energy Package" enactment. First, RED III (Directive (EU) 2023/2413) substantially revised renewables targets and permitting, and also updated parts of RED II's consumer and market provisions (including elements that interact with community energy such as PPAs and certification)[34]. Second, the electricity market design reform (Directive (EU) 2024/1711) amended both RED II and Directive 2019/944 and notably introduced an explicit "energy sharing" concept and a detailed right to energy sharing (including vulnerable customer access) in the Electricity Directive's consumer chapter, with an obligation for system operators and Member States to operationalize data flows and registration[35].

key EU primary legal acts and major revision points (binding law) establishing and evolving the REC/CEC are:

- Directive (EU) 2018/2001 (RED II, recast): definition of renewable energy community and mandatory enabling framework (Article 22).
- Directive (EU) 2019/944 (recast Electricity Directive): definition of citizen energy community (Article 2) and enabling framework for CECs (Article 16).
- Regulation (EU) 2019/943 (electricity market regulation): referenced in community provisions where balancing responsibility, network charges, and market design are involved.
- Directive (EU) 2023/2413 (RED III): amends RED II and the Governance Regulation for updated renewables targets and market/permitting provisions.
- Directive (EU) 2024/1711 (electricity market design reform): amends both RED II and Directive 2019/944 and introduces/strengthens "energy sharing" and related consumer protections and implementation duties.

A critical interpretive EU "bridge" document is the Commission staff working document that clarifies conceptual overlap and differences between RECs and CECs (including the "local" nature of RECs and broader "communities-of-purpose" potential for CECs)

The REC enabling framework (RED II, Article 22) requires Member States to establish a supportive environment for energy communities. This includes removing unjustified barriers, ensuring fair and proportionate administrative procedures (such as registration and licensing), and applying network charges that reflect actual costs based on a cost–benefit analysis. It also mandates the prevention of discriminatory treatment and requires that participation be accessible to all users, including low-income and vulnerable households.

3.1.2 Italy

Italy's implementation is characterized by

Table 3.1: EU-level milestones shaping REC/CEC concepts.

Date	EU act	Legal type	What changed for REC/CEC
30 Nov 2016	“Clean Energy for All Europeans” (COM(2016) 860)	Commission package framing	Sets policy direction: consumer empowerment, decentralization, investment.
11 Dec 2018	Directive (EU) 2018/2001 (RED II)	Directive	Creates REC definition (Art. 2) and obliges enabling framework (Art. 22).
5 Jun 2019	Directive (EU) 2019/944	Directive	Creates CEC definition (Art. 2) and obliges enabling framework (Art. 16).
18 Oct 2023	Directive (EU) 2023/2413 (RED III)	Directive amending RED II	Revises RED II for updated targets and related provisions that can affect community renewables deployment.
13 Jun 2024	Directive (EU) 2024/1711	Directive amending RED II +2019/944	Introduces “energy sharing” definition and detailed right/implementation duties; affects community energy operation.

1. an early “transitional” pilot phase launched through art. 42-bis of Decree-Law 162/2019 (converted by Law 8/2020), limited to 200 kW renewable plants and tight geographical constraints
2. full transposition via Legislative Decree 199/2021 (RED II) and Legislative Decree 210/2021 (Electricity Directive), which translated EU community concepts into the Italian market and network context
3. a major incentive and operationalization phase via the “Decreto CACER” (Ministerial Decree 7 December 2023, no. 414) with GSE/ARERA implementation
4. a 2025–2026 sequence of amendments (Ministerial Decree 16 May 2025, no. 127; Legislative Decree 7 January 2026, no. 3; Legislative Decree 9 January 2026, no. 5) aligning Italy with the EU’s post-2023 reforms and expanding eligibility and operational rules.

A defining Italian design choice is the coupling of “energy community” concepts to a specific "virtual" accounting of locally shared electricity based on metered injections and withdrawals (shared energy as the minimum within a time interval) and to a network-topological perimeter (notably the "cabina primaria" requirement for certain incentives). This ties community benefits to distribution-grid impacts and supports a cost-reflective argument for reduced grid components and incentive payments, but raises persistent implementation challenges: administrative complexity, uneven access to finance and technical capacity, and distributional questions about network cost recovery and cross-subsidies

Italy introduced a "transitional" regime explicitly "nelle more del completo recepimento" of RED II, enabling collective self-consumption and RECs under art. 42-bis of Decree-Law 162/2019, justified as a way to generate evidence and experience ahead of full transposition (monitoring "funzionale all'acquisizione di elementi utili"). This transitional design was intentionally narrow: renewable plants capped at 200 kW, entry into operation after the conversion law and within a defined window, and sharing constrained to the relevant distribution network portion (the original framework tied to a "cabina secondaria" type perimeter, as later described by ARERA)

Italy's legislative framework for energy communities follows the structure of EU directives. Legislative Decree 199/2021, which transposes RED II, defines the legal conditions for renewable self-consumption and RECs in Title IV (Articles 30–33). It also introduces key elements related to incentive schemes and geographical eligibility, notably the reference to the "cabina primaria" for accessing incentives. In parallel, Legislative Decree 210/2021 transposes Directive 2019/944 and establishes the framework for active customers and CECs. This includes their legal definition and the possibility for CECs to manage distribution networks under specific authorization and sub-concession arrangements, subject to regulatory oversight by ARERA, particularly regarding applicable charges.

The modern Italian incentive framework for self-consumption referred to as "widespread self-consumption", and renewable energy communities (RECs) are defined by the Ministerial Decree of 7 December 2023, No. 414 (commonly known as the "CACER Decree"). This regulation entered into force in January 2024 and was officially published in the Official Gazette. A key legal and economic feature of this framework is the dual structure of incentives. Italy recognizes both (i) a premium tariff applied to the "shared energy quota" (i.e., the portion of energy simultaneously generated and consumed within the community), and (ii) a separate "remuneration component" linked to tariff elements defined by the regulatory authority (now structured under the TIAD framework). The implementation of this scheme is carried out by the energy services operator (GSE), which manages standardized contracts, digital platforms, and operational procedures [47]. Furthermore, the legal and economic feasibility of this decree required approval under EU State aid rules. In this regard, the European Commission authorized a large-scale Italian support scheme under the recovery and resilience facility, aimed at promoting renewable energy communities and self-consumption initiatives [33].

Italy expanded and adjusted the PNRR capital-grant dimension of the CACER scheme through Ministerial Decree 16 May 2025, no. 127 (notably widening the beneficiary “municipality population” threshold and adjusting cash flow features such as advances), with those changes reflected in updated operational rules [69]. Crucially, Italy implemented Directive (EU) 2024/1711 through Legislative Decree 7 January 2026, no. 3 (effective 24 January 2026), introducing a structured “organizer” concept for energy sharing/renewable sharing and changing “energia condivisa” accounting from “per hour” to a “periodo rilevante non superiore all’ora (not exceeding one hour)”, aligning with imbalance settlement evolution and EU 2024 market rules. Italy also implemented RED III via Legislative Decree 9 January 2026, no. 5 (effective 4 February 2026), which, among other changes, updated definitions relevant to communities and introduced explicit simplifications for guarantees of origin procedures for plants under 50 kW and for plants inside renewable energy community configurations[89]

To ensure the renewable origin of energy within an REC, Guarantees of Origin (GOs) are issued. Under EU law, GOs function as a certification and disclosure mechanism to verify the renewable source of energy that is supplied or consumed. In Italian legislation, this role is explicitly defined: a GO “serves solely to demonstrate to final customers” the share of renewable energy within a supplier’s energy mix, as well as the portion delivered under renewable energy contracts. Italy assigns GO issuance, registry management, transfer, and cancellation to the national incentive operator, GSE, requiring electronic handling, fraud-resistance, and compliance with the relevant European standard. Italy’s GO framework also states key integrity constraints, one GO per unit of energy, one-time accounting of renewable energy, validity limits (12 months from production), and expiry accounting into the national residual mix if not canceled.

The timeline of Italian decrees and amendments is shown in Fig. 3.2

In the latest update, the CACER Decree established an incentive tariff for all configurations established by the TIAD and changed the maximum size of individual plants from 200 kW to 1 MW. It also allowed all users and consumers of a single renewable power plant to be installed downstream of the same HV/MV station, thereby expanding the area of interest of the REC. The incentive tariff for RECs is calculated in time intervals up to one hour [88] and determined by a fixed base and a variable component, depending on the hourly zonal price and plant size. The tariff cannot exceed 100 €/MWh for plants with a rated size greater than 600 kW, 110 €/MWh for plants between 200 and 600 kW, and 120 €/MWh for plants of less than 200 kW of rated size. Table 3.3 illustrates the price of incentive for energy sharing within EC.

The RECs that use the existing power grid can include various kinds of users, residential buildings, tertiary sector buildings (offices, hospitals, etc.), industrial properties, and public administration buildings. This plan allows legal entities and users who form a community to plan the installation of renewable energy resources and collectively share energy for their own purposes. It is obvious that due to the non-dispatchable nature of renewable resources, the possibility of bi-directional interaction with the grid is preserved. The incentive is granted for 20 years by GSE to the RECs’ representative and is calculated on the basis of energy sharing. In

Table 3.2: Italy milestones shaping REC/CEC concepts.

Date	No.	type	What changed for REC/CEC
2020	ARERA deliberation 318/2020/R/eel [11]	Resolution	transitional economic settlement for shared energy + related attachments
2021	199/2021 (RED II transposition) Art. 30-33,46	Legislative Decree	self-consumption, REC, system interaction and GOs
2021	210/2021 Art. 3,14	Legislative Decree	definitions including CEC, active customers + CEC operational conditions; network management possibility and ARERA oversight
7 Dec 2023	no. 414 ("Decreto CACER")	Ministerial Decree	Identification of an incentive tariff for systems included in REC and in the configurations of individual, remote, and collective self-consumption.
16 May 2025	no. 127	Ministerial Decree	ministry announcement and GSE updated operational rules referencing the decree.
7 Jan 2026	no. 3 (transposition of Directive (EU) 2024/1711)	Legislative Decree	introduces the organizer role and updates shared energy time interval and related rights
9 Jan 2026	no. 5 (transposition of RED III)	Legislative Decree	updates definitions (including "energia condivisa") and introduces simplified GO procedures for plants inside REC configurations.

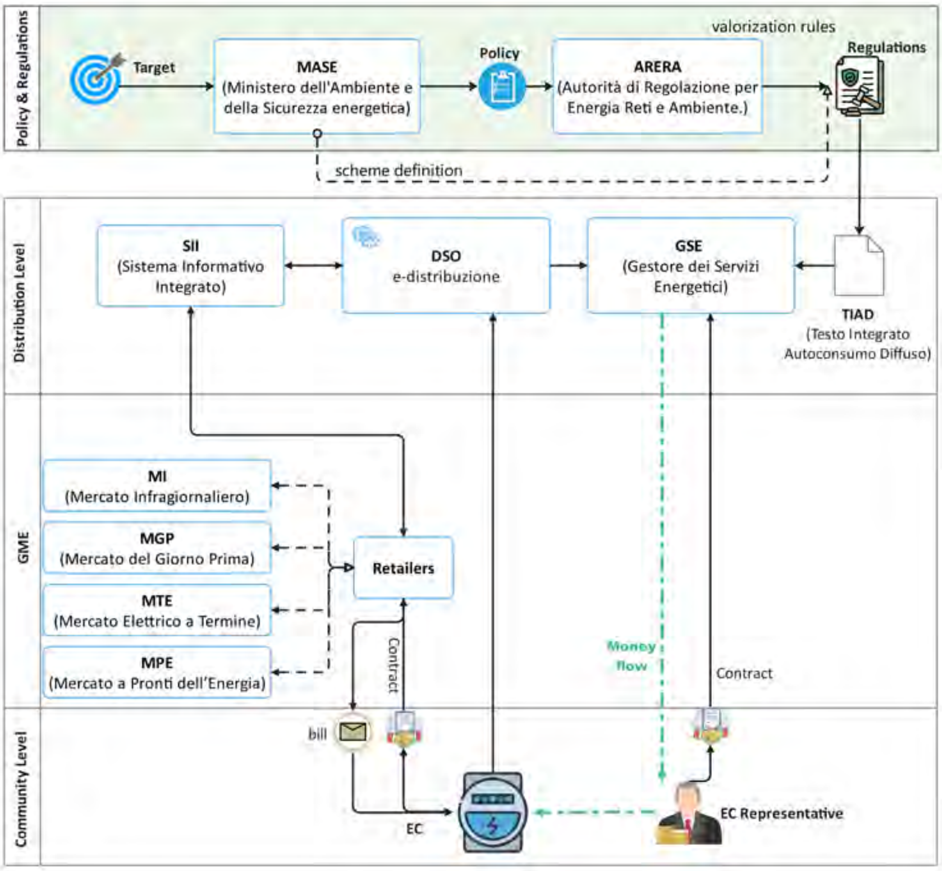

Figure 3.1: EC Incentive mechanism in italy

fact, the incentive amount accounts for two factors: the "price of electricity," which is produced and used on-site simultaneously, and the "transmission tariff per MWh," which is avoided in this scheme and paid back to customers in the form of an incentive. The energy sharing is evaluated by the GSE without any burden for the members of the community, based on the measurements collected by the Distribution System Operator for billing purposes and then transmitted to the GSE. For each time interval, the GSE will calculate the amount of energy produced by all renewable power plants inside the same REC and the amount of energy consumed from the grid by all users belonging to the configuration [29]. Then, according to the definition by GSE, shared energy will be equal to the minimum value between the two mentioned terms in each hour according to 3.1

$$min[P_h^{GEN}, P_h^{CON}], \quad \forall h \in \{1, \cdots, 24\} \tag{3.1}$$

However, as mentioned earlier, the time interval for calculating the shared energy is allowed to be less than one hour.

Previously, in other GSE incentivization schemes, the total amount of monthly production, consumption, and sold energy was calculated, and users just had to pay the amount of energy they imported from the grid and got paid for the energy they injected into the grid [48].

Table 3.3: CACER Incentive Tariff Structure

Nominal Power (kW)	**Fixed Tariff**	**Variable (Zonal Price)**	**Max Tariff Non-PV**	**Max Total Tariff for PVs**		
				South	**Center**	**North**
$P \leq 200$	80 €/MWh	0–40 €/MWh	120 €	120 €	124 €	130 €
$200 < P \leq 600$	70 €/MWh	0–40 €/MWh	110 €	110 €	114 €	120 €
$P > 600$	60 €/MWh	0–40 €/MWh	100 €	100 €	104 €	110 €

However, in the new plan for RECs, by including the factor “time”, the simultaneous equality between generation and consumption has been highlighted. The goal is to promote real-time self-consumption by incentivizing collective use of green electricity and reducing the time window over which generation and consumption are evaluated. In other words, the local power balance will be more emphasized in the future, although the REC remains grid-connected. By comparing the mentioned incentives with others deployed for renewable energy expansion, it can be inferred that mere renewable energy production is not the only target of this plan. The concurrent equilibrium between REC’s production and consumption is another objective of this plan, which can be considered another step toward an ideal and autonomous REC. Thus, an effective EMS of the community is the backbone to fulfill this target. The methodology proposed in the following sections aims to effectively address individual benefit concerns while obtaining the maximum incentive offered by the GSE.

3.2 Community model

This section introduces the proposed energy community model and motivates the design choices adopted in its architecture and decision-making process. An energy community is placed at the intersection of physical power flows, market transactions, and member-level preferences; therefore, a workable model must simultaneously represent generation and storage dynamics, flexible and inflexible demand, and the settlement rules that determine how costs and benefits are allocated among participants. If any of these layers is simplified too aggressively, the resulting conclusions risk being valid only “on paper” and not under the operational and regulatory conditions in which communities actually function.

Building on the Italian market context described in the previous section, the proposed model is formulated to reflect how an energy community can coordinate self-consumption, sharing, and possible flexibility services while respecting the roles of external actors and the constraints imposed by the grid. The model explicitly distinguishes between individual members and the community as a whole, so that both private objectives (bill reduction, comfort preservation, autonomy) and collective outcomes (community cost, peak reduction, renewable utilization, fairness) can be evaluated in a coherent way.

The community consists of several active members who produce, consume, or both produce and consume their renewable resources through an aggregated collaboration. In the first stage, a set of participants, whose size varies across scenarios, is assumed to form the energy community. Each participant may be a producer, prosumer (i.e., simultaneously producing and consuming), or a pure consumer. Although in reality, generation and consumption occur at the same premises and at the same physical connection point, our model separates these functions to represent them more explicitly. Concretely, we treat the consumption-side and production-side behaviors of the same member as two distinct entities within the optimization. For instance, a household that operates an EV and domestic appliances while also owning a rooftop PV system is represented twice: once as a consumer entity (with its local generation set to zero) and once as a producer entity (with its local consumption set to zero). In this way, community members are modeled according to their operational role, so that energy injections and withdrawals can be accounted for independently and integrated more cleanly into the scheduling and settlement logic. It's worth noting that in our modeling, ESSs are modeled at the generation side. In the Italian regulatory framework, an ESS is typically modeled on the generation side because, from a regulatory and settlement perspective, storage is treated as functionally connected to a production asset rather than as an independent consumption load.

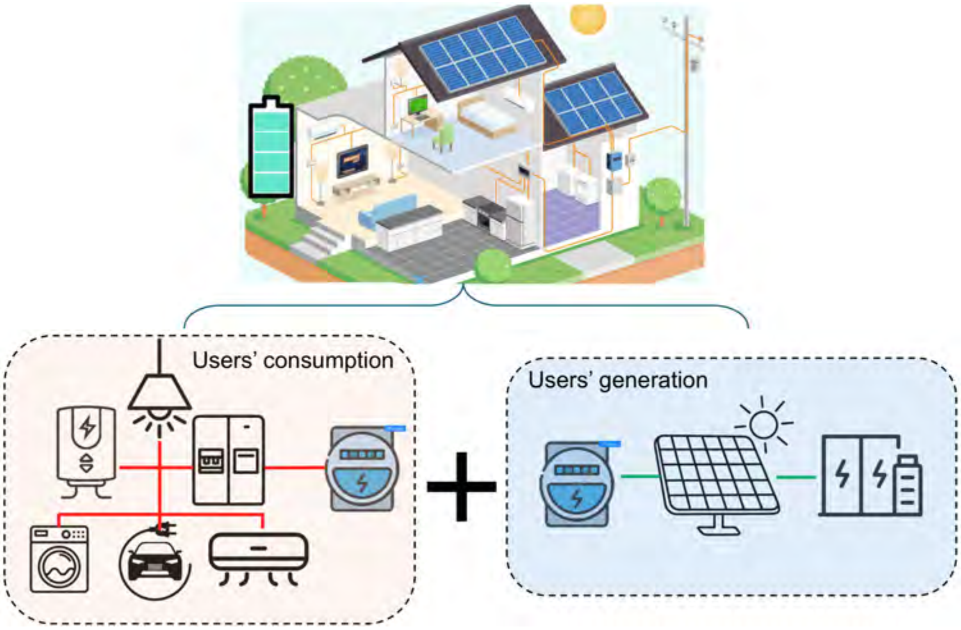

Figure 3.2: Prosumer decomposition

When an ESS is charged from a PV system and later discharges, the discharged energy is still considered renewable generation for accounting purposes. Therefore, in most configurations, the ESS is associated with the generation unit to preserve traceability of renewable origin and to avoid double counting. If an ESS were modeled as a pure consumer when charging and as a separate producer when discharging, without linking it to the renewable source, it would complicate the regulatory accounting of incentives, network components, and guarantees of origin. Associating storage with the generation side simplifies compliance with metering rules and settlement mechanisms defined by ARERA and implemented by GSE. For modeling purposes, placing ESS within the generation entity ensures that optimization reflects its role in maximizing shared renewable output rather than merely shifting demand. However, if a user is merely a consumer having an ESS, the storage can be modeled on the consumption side, shifting loads within the user's property.

In the Point of Delivery (POD) of electricity, two separate measurements are assigned to the generation and consumption. Although measurements transmit data in smaller time intervals, we assume an hourly load/generation profile in our modeling. Figure 3.3 shows a typical configuration of EC within our model. as it is illustrated in Figure 3.3, we have separated the generation and consumption sides of the same user, although they might belong to the same premises.

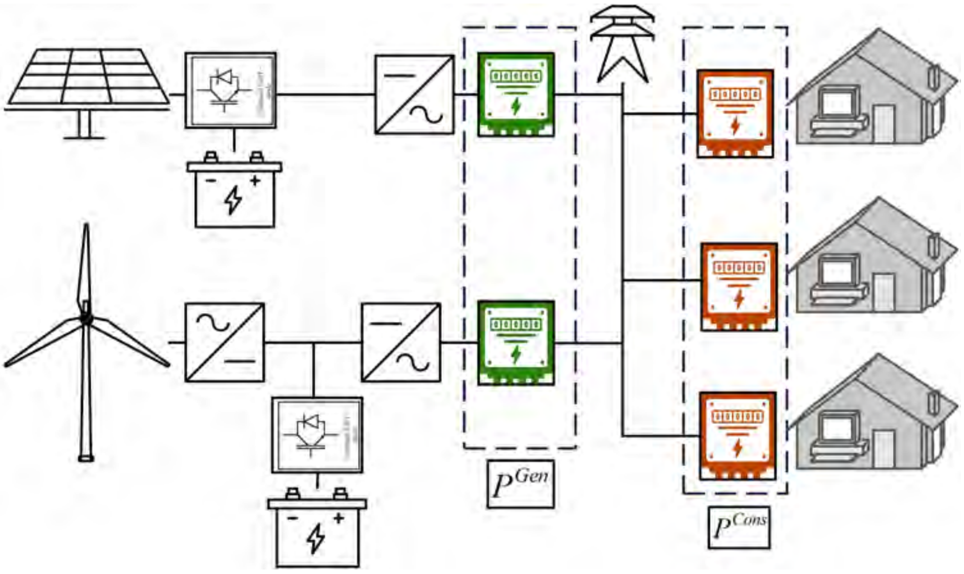

Figure 3.3: A Configuration model of an EC

As discussed in subsection 2.1.1.2, electrical loads can be defined and classified using multiple criteria (e.g., sector, temporal profile, controllability, or physical behavior). Since this thesis is concerned with the coordinated management of demand and local generation, we rely on the categorization introduced in that subsection and apply it consistently throughout the remainder of the work to ensure a coherent modeling and scheduling framework. Accordingly, we represent demand using three load types:

- **Critical (base) loads**, which must be supplied as required and are treated as non-flexible;
- **Shiftable loads**, whose operation can be moved in time within predefined user- and device-specific windows while preserving the required energy service;
- **Adjustable loads**, whose power level can be modulated (within allowable bounds and comfort/technical constraints) to provide flexibility without fully shifting the task.

These classes reflect the operational characteristics described in subsection 2.1.1.2 and provide a practical balance between modeling accuracy and computational tractability for the optimization and coordination strategies developed in this thesis.

3.3 Formulation

This subsection presents the mathematical formulation of the proposed energy community model. The objective is to provide a structured representation of the operational interactions among community members, their loads, and local generation resources within the regulatory and technical constraints previously described. The formulation translates the physical behavior of distributed energy resources, user demand flexibility, and community-level coordination mechanisms into a tractable optimization framework.

The model is developed to capture both individual level decision making and EC level coupling effects. Each participant is represented according to its operational role (production and/or consumption), while shared constraints, such as community power balance, incentive-related accounting, and technical limits are embedded to reflect the collective nature of the energy community. The formulation explicitly incorporates the load classifications introduced earlier (critical, shiftable, and adjustable loads), allowing differentiated flexibility modeling consistent with realistic appliance behavior. Furthermore, the objective function and constraints are designed to align with the Italian REC regulatory framework, including the treatment of shared energy and relevant economic components. In this way, the formulation does not remain purely theoretical but reflects real-world operational and settlement conditions.

Referring to energy sharing, defined by the GSE, the hourly minimum between the energy consumed and the energy produced by REC users can be seen in the Figure. 3.4.

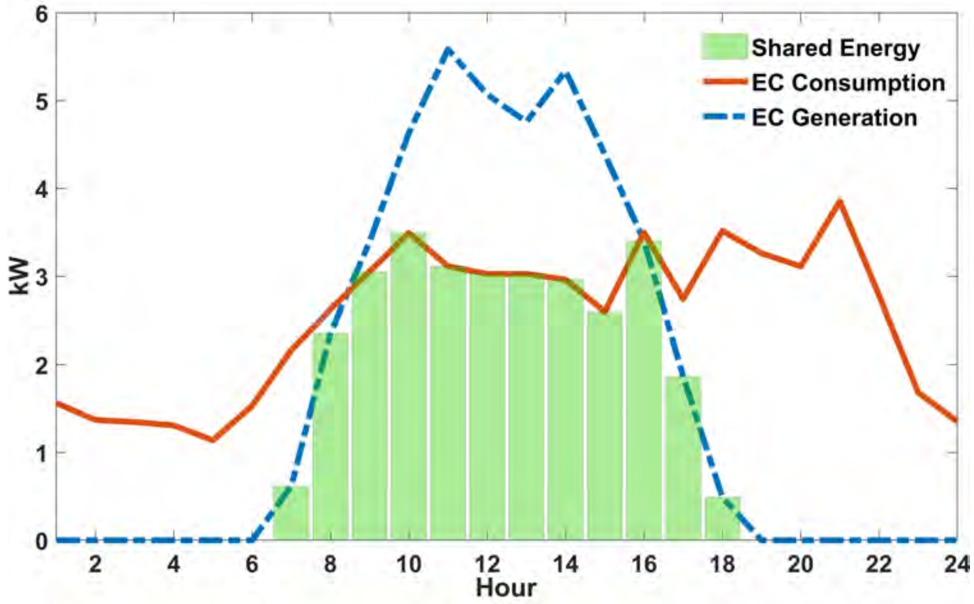

Figure 3.4: Daily Consumption and Generation in an EC

It can be deduced that the maximum benefit for energy communities will occur if the collective consumption of all users is almost equal to the hourly generation of the systems that are part of the configuration (considering the batteries on the generation side). Thus, maximizing energy sharing hour by hour follows Eq. (3.2).

$$\mathbf{max}(min[P_h^{GEN}, P_h^{CON}]), \quad \forall h \in \{1, \cdots, 24\} \tag{3.2}$$

Where P_h^{GEN} and P_h^{CON} are the total energy generation and consumption of the REC in hour h. To operate an energy community in a manner that maximizes both collective and individual benefits, the presence of an efficient EMS is essential.

Such a system must be capable of coordinating the actions of all participants and energy resources within the community, including generation units, flexible loads, and storage devices, in order to determine operational strategies that improve overall performance. In the literature, EMS architectures for energy communities are generally categorized into centralized, decentralized, and hybrid approaches [98]. These categories do not merely represent different communication or information-exchange structures; they also fundamentally influence how decisions are made, how information is shared among participants, and ultimately how effectively the overarching objectives of the REC and its individual members are achieved.

In a centralized EMS, a single coordinating entity collects operational data from all members and solves a global optimization problem to determine the scheduling of generation and demand. In theory, this approach can achieve globally optimal solutions because the central controller has full visibility of the system and can coordinate resources efficiently. However, this benefit comes at the cost of requiring extensive access to private information about individual users, such as detailed consumption profiles, device characteristics, and operational preferences [53]. From a practical perspective, such data centralization raises concerns related to privacy, scalability, and trust. Moreover, the resulting operational strategy is designed to optimize the community-wide objective function, which may restrict the autonomy of individual members and limit their ability to apply their own consumption policies or preferences.

Conversely, in a decentralized scheme, each participant operates its own local management system and independently determines its optimal strategy based on locally available information. This approach enhances user autonomy and significantly reduces the need for sharing sensitive consumption data. Each member aims to maximize its own benefit while interacting with the rest of the community through limited information exchange or market signals. However, the absence of a central coordinating entity introduces new challenges. In particular, reaching a stable and efficient operating point becomes more complex, since no single agent possesses complete information about the entire community. As a result, purely decentralized strategies may lead to suboptimal outcomes or coordination difficulties when the actions of participants are strongly interdependent.

Recognizing the limitations of both centralized and fully decentralized frameworks, this work proposes a decentralized game-theoretic approach in which community members interact through a simultaneous game. In this framework, each participant optimizes its own objective while considering the strategies of other members, and the community operation evolves iteratively toward a stable equilibrium. This approach preserves user autonomy and privacy while still enabling coordinated behavior that approximates efficient community-level operation.

3.3.1 Objective Function

In the decentralized design, control is fully distributed across the renewable energy community. Each REC participant operates an individual EMS responsible for scheduling its own consumption and managing local storage (if it exists). This HEMS has access only to the member's internal data such as appliance characteristics and operating constraints, while exchanging limited information with the other HEMS units within the community.

To maximize the received reward besides minimizing energy cost, one term of the objective function for each member will be to decrease the hourly gap between the whole REC energy production and the whole REC energy consumption. To capture this, the local objective includes a coordination term that penalizes mismatches between the REC's aggregate generation and aggregate consumption at each hour. Accordingly, the problem in (3.2) is rewritten over a 24-hour horizon by introducing C_s, a fixed incentive coefficient (€/kWh) associated with shared energy, yielding:

$$\max\left(-C_s \sum_{h=1}^{24} \left|P_h^{GEN} - P_h^{CON}\right|\right) \tag{3.3}$$

If the total energy produced and the total energy consumed over the horizon are fixed (i.e., only their temporal allocation can change), then the optimal solution of (3.2) coincides with that of (3.3). In other words, both formulations reach their optimum at the same operating point. As indicated in (3.4), the highest benefit is obtained when the day-long mismatch between generation and consumption is minimized, ideally such that, across the day, one profile is entirely contained within the other (so that overlap is maximized and residual surplus/deficit is minimized).

$$\begin{gathered}\textbf{arg max}(F) = \textbf{arg min}\Big(\sum_{h=1}^{24} \left|P_h^{GEN} - P_h^{CON}\right|\Big) \\ \textit{where:} \quad F = min[P_h^{GEN}, P_h^{CON}]\end{gathered} \tag{3.4}$$

To prove that, let the two nonnegative curves be $G_{(t)}$ (generation) and $C(t)$ (consumption) over a horizon T. Assume their totals are fixed (in continuous form):

$$\int_T G(t)\,dt = \bar{G}, \qquad \int_T C(t)\,dt = \bar{C}. \tag{3.5}$$

where $\bar{G}$ and $\bar{C}$ are constant. The "shared/overlapped" energy at each time is $min\{G_{(t)}, C_{(t)}\}$

So the total shared energy is:

$$S = \int_T \min\{G(t), C(t)\}dt \tag{3.6}$$

On the other side, we know that:

$$\min\{a, b\} = \frac{a + b - |a - b|}{2} \tag{3.7}$$

Similarly for $G_{(t)}$and $C_{(t)}$, the shared energy will be equal to:

$$S = \int_T \min\{G(t), C(t)\}dt = \int_T \frac{G(t) + C(t) - |G(t) - C(t)|}{2} dt \tag{3.8}$$

but from (3.5) we know that $S = \int_T G(t), C(t)dt$ is equal to $\bar{G} + \bar{C}$. Therefore the equation (3.8) can be written as:

$$S = \frac{\bar{G} + \bar{C}}{2} - \int_T \frac{|G(t) - C(t)|}{2} dt \tag{3.9}$$

Since $\bar{G}$ and $\bar{C}$ are constants, maximum of S happens where the other term of the S is minimized

$$\max S = \min \int_T \frac{|G(t) - C(t)|}{2} dt \tag{3.10}$$

By substituting S, $G_(t)$, and $C_{(t)}$ with F, P^{GEN}, and P^{CON} respectively, and rewriting (3.10) in discrete form, (3.4) can be inferred. By multiplying the mismatch term in (3.4) by the incentive coefficient $(-C_S)$, the objective explicitly assigns an economic value to shared energy inside the REC: any deviation between generation and consumption is treated as a penalized quantity. This leads to

$$\max F_S = \max \sum_{t \in T} \left(-C_S \left| P_t^{GEN} - P_t^{CON} \right| \right) \tag{3.11}$$

which interprets the scheduling task as the reduction of a "lost opportunity." This lost opportunity represents every hour in which the community generates more than it consumes, associated with the energy that could have been locally used (and rewarded) but is instead left unmatched; similarly, every hour in which consumption exceeds generation represents a missed chance to cover demand with local renewable production.

With this formulation, taking into account a negative price for both the surplus and deficit between generation and consumption, the optimization problem prioritizes firstly the self-sufficiency of the REC to maximize rewards, and secondly, the sale of excess energy that cannot be stored or consumed within the REC. When generation exceeds consumption, two actions are possible: selling the surplus energy to the grid or charging the batteries. According to the EC topology illustrated in Figure 3.3, the first option does not reduce the generation profile and therefore does not help minimizing the gap between P_{GEN} and P_{CON}. In contrast, charging the batteries reduces the effective generation profile (since the batteries are installed upstream of the measurement point), thereby bringing the generation curve closer to the consumption curve. At this stage, it follows that battery charging has priority over selling energy back to the grid. However, there is a third option that can further reduce the gap between the two curves, namely increasing the load. In typical EC scenarios, consumption often exceeds generation, and since the total daily consumption is assumed to remain unchanged, increasing the load at hour t implies a corresponding reduction at another hour (for example, $t + 5$) where consumption is higher than generation. This operation reduces the mismatch between generation and consumption in both hours simultaneously. Because the optimization explores the feasible solutions space over the full 24-hour horizon, it identifies this solution yielding better overall performance by redistributing load across hours, rather than relying solely on battery charging at a single time step. Based on this reasoning, the priority order becomes firstly self-consumption, secondly battery charging, and in third place, selling energy to the grid. It should be noted, however, that this hierarchy may change if the fixed incentive reward or the selling price of exported energy varies significantly.

When the minimum amount between two terms (P^{GEN} or P^{CON}) moves towards its maximum (see Figure 3.4), it gets closer to the above curve (generation or consumption curve, depending on the situation). Even if one profile is pushed upward enough to exceed the other, the incentive-based benefit does not increase further, because the shared (rewarded) energy is ultimately capped by the smaller of the two at each time—the new limiting factor becomes the minimum term. In contrast, the L_1 mismatch introduced in Equation (3.3) continues to penalize any separation between the curves. Once overtaking occurs, $\left|P^{GEN} - P^{CON}\right|$ grows rather than shrinks, so the objective provides no reason to force one curve beyond the other. As a result, the optimization naturally avoids creating crossings and instead steers the solution toward tighter alignment between generation and consumption. Therefore, seeking to minimize the distance between these two terms follows the same target as (3.2).

Despite this equivalence, the reformulated problem is not fully identical to the original objective in (3.2) once the physical layout of the community is taken into account. The key issue is the typical REC topology considered here: storage is installed on the generation side (Figure 3.3). With batteries located upstream of the community metering point, charging and discharging actions do not merely "shift energy in time"; they directly modify the net power seen as community generation. As a result, both aggregate profiles, $P^{GEN}$and P^{CON}, can contain decision-dependent variables rather than being purely exogenous trajectories.

Under such a topology, minimizing the mismatch $\sum_T \left|P^{GEN} - P^{CON}\right|$ can be achieved through qualitatively different mechanisms. One mechanism increases overlap by raising the limiting side, for instance by shifting flexible demand into hours with renewable surplus or by discharging storage to cover deficits; this enlarges the portion of energy that is actually shared/consumed locally. Another mechanism reduces the mismatch by lowering the dominant side, for example by charging storage during high-generation hours (thereby reducing net exported generation) or by curtailing production if it is allowed. Both strategies shrink the absolute gap, but they do not represent the same operational outcome: the former improves the effective utilization of renewable energy by increasing served load from local sources, while the latter may simply hide surplus behind the battery or reduce exported power without necessarily increasing the energy delivered to loads.

This issue can be mitigated by adopting the proposed distributed optimization structure. Instead of allowing a single optimizer to act on both sides of the mismatch (generation and consumption) simultaneously, thereby being free to close the gap either by manipulating consumption or generation, the problem is decomposed so that generation-side and consumption-side decisions are controlled by different agents. In other words, each optimizer will possess decision variables associated with only one side of this equation simultaneously.

In this architecture, each optimizer is assigned a clearly bounded control domain. A consumption-side HEMS schedules only local demand variables and cannot directly manipulate the community generation profile. Conversely, the generation-side controller manages only generation-related variables and does not alter user consumption schedules. The coupling between the two is handled through exchanged signals that will be studied further, rather than by granting one entity control over both P^{GEN} and P^{CON}

The proposed energy community comprises participating members (including prosumers) and a set of renewable resources, such as photovoltaic and wind units, that are assumed to be jointly owned and operated at the community level. On the demand side, each member's electricity use is represented through three load classes: (i) base/critical demand that must always be supplied, (ii) shiftable loads whose operation can be moved in time, and (iii) adjustable loads whose power can be modulated through a finite number of discrete levels. Under these definitions, the daily electricity consumption of a generic user (P_d^{con}) can be expressed as follows:

$$P_d^{con} = \sum_{h=1}^{24}(P_h^b + P_h^{SH} + P_h^{ADJ}) \tag{3.12}$$

where P_h^b, P_h^{SH}, and P_h^{ADJ} denote, respectively, the hourly base (critical), shiftable, and adjustable demand components. The shiftable-load decision is modeled by a binary variable $\delta \in \{0, 1\}$, indicating the OFF/ON status of each shiftable appliance at hour h. Adjustable loads are represented through a discrete modulation variable $\beta \in \{0, \Delta, 2\Delta, \dots, 1\}$, which specifies the selected fraction of the nominal adjustable demand level (in increments of Δ). Let P_h^{sh} and P_h^{adj} denote the hourly energy consumption of the j^{th} shiftable appliance and the k^{th} adjustable appliance, respectively. Using these definitions, the equation (3.12) can be equivalently expressed as follows:

$$P_d^{con} = \sum_{h=1}^{24}(P_h^b + \sum_{j=1}^{S} \delta_{h,j} P_j^{sh} + \sum_{k=1}^{A} \beta_{h,k} P_k^{adj}) \tag{3.13}$$

In which $j \in \{1, ..., S\}$ and $k \in \{1, ..., A\}$ denote a set of shiftable and adjustable loads and h the hour of the day. The consumption of the whole community is equal to the sum of (3.13) across all N users of the community (i) where $i \in \mathscr{I} \triangleq \{1, ..., N\}$.

$$P_d^{CON} = \sum_{i=1}^{N} P_d^{con} = \sum_{i=1}^{N}\sum_{h=1}^{24}(P_h^b + \sum_{j=1}^{S}\delta_{h,j}P_j^{sh} + \sum_{k=1}^{A}\beta_{h,k}P_k^{adj}) \tag{3.14}$$

it should be noted that in the above equation and in the following, the subscript of d refers to the daily amount, and the superscripts with uppercase denote the summation amount of all users while the same letter in lowercase indicates the same for a single user.

On the supply side, the community's total generation is modeled as the aggregate output of its small-scale generation units. In this work, only photovoltaic and wind technologies are included, as they are the most common renewable sources adopted in RECs [19]. Accordingly, the REC generation portfolio, comprising RES (PV and wind) together with the storage system, delivers energy according to (3.15).

$$P_d^{GEN} = \sum_{r=1}^{R} P_d^{gen} = \sum_{r=1}^{R}\sum_{h=1}^{24}(P_{r,h}^{RES} + ds_{r,h}^{d}Ps_r^d - ds_{r,h}^{c}Ps_r^c) \tag{3.15}$$

where $r \in \mathfrak{R} \triangleq \{1, ..., R\}$ represents a set of RES and integrated ESS and $P_{r,h}^{RES}$ denotes the produced energy from r^{th} RES in hour h. ds^c and ds^d are binary variables indicating the charging or discharging state of batteries. Ps^d and Ps^c describe the power of discharging and charging of batteries, which depends on battery technology and also the C factor of the battery.

It's worth noting that here Ps^d and Ps^c are considered to follow a predefined rule-based strategy. In this way the equation (3.15) will be linear. The reason behind this is the control scheme of ESS for self consumption scenarios [86]. In these rule-based self-consumption controllers, considering $\overline{Ps^d}$ as maximum discharge power, discharge power is typically implemented as (3.16):

$$Ps^d = \min[\max[0, P^{GEN} - P^{CON}], \overline{Ps^d}] \tag{3.16}$$

therefore it is variable in time but not a decision variable. Greedy control is a commonly adopted rule-based strategy for RES self-consumption [82]. At each time step, it computes the net residual power as the difference between local generation and demand, and then dispatches the battery accordingly. Any surplus generation is charged into the battery until the upper SOC bound is met, while any deficit is covered by discharging the battery until the lower SOC limit is reached.

The problem (3.3), by substituting (3.14) and (3.15), can be written as (3.17):

$$\mathbf{max}\left(-C_i\sum_{h=1}^{24}\left|\sum_{r=1}^{R}(P_{r,h}^{RES} + ds_{r,h}^{d}Ps_r^d - ds_{r,h}^{c}Ps_r^c) - \sum_{i=1}^{I}(P_{i,h}^b + \sum_{j=1}^{S}\delta_{h,j}P_j^{sh} + \sum_{k=1}^{A}\beta_{h,k}P_k^{adj}) \quad \right|\right|\right) \tag{3.17}$$

However, the community's overall economic outcome cannot be explained by incentive revenues alone. The final benefit is shaped by several additional cost and revenue streams that the EMS must account for explicitly. In particular, transactions with the the grid which contribute a grid-interaction term (F_G). Storage operation introduces an additional cost component (F_{ESS}), which reflects the economic impact of battery usage (e.g., degradation or wear) and is commonly modeled as a cost per kWh of charged/discharged. Finally, demand-side flexibility comes with a price: shifting appliance operation away from preferred times imposes an inconvenience on users, captured through a discomfort term (F_L). Accordingly, the objective is extended to include these elements alongside the incentive-related component, as summarized below.

$$\mathbf{max}\,(F_R + F_G - F_{ESS} - F_L) \tag{3.18}$$

$$F_{ESS} = \sum_{h=1}^{24}\sum_{r=1}^{R}(d^{d}_{h,r} + d^{c}_{h,r})Cs_r Ps^{d,c}_r \tag{3.19}$$

$$F_G = \sum_{h=1}^{24} Cg^{+}_h P^{CON}_h - Cg^{-}_h Pg^{-}_h \tag{3.20}$$

$$F_L = \sum_{h=1}^{24}\sum_{i=1}^{N} Kc(P^{con^*}_{h,i} - P^{con}_{h,i})(\mathbf{1}_{(P^{con^*}_{h,i} \leq P^{con}_{h,i})}) \tag{3.21}$$

Cg^{+}_h,Cg^{-}_h, and Pg^{-}_h are the prices of buying and selling transactions with the grid, and the sold power, respectively. In the aforementioned cost functions, Cs_r describes the fixed cost of ESS usage per kilowatt hour of charging/discharging which can be calculated by having the lifetime (in cycles) and price of the battery[17]. In order to keep the representation of the methodology simple, we considered a lifetime for ESS that is described with a full cycle (let's denote it with L). In the proposed formulation, the battery has a price, which we temporarily denote it with (P), and the capacity of a full charge, which is indicated with (C). The degradation cost will be ($P/(L.E)$), where E is the square of roundtrip efficiency of the battery. By assuming that the battery is replaced once it reaches the lifetime cycle and $L \approx 2N_{cyc}C$, (the factor 2 is here considered because each cycle consists of a full charge and discharge) it can be inferred that the price of each kWh of battery usage will be $P/(2.N_{cyc}.C.E)$.

Moreover, K_c is a penalty factor to map users' discomfort into monetary terms, and $P^{con^*}_{h,i}$ denotes the desired demand of the user i in hour h according to their initial load preferences. This discomfort cost represents the hidden cost incurred by users when their actual load consumption deviates from their originally scheduled usage [56]. The term $(1_{(P^{con^*}_{h,i} \leq P^{con}_{h,i})})$ is introduced in the discomfort formulation to penalize only the hours in which a user is forced to consume below the desired profile. In other words, it activates the discomfort cost only when the scheduled demand at a given time step is less than the user's preferred consumption. The motivation is tied to the way flexibility is modeled in this work. We assume that load shifting preserves the daily energy requirement. The use of appliances are not curtailed, but they are merely rescheduled. Therefore, any reduction in consumption at hour (h) must be offset by an increase at another hour within the same day. That compensating increase is not necessarily a "loss" from the user's perspective, but an unavoidable counterpart of shifting, and it may even occur during a more acceptable period. The main inconvenience arises when the user cannot use electricity at the time they originally intended, i.e., when the schedule creates a deficit relative to the preferred profile. If $(1_{(P^{con^*}_{h,i} \leq P^{con}_{h,i})})$ were omitted and the discomfort term penalized absolute deviations symmetrically, the same shifting action would be charged twice: once for the downward deviation (deficit) and again for the upward deviation (surplus) that restores the daily total. This would overstate inconvenience by treating the necessary consumption as an additional discomfort event. By using the mentioned term, the model counts the discomfort only once at the hours where the user experiences reduced consumption compared to their desired schedule, while still allowing energy to be reallocated to other hours to satisfy the fixed daily demand.

3.3.2 Constraints

The constraints are mainly technical and operational constraints. As mentioned earlier, we prohibit any reduction in load as shown below:

$$P_d^{con^*} = \sum_{h=1}^{24}(P_h^b + \sum_{j=1}^{S}\delta_{h,j}P_j^{sh} + \sum_{k=1}^{A}\beta_{h,k}P_k^{adj}) \tag{3.22}$$

$P_d^{con^*}$ is the daily desired consumption of the user. In this way, the total optimized energy consumption must equal the initially specified desired energy. $P_d^{con^*}$ expresses the user's preferred consumption profile, i.e., the baseline demand trajectory the user would follow in the absence of any scheduling intervention. In this Thesis, $P_d^{con^*}$ is taken from the pre-optimization scenario built from measured load profiles, and it therefore represents the user's "natural" or reference behavior. More generally, P^{con*} does not have to be assumed as a fixed, perfectly known curve. In an operational setting it can be estimated through a hybrid procedure: first, the EMS infers a likely preferred profile by learning from historical metering data (capturing recurring habits, occupancy patterns, and appliance usage). Then, this data-driven estimate is refined using explicit user input—such as preferred time windows for appliances, comfort priorities, or constraints the user is unwilling to violate. The result is a reference profile that remains grounded in observed behavior while still reflecting stated preferences, and it can be updated over time as habits or constraints change.

To ensure physical feasibility at the POD, the optimization includes a constraint that limits the aggregated power drawn by each member to the contractual maximum withdrawable capacity.

$$\overline{P^{con}} \geq (P_h^b + \sum_{j=1}^{S}\delta_{h,j}P_j^{sh} + \sum_{k=1}^{A}\beta_{h,k}P_k^{adj}) \qquad \forall h \in \{1,\dots,24\} \tag{3.23}$$

Where $\overline{P^{con}}$ is the maximum withdrawal power of users. In practice, the POD connection defines an upper bound on instantaneous import. Exceeding this limit is not admissible and would violate the connection agreement and protection settings. Therefore, for every time step, the scheduled net demand is constrained such that the power withdrawn from the POD does not exceed $\overline{P^{con}}$, guaranteeing that the optimized schedule remains compatible with the user's grid connection limits. It should be noticed that in Italy, the allowed power thresholds at POD are different based on users' requests, and they are not all the same for similar type of users.

After optimization, each user's shiftable appliances are assumed to deliver the same daily service as in the original (preferred) schedule; the EMS is allowed to change when an appliance operates, but not whether it operates over the day. This energy/service preservation requirement is enforced by keeping the total number of ON hours for each shiftable appliance unchanged over the 24-hour horizon, as stated in (3.24):

$$\sum_{h=1}^{24} \delta_{h,j} = \sum_{h=1}^{24} \delta^*_{h,j} \tag{3.24}$$

where $\delta_{h,j} \in \{0, 1\}$ is the optimized ON/OFF status of the appliance j at hour h, and $\delta^*_{h,j}$ denotes the corresponding desired (baseline) ON/OFF status taken from the original user profile. With this constraint, the scheduler can shift the operating hours of the appliance j to improve community objectives, while ensuring that the appliance still runs for the same total duration during the day and thus provides the same intended service to the user.

In addition, adjustable loads are subject to operating constraint that sets a minimum on the time slots they can remain in the ON (or high-power) state. With a fixed amount of adjustable loads usage, this prevents the optimizer from exploiting flexibility by concentrating the entire adjustable demand into a single hour; an outcome that may be mathematically attractive for cost or mismatch reduction but unrealistic from a comfort and usability perspective. By bounding the admissible ON duration (or equivalently enforcing minimum spreading across the day), the formulation preserves the intended service quality of adjustable appliances and ensures that modulation reflects feasible user preferences.

$$\underline{\beta_{k_i}} \leq \beta_{k_i} \leq 1 \tag{3.25}$$

$$\|\beta_{k_i}\|_0 \geq \underline{\|\beta^*_{k_i}\|_0} \tag{3.26}$$

$$\sum_{h=1}^{24} \beta_{i,h,k_i} P_{i,h,k_i} = \sum_{h=1}^{24} P_h^{adj^*} \tag{3.27}$$

Where $\underline{\|\beta^*_{k_i}\|_0}$ is the minimum desired number of ON states of adjustable loads in a day, and $\underline{\beta_{k_i}}$ is the minimum percentage of the adjustable load that can be used in every hour. Taken together, (3.25) and (3.26) provide a more realistic representation of the practical operating condition of adjustable loads.

For the generation side considered in this study, RES are assumed to operate in a maximum power extraction mode, meaning that all available renewable generation is harvested whenever it is accessible. Accordingly, the optimization problem does not curtail RES output, and the controllable decision variables on the generation side are limited to the operating states of the battery energy storage systems. In other words, the dispatch flexibility of the supply side is provided exclusively through battery charging and discharging decisions. To model battery operation realistically, each battery is allowed to operate in one of three feasible states during each time interval: charging, discharging, or idle. This behavior is enforced by constraining both the charging and discharging power to remain within their corresponding maximum allowable rates, while also preventing simultaneous charging and discharging. These operational limits are expressed in (3.28):

$$\begin{aligned} ds^c_{r,h} Ps^c_r &\le \overline{Ps^c_r}, \\ ds^d_{r,h} Ps^d_r &\le \overline{Ps^d_r}, \\ ds^d_{r,h} + ds^c_{r,h} &\le 1 \end{aligned} \tag{3.28}$$

$\overline{Ps^c_r}$ and $\overline{Ps^d_r}$ are maximum charging and discharging power flows. It should be noted that, under the self-consumption scenario adopted in this work, battery operation is governed by a rule-based control mechanism rather than by the optimization algorithm. Hence, ESS power is not treated as a decision variable, but instead follows a predefined rule-based strategy aimed at maximizing local renewable energy utilization. From this perspective, the inclusion of explicit upper and lower bounds for battery power in the optimization model may be redundant, because the optimizer does not directly manipulate battery charging or discharging power.

Also, to simulate the real conditions of ESS, the following constraints are considered for State Of Charge (SOC), and for each hour we inhibit charging batteries from the grid through (3.31)

$$\underline{SoC_r} \le SoC_{r,h} \le \overline{SoC_r} \tag{3.29}$$

$$SoC_{r,h} = SoC_{r,h-1} + \frac{(Ps^c_r \eta^c_r ds^c_{r,h} - Ps^d_r ds^d_{r,h} / \eta^d_r)}{\overline{C_r}} \tag{3.30}$$

$$ds^c_{r,h} Ps^c_{r,h} \le \sum_{r=1}^{R} P^{RES}_{r,h} - P^{CON}_{h} \tag{3.31}$$

$\underline{SoC_r}$, $\overline{SoC_r}$, and $\overline{C_r}$ denote the minimum and maximum allowable SOC, and the battery capacity, respectively. Finally, for sustainable system operation, the battery SOC at the end of the planning horizon must lie within an acceptable margin of its initial SOC. This constraint avoids unrealistic scheduling outcomes in which the storage system is used aggressively within the studied horizon without regard for its readiness for subsequent operation. In this way, the battery is maintained in a feasible and balanced energy state, supporting continuity and practicality in real-world operation.

$$0.9SoC_{r,h=1} \leq SoC_{r,h=24} \leq \min[1.1SoC_{r,h=1}, 1] \tag{3.32}$$

3.3.3 Secure distirubuted scheme

As discussed earlier, the optimization performed at each user's premises seeks to modify both the consumption profile and the local generation-related storage profile. Specifically, the consumption curve is optimized through the decision variables (δ, β), while the generation-side flexibility is represented through the ESS charging and discharging state variables (ds^c, ds^d). Therefore, each local EMS optimizes user-side demand flexibility together with storage operation to improve the overall self-consumption performance.

In this study, the "loss of opportunity" associated with self-consumption incentives is formulated as the temporal distance between the producer curve and the consumer curve. This representation reflects the fact that any mismatch between local generation and local consumption reduces the amount of energy that can be instantaneously self-consumed and, consequently, reduces the attainable incentive. Such an arrangement not only has a clear physical interpretation and goal prioritization but also facilitates the mathematical management of the optimization variables.

Furthermore, for both consumption and generation, the corresponding expressions are decomposed into terms associated with the user's own decisions and terms associated with the decisions of the other players. By separating "user's own decisions" and those resulting from the "decisions of other players" from each consumer-side and producer-side optimization subproblem, the resulting formulations are given by (3.33) and (3.34), respectively.

$$\begin{aligned} P_h^{CON} &= \sum_{i=1}^{N}(P_{i,h}^{b} + \sum_{j=1}^{S} P_{i,h}^{SH} + \sum_{k=1}^{A} P_{i,h}^{ADJ}), \quad i \in \mathscr{I} \triangleq \{1, ..., n, ..., N\} \\ &= \sum_{I=1}^{N} P_{I,h}^{con} + (P_{n,h}^{b} + \sum_{j=1}^{S} \delta_{n,h,j} P_{n,j}^{sh} + \sum_{k=1}^{A} \beta_{n,h,k} P_{n,k}^{adj}), \quad \forall I \in \mathscr{I} \backslash \{n\} \end{aligned} \tag{3.33}$$

$$\begin{aligned} P_h^{GEN} &= \sum_{r=1}^{R}(P_{r,h}^{pv} + ds_{r,h}^{c} P_{r,h}^{c} - ds_{r,h}^{d} P_{r,h}^{d}), \qquad r \in \mathfrak{R} \triangleq \{1, ..., m, ..., R\} \\ &= \sum_{\rho=1}^{R} P_{\rho,h}^{gen} + (P_{m,h}^{pv} + ds_{m,h}^{c} P_{m,h}^{c} - ds_{m,h}^{d} P_{m,h}^{d}), \quad \forall \rho \in \mathfrak{R} \backslash \{m\} \end{aligned} \tag{3.34}$$

Where n and m are every individual consumer and producer whose self-optimization is running in their premises, I and ρ are the set of communities' members (consumer and producer), excluding n and m, respectively. Having formulated (3.33) and (3.34), the problem (3.18) can be customized for consumers and producers as (3.35) and (3.36) respectively.

$$\mathbf{max} \sum_{h=1}^{24} \left(\begin{array}{l} -\, Ci \left| P_h^{GEN} - (\sum_{I=1}^{N} P_{I,h}^{con} + P_{n,h}^{b} + \sum_{j=1}^{S} \delta_{n,h,j} P_{n,j}^{sh} + \sum_{k=1}^{A} \beta_{n,h,k} P_{n,k}^{adj}) \right| \\ +\, Cg_{n,h}^{-} Pg_{n,h}^{-} - Cg_{n,h}^{+} Pg_{n,h}^{con} - Kc_n (P_{n,h}^{con^*} - P_{n,h}^{con}) \end{array} \right) \tag{3.35}$$

$$\mathbf{max} \sum_{h=1}^{24} \left(\begin{array}{l} -\, C_i \left| P_h^{CON} - (\sum_{\rho=1}^{R} P_{R,h}^{RES} + Ps_{R,h} + (ds_{m,h}^{d} Ps_{m,h}^{d} - ds_{m,h}^{c} Ps_{m,h}^{c}) \right| \\ -\, (ds_{m,h}^{d} Ps_{m,h}^{d} + ds_{m,h}^{c} Ps_{m,h}^{c}) Cs_m \end{array} \right) \tag{3.36}$$

It is worth noting that when a community member is a prosumer, that is, an entity simultaneously involved in both electricity consumption and local energy production, both optimization subproblems become relevant to that participant. In such a case, the consumer-side optimization is applied to the demand-related components of the member, while the producer-side optimization is applied to the generation and storage-related components. Therefore, the prosumer is modeled as participating in both sides of the scheduling framework, with each optimization problem acting on its corresponding set of variables and assets.

The optimization problem associated with each entity can be decomposed into two main components: one representing the aggregated effect of the actions taken by the other members of the REC, and the other containing the entity's own decision variables. This structure is particularly important because it highlights the coupled nature of the problem. Although each participant optimizes only its local variables, the final outcome is still influenced by the collective behavior of the entire community.

This problem exhibits several key characteristics, such as:

1. **Multiple decision-makers:** the REC consists of multiple users, each of whom can make decisions regarding the scheduling and management of their own consumption.

2. **Strategic interdependence:** the effect of each user's decision is not isolated, since it influences not only the overall operational objective of the REC but also the outcomes experienced by the other members. Thus, the benefit obtained by each player depends on both its own actions and the actions of the others.

3. **Known and measurable outcomes:** for any given combination of strategies adopted by the players, a specific system outcome is produced, which can be evaluated in terms of

technical or economic performance.

4. **Rational behavior:** each player is assumed to act rationally, meaning that it selects its strategy in a way that improves its own objective according to the information available to it.

5. **Payoff structure:** every feasible outcome is associated with a payoff or cost, such as incentive gains, electricity expenses, or other economic consequences reflected in the user's bill.

These properties make the problem well-suited to a game-theoretic formulation for determining an appropriate operating state of the REC [103]. In particular, the presence of multiple autonomous participants, together with the mutual dependence of their decisions, naturally motivates the use of a decentralized game-based approach.

Accordingly, at this stage, a non-cooperative game-theoretic approach will be introduced in the next subsection and employed. Under this formulation, each entity independently solves its own subproblem by optimizing only the decision variables that are locally accessible and controllable. In other words, each player acts autonomously and does not directly optimize the variables belonging to the other members. The components of the problem that arise from the actions of the other players are instead represented through available shared information or previously exchanged data. As this method requires shared information, the following subsection is assigned to study the security of this procedure.

3.3.4 Secret Sharing

In energy communities and smart-grid environments, privacy protection is not only a cybersecurity requirement but also an operational necessity. Fine-grained load, generation, storage, and flexibility data can reveal highly sensitive information about users, including occupancy patterns, appliance usage, behavioral routines, and economic characteristics. If such data are directly exchanged among members or collected by a central coordinator, they become vulnerable to external attacks such as eavesdropping, traffic analysis, interception, and data tampering, as well as internal privacy leakage, where other users inside the energy community may infer private information that is not required for coordination. For this reason, privacy-preserving mechanisms are essential both against outside attackers and against unnecessary exposure to other legitimate participants within the EC itself [54, 108].

Additive secret sharing is a privacy-preserving cryptographic primitive in which a secret is simply encrypted and distributed among different parties such that only an authorized subset or member can reconstruct it, while any unauthorized subset learns nothing about the underlying value (still, they can perform mathematical operations on data and merge their own data with the secret). Secret sharing is highly suitable for distributed energy systems, where coordination among multiple actors is required but disclosure of individual user data must be minimized.

In energy communities, the exchange of detailed consumption and production information may expose users to external attacks and internal privacy leakage from other members, while mathematical operations need to be performed on this data by users. By replacing direct data sharing with secret-sharing methods, aggregation and optimization tasks can be executed without revealing raw user-level information, thereby strengthening both cybersecurity and intra-community privacy protection [97].

The homomorphic property is required in the proposed encryption framework because the operation of an energy community inherently depends on performing mathematical operations on users' data while preserving the confidentiality of that data. In particular, the EMS or coordinating entities often need to compute aggregated quantities, such as total demand, total generation, shared energy, or incentive-related indicators, in order to carry out scheduling and decision-making. If normal encryption were used, these computations would require prior decryption of the users' data, thereby exposing sensitive consumption and generation information. By contrast, homomorphic encryption allows specific algebraic operations to be executed directly on ciphertexts, so that the final decrypted result matches the outcome that would have been obtained had the operations been performed on the plaintext values themselves. This property is especially important in ECs, where private user-level profiles should remain hidden not only from external attackers but also from intermediate entities and other members of the community. For this reason, homomorphic encryption provides a suitable balance between privacy preservation and operational coordination, enabling the system to process the data it needs without revealing the underlying sensitive information.

Homomorphic encryption schemes are generally classified according to the range of computations they allow to be performed directly over encrypted data. The simplest category is Partially Homomorphic Encryption (PHE), in which the cryptosystem supports only one algebraic operation over ciphertexts, typically either addition or multiplication. A more advanced category is Somewhat Homomorphic Encryption (SHE), which supports both addition and multiplication, but only for a limited number of operations. Finally, Fully Homomorphic Encryption (FHE) extends this capability by enabling arbitrary computations on encrypted data, making it theoretically possible to evaluate any computable function without first decrypting the underlying information [4]. This hierarchy reflects a fundamental trade-off: as the expressive power of the encryption scheme increases, so does the computational complexity, memory requirements, and implementation burden.

From a practical perspective, the selection of a homomorphic encryption scheme should be guided by the actual operational needs of the application rather than by the maximum cryptographic capability available. In energy community management, not all privacy-preserving tasks require rich encrypted-domain computation. In many cases, the coordinator or the participating EMSs only need to derive aggregate quantities, such as the total load demand, total generation, or shared energy amount, from the individual users' profiles. When the required encrypted-domain computation is limited to summation, adopting a sophisticated somewhat or fully homomorphic scheme would provide capabilities that are not actually needed, while also imposing a significantly higher computational overhead. Therefore, the use of a highly expressive homomorphic framework would make the implementation unnecessarily complex for the problem at hand. Here, the objective of the privacy-preserving mechanism is only to enable the secure aggregation of users' load profiles. More specifically, the system needs to compute the sum of individual consumption values without exposing each user's raw data to other members of the energy community or to intermediate processing entities. Since this task only requires an additive operation over protected values, a partially homomorphic encryption scheme with additive homomorphism is sufficient. Such a scheme allows ciphertexts corresponding to individual loads to be combined directly, so that the decrypted result yields the aggregated load profile while preserving the confidentiality of each participant's data. This makes additive PHE a more appropriate choice than SHE or FHE for the proposed framework.

Among the common partially homomorphic cryptosystems, RSA and ElGamal are naturally multiplicatively homomorphic, whereas Paillier is additively homomorphic. Since the proposed energy community framework requires only the secure aggregation of users' load profiles, the additive property is the relevant one. For this reason, Paillier provides a more suitable cryptographic basis than RSA or ElGamal, as it allows direct computation of sums over ciphertexts without requiring additional encoding mechanisms [63, 81]. Although Paillier generally incurs a larger ciphertext size and higher computational overhead, its native support for encrypted addition makes it a better match for privacy-preserving load aggregation in the present application.

The procedure of load profile sharing is as follows:

The proposed privacy-preserving aggregation procedure begins with the selection of an initial member, who is randomly designated to initiate the encryption process. This member first generates the required cryptographic parameters, including the public and private keys, together with the random values needed by the encryption scheme to satisfy its security requirements. After key generation, the initial user encrypts its own load and/or generation profile using the public key and forwards the resulting ciphertext to another participant in the community.

Each subsequent member performs the same procedure on its local data. More specifically, upon receiving the encrypted message, the member encrypts its own load or generation profile using the same public key and combines it with the received ciphertext through ciphertext multiplication. Owing to the additive homomorphic property of the adopted encryption scheme, this multiplication operation corresponds to the addition of the underlying plaintext values, while keeping the individual data concealed. The updated ciphertext, now containing the protected contribution of all members involved up to that stage, is then passed to the next participant. This process continues sequentially until all users have incorporated their own profiles into the encrypted aggregate, and the final ciphertext is returned to the initial member.

At the end of the process, the initial member, who alone possesses the corresponding private key, decrypts the final aggregated ciphertext. The recovered plaintext does not reveal the individual contribution of any participant; rather, it yields only the total aggregated consumption and/or generation of all users. In this way, the method enables the community to obtain the collective profiles required for coordination and optimization without exposing the private data of individual members to other participants. The resulting aggregate value can then be shared with all authorized members of the community, as illustrated in Figure 3.5.

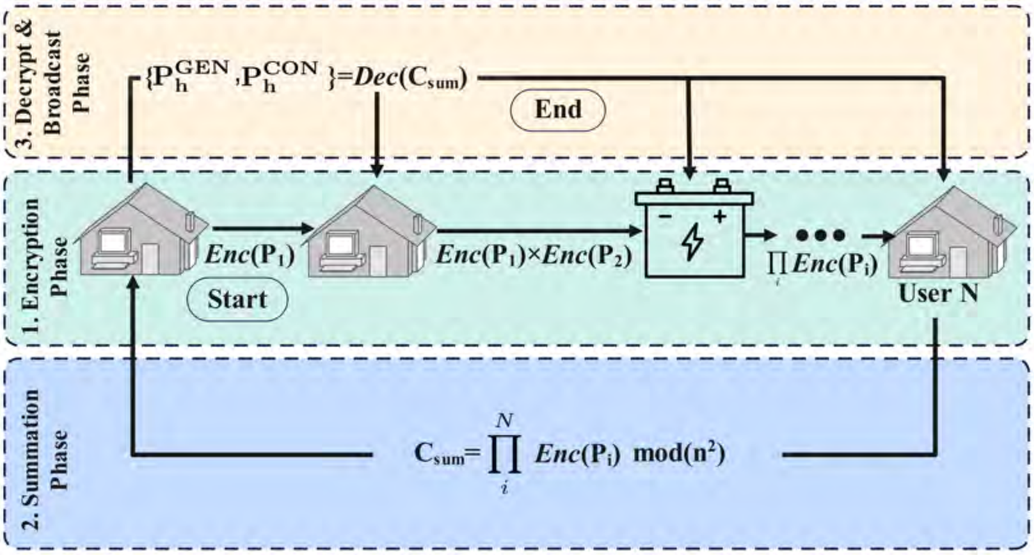

Figure 3.5: Partial Paillier encryption and sharing process in the proposed method.

The process of encryption starts with the selection of random prime numbers as p and q. with multiplication of p and q we will have l in a way that:

$$l = p.q \begin{cases} \forall d \in \mathbb{Z}, (1 < d < p) \Rightarrow (p \mod d \neq 0) \\ \\ \forall d \in \mathbb{Z}, (1 < d < q) \Rightarrow (q \mod d \neq 0) \end{cases} \tag{3.37}$$

By choosing g from the set $Z_{l^2}^*$ (relatively prime to l^2) the public keys (l, g) are available for encryption while the corresponding private key is derived from parameters related to p and q. The public key is shared with all authorized users so that they can encrypt their data and merge it to the received ciphertext, whereas the private key is kept secret by the decrypting party. In practical terms, this means that any participant can protect its own data using the public key, but only the holder of the private key can recover the underlying plaintext values. Besides the generation of public keys, the initial user who started the process of encryption produces private keys too. in this regards, λ is created through (3.38)

$$\lambda = \text{lcm}(p - 1, q - 1) \tag{3.38}$$

Where lcm is the least common multiple. by having λ, the second part of the private key can be obtained by (3.39)

$$\mu = \left(L\left(g^{\lambda} \bmod l^2\right)\right)^{-1} \bmod l \tag{3.39}$$

where the function L is defined as below

$$L(x) = \frac{x-1}{l} \tag{3.40}$$

It should be noted that the term 'inverse' in (3.39) refers specifically to the modular inverse. By having l, g,λ, and μ, all public and private keys are generated.

During encryption, a plaintext message m is not transformed into a ciphertext deterministically. Instead, Paillier introduces a fresh random value o for every encryption [57, 58]. The ciphertext is then generated in the form

$$c = g^m o^l \bmod l^2. \tag{3.41}$$

The inclusion of the random term o^l is essential because it ensures that the same plaintext encrypted twice will generally produce two different ciphertexts. This probabilistic behavior provides semantic security and prevents an observer from inferring information by comparing repeated encryptions of the same value. In other words, even if two users encrypt the same load value, their resulting ciphertexts will not appear identical, which significantly strengthens privacy protection.

The main advantage of Paillier lies in its homomorphic property. If two plaintext values m_1 and m_2 are encrypted separately as c_1 and c_2, then multiplying the two ciphertexts modulo l^2 produces a new ciphertext that corresponds to the encryption of $m_1 + m_2$. Therefore, encrypted values can be aggregated without first decrypting them. This is because each ciphertext is structured as (3.41), and multiplying two such ciphertexts yields the summation of plaintext messages after decryption, as proved in (3.42), demonstrating Paillier's additive homomorphism.

$$\begin{aligned} c_1 \cdot c_2 = g^{m_1} g^{m_2} \cdot (o_1 o_2)^l \bmod l^2 =& g^{m_1+m_2} \cdot (o')^l \bmod l^2 \\ =& C = Enc(m_1 + m_2) \end{aligned} \tag{3.42}$$

In the context of an energy community, this means that individual users can encrypt their own load or generation profiles, and these encrypted values can then be combined to obtain an encrypted aggregate profile. Only after the final aggregation is completed does the authorized decrypting party apply the private key to recover the total value. At no point during the intermediate steps is it necessary to reveal the individual contributions of the users. This is precisely why Paillier is well-suited to privacy-preserving coordination in ECs.

Finally, decryption is performed using the private key and a specific transformation that extracts the message from the ciphertext in $\mathbb{Z}_{N^2}$. Although the detailed arithmetic of decryption is more involved than in ordinary public-key schemes, its essential purpose is straightforward: it maps the protected ciphertext back to the original plaintext value. The message m (which in this thesis is the load or generation profile) can be reconstructed from cipher text c through

(3.43)

$$m = L\left(c^{\lambda} \bmod l^2\right) \cdot \mu \bmod l \tag{3.43}$$

3.4 Game Theory

This thesis addresses an energy management problem in which multiple participants interact within a shared operational environment while pursuing their own local objectives. Since the decisions of each member influence not only its individual outcome but also the overall performance of the energy community and the outcomes of the other members, the resulting problem is inherently interactive and strategically coupled. Such a structure goes beyond a conventional isolated optimization problem and requires a modeling framework capable of capturing the mutual dependence among decision-makers.

In this regard, game theory constitutes an appropriate methodological basis for the proposed approach. It enables the representation of decentralized decision processes in systems where several rational entities act in parallel, each seeking to improve its own payoff in response to the decisions of the others. Accordingly, the proposed framework adopts a game-theoretic perspective to characterize and analyze these interactions. The essential concepts underlying this perspective are discussed in this subsection.

Game theory is a mathematical framework for analyzing situations in which multiple decision-makers interact, and the outcome obtained by each participant depends not only on its own action but also on the actions chosen by the others. Its modern foundations are commonly traced to the work of von Neumann and Morgenstern, who formalized strategic interaction as a rigorous analytical problem, and to Nash, who introduced the equilibrium concept that later became central to non-cooperative analysis[77]. At its core, a game is defined by a set of **players**, a set of available **strategies** for each player, and a **payoff** or utility associated with every possible combination of strategies. A player is any decision-making entity participating in the interaction. A strategy is the rule or plan according to which that player acts. In simple simultaneous-move settings, a strategy may coincide with a single action, whereas in sequential settings it is a complete contingent plan specifying what the player will do at every possible decision point. The payoff function maps the selected strategy profile into an outcome, usually represented in terms of cost, reward, profit, welfare, or utility.

A central feature that distinguishes game-theoretic problems from ordinary single-agent optimization is strategic interdependence. In a strategic environment, the desirability of one player's decision depends on what the other players do. Consequently, a player cannot determine its best course of action in isolation; it must form expectations, explicitly or implicitly, about the behavior of the others. This is why game theory is especially appropriate for decentralized systems composed of autonomous entities whose objectives are coupled through shared resources, market conditions, or collective constraints[43].

Several basic terms are repeatedly used in game-theoretic analysis. we start from the distinctions between types of the game itself. These classifications help determine the appropriate modeling framework and solution concept for each problem.

3.4.1 Types of the game

3.4.1.1 Cooperative VS non-cooperative

One of the most fundamental distinctions in game theory is between cooperative and non-cooperative games. In cooperative games, players are allowed to form binding agreements and coalitions. The main focus is on how the total benefit generated by cooperation can be distributed among coalition members. Concepts such as the core, Shapley value, and bargaining solutions are commonly used in this setting. In non-cooperative games, binding agreements are not assumed. Each player independently chooses a strategy to maximize its own payoff while anticipating the responses of others. This distinction is especially important because many real-world decentralized systems are more naturally modeled as non-cooperative games, while coalition formation problems are often better represented through cooperative frameworks.

3.4.1.2 Static VS dynamic

A static game (or simultaneous-move game) is one in which all players choose their actions without observing the choices of the others. Even if actions are taken at the same physical time only approximately, the essential feature is that decisions are made without prior knowledge of rivals' moves. Classical matrix games, such as the Prisoner's Dilemma, are examples of static games. A dynamic game (or sequential game) is one in which players act over time, and at least some players can observe earlier actions before choosing their own. These games are often represented in extensive form, where the order of moves, possible actions, and information available at each stage are explicitly modeled. Important solution concepts include subgame perfect equilibrium, which refines Nash equilibrium by requiring optimal behavior in every subgame. Dynamic games are particularly suitable when decisions are updated iteratively or when agents respond to previous behavior.

3.4.1.3 Complete VS incomplete information

A game of complete information is one in which all players know the structure of the game, including the available strategies, payoff functions, and relevant parameters of all participants. A game of incomplete information is one in which at least one player lacks full knowledge of another player's payoffs, preferences, capabilities, or type. These games are often modeled as Bayesian games, where uncertainty about other players is represented probabilistically. The appropriate solution concept in such settings is typically the Bayesian Nash equilibrium. This class of games is highly relevant in practical systems where agents do not fully reveal their preferences, costs, or private constraints.

3.4.1.4 Discrete VS continuous

In a discrete game, players choose from a finite or countable set of actions, such as cooperate/defect, buy/sell, or select one among several possible schedules, while in a continuous game, strategies are chosen from a continuous range, such as power levels, prices, quantities, or bids. These games often require optimization tools and differential analysis rather than simple payoff matrices.

3.4.1.5 Simultaneous VS sequential moves

Although closely related to static and dynamic games, it is often useful to state explicitly whether moves are made simultaneously or sequentially. In simultaneous-move games, no player observes the current choices of others before acting. In sequential-move games, one or more players move after observing previous actions, which creates possibilities for commitment, leadership, and response strategies. Stackelberg games are a well-known example, where a leader moves first and followers respond optimally.

However, there are more categories of games. The classification of games in game theory is essential for selecting an appropriate analytical framework and solution concept. Games may differ according to whether cooperation is possible, whether actions occur simultaneously or sequentially, whether information is complete or incomplete, whether payoffs are fully conflicting or partially aligned, and whether uncertainty or repetition is present. In practice, many real problems combine several of these features simultaneously. Therefore, understanding the major types of games provides the conceptual foundation for rigorous modeling of strategic interactions.

3.4.2 Fundamental Concepts: Strategy and Equilibrium

Another frequently used term in game theory is "**strategy**". In game theory, a strategy is a complete plan that tells a player what action to take in every situation covered by the game. It does not refer merely to the action taken at the present moment; rather, it denotes the complete rule that specifies how an agent will act whenever its turn or decision point arises. The most fundamental type is the pure strategy, in which a player chooses one specific action with certainty. This is the simplest form of decision-making and is commonly used when the player has a clear preferred action under given conditions. A second important type is the mixed strategy, where a player assigns probabilities to two or more possible actions and selects among them randomly according to those probabilities. Mixed strategies are particularly relevant when no single deterministic action is always optimal, and they are often used to describe equilibrium behavior in competitive games. Another important concept is the dominant strategy. A strategy is called dominant if it provides a payoff that is at least as good as every other available strategy, regardless of the strategies chosen by the other players. When such a strategy exists, it strongly simplifies the decision process because the player can adopt it without needing to predict opponents' behavior. Another important strategy that we will refer to more is the best response strategy, which refers to the strategy that yields the highest payoff against a given set of strategies selected by the other players. In many game-theoretic models, equilibrium is reached when every player adopts a best response to the others. A player's best response is a strategy that maximizes its payoff given the strategies selected by the others. Here, a new term, "**equilibrium**," is introduced: an equilibrium is a stable strategy profile in which no player has an incentive to deviate unilaterally.

The equilibrium concept used depends on whether the game is simultaneous or sequential, and whether players have complete or incomplete information. Standard game-theory texts treat Nash equilibrium, dominant-strategy equilibrium, Bayesian Nash equilibrium, and subgame-perfect equilibrium as the main noncooperative solution concepts [110]. The most widely used notion is the Nash equilibrium, defined as a profile of strategies such that each player's strategy is a best response to the strategies of the remaining players. In finite games, Nash established the existence of at least one equilibrium in mixed strategies. A more restrictive case is the dominant-strategy equilibrium. This occurs when every player has a dominant strategy, meaning a strategy that performs at least as well as any alternative regardless of what the other players do. Because it does not depend on expectations about others' actions, this equilibrium is particularly robust, although it exists only in a limited class of games[10]. For games with incomplete information, the relevant notion is the Bayesian Nash equilibrium. In this setting, players do not know some characteristics of the other players, such as costs, preferences, or available resources, and instead act on beliefs represented probabilistically. An equilibrium is obtained when each player's strategy maximizes expected payoff given those beliefs and the expected strategies of the other players[14]. In dynamic sequential games, a subgame perfect equilibrium (SPE) is a refinement of Nash equilibrium used in dynamic or sequential games. It is a strategy profile in which the players' strategies form a Nash equilibrium in every subgame of the original game, not only in the game as a whole. In other words, it requires that each player's strategy remains optimal at every possible decision point, even after any history of previous moves. However, in this study, the term equilibrium specifically refers to a Nash equilibrium, in which no player can obtain a higher payoff by unilaterally changing their decision, here represented by their consumption or generation profile.

The main characteristics that make a problem suitable for game-theoretic treatment can now be summarized. First, the problem must involve multiple rational decision makers. Second, each player must possess a set of feasible actions or strategies. Third, the result obtained by each player must depend on the joint action of all players rather than on its own action alone. Fourth, the game must admit an outcome measure, usually expressed as a payoff, utility, or cost. Finally, the model normally assumes some degree of rational behavior, meaning that each player selects strategies intended to improve its own objective according to the information available. When these elements are present, game theory provides an approach for formulating and studying the interaction.

3.4.3 Existence of equilibrium

Before expressing how the method seeks to obtain the equilibrium, it is crucial to ensure its existence, which can be examined through analysis of the problem.

In the proposed framework, the interaction among users can be modeled as a finite strategic game. The set of players is finite, since the community consists of a limited number of users. Moreover, for each player, the set of admissible strategies is also finite, because each load profile is selected from a bounded and discretized feasible set determined by technical and operational constraints. Consequently, the overall action space of the game is finite. Under these conditions, the existence of at least one Nash equilibrium follows from standard results in finite game theory. Since each player's payoff is well defined for every feasible combination of strategies, the game admits at least one equilibrium in mixed strategies. Furthermore, because the strategy sets are bounded and closed, the feasible decision region is well posed, ensuring that every player's optimization problem is defined on a valid admissible set. These properties exclude pathological cases such as unbounded improvement directions or infeasible response mappings.

If, in addition, the equilibrium reached in the proposed iterative procedure is a profile at which no player can further improve its objective by unilaterally modifying its own load profile, then that operating point satisfies the definition of a Nash equilibrium. In other words, once convergence is achieved, each user's selected schedule is a best response to the schedules chosen by the others. Therefore, no member has an incentive to deviate individually, which confirms that the final solution corresponds to a Nash equilibrium of the game.

A more formal statement may be written as follows:

Theorem 1. *For the game G there is at least one mixed strategy equilibrium.*

Proof.

1. The set of players $\mathscr{I}$ is finite.
2. The binary variable δ for shiftable loads and constrained variable β for adjustable loads cause finite strategies.
3. Variables are both bounded and closed, therefore the problem is compact.

Every game with a finite number of players choosing from finite compact strategies has at least one mixed-strategy Nash Equilibrium[43]. Thus, the game G has an equilibrium point. □

Let G represent this game with $\mathscr{I}$ as a set of players, and $\mathbb{S}$ set of strategies for each player. For each decision, players are rewarded with U according to their decision ($\mathcal{S}_i$) and also other players' actions ($\mathcal{S}_{-i} : -i \triangleq \mathcal{I} \setminus \{i\}$).

$$G = \langle N, (\mathbb{S}_i)_{i\in\mathcal{I}}, (U_i)_{i\in\mathcal{I}} \rangle \tag{3.44}$$

according to the Nash Equilibrium definition, in one round of the game, $\mathcal{S}^* = (\mathcal{S}_1^*, ..., \mathcal{S}_N^*)$ will be the pure strategy Nash Equilibrium if (3.45) is true for all $i \in \mathcal{I}$ and all $\mathcal{S}_i \in \mathbb{S}_i$ [87]

$$U_i(\mathcal{S}_i^*, \mathcal{S}_{-i}^*) \geqslant U_i(\mathcal{S}_i, \mathcal{S}_{-i}^*)) \rangle \tag{3.45}$$

in other words, with given action $\mathcal{S}_{-i}^*$ from other players, $\mathcal{S}_i^*$ is an action that maximizes the reward of the user i [87].

$$\mathcal{S}_i^* = \underset{s_i}{\operatorname{argmax}}\, U_i(\mathcal{S}_i, \mathcal{S}_{-i}^*) \tag{3.46}$$

To find $\mathcal{S}_i^*$, other $\mathcal{S}_{-i}$ are set to be $\mathcal{S}_{-i}^*$. The optimization executed in the EMS guarantees that other players are playing their optimal decision of $\mathcal{S}_{-i}^*$ chosen from the multiplicity set of equilibria ($\mathbb{S}_i^*$). Since the problem is convex, as iterations of the game proceed, users' decisions converge to only one decision, which is $\mathcal{S}_i^*$.

3.5 overview on methodology

In the proposed distributed framework, the execution of the local optimization subproblems by all participating nodes constitutes one round, or equivalently, one iteration of the game. During each round, every member independently solves its own optimization problem on the basis of the locally available information and the shared aggregate information obtained from the previous round. Since the proposed scheme does not rely on a central optimizer that simultaneously determines the decisions of all users, the final operating point must instead emerge through repeated strategic interactions among the members of the energy community.

At the end of each round, the participants are informed of the aggregated effect of the other members' actions in the previous iteration. This information is obtained through the Paillier secret sharing procedure described earlier. Once this aggregate information becomes available, each member can update its understanding of the collective behavior of the community and, in the next round, revise its own decision variables accordingly in an attempt to improve its individual benefit. Therefore, the game evolves iteratively in a way that each user reacts to the previously observed aggregate actions of the others, re-optimizes its own local schedule, and then contributes again to the updated aggregate state of the community.

This iterative process continues until the players' decisions no longer exhibit meaningful changes from one round to the next. In other words, when no player has an incentive to further modify its decision variables, or equivalently, when the resulting schedule updates fall below a predefined threshold and become negligible, the iterative game is considered to have converged. At this stage, no participant can improve its objective through unilateral re-optimization given the prevailing decisions of the others, and the system is said to have reached an equilibrium state. The complete procedure is summarized in the flowchart shown in Figure 3.6. As illustrated there, the process begins with the first user generating a random ordering of the participating members. Then, through the sequential exchange and aggregation of Paillier-encrypted ciphertexts, the total consumption and generation of the energy community in the previous iteration are computed, decrypted by the initiating user, and broadcast to the other members, as described in Algorithm 1. Subsequently, each user solves its own local optimization problem and determines whether its updated load schedule differs from that of the previous iteration. If at least one member broadcasts a change message, the same sequence is repeated as a new iteration of the game. The procedure continues until no participant further changes its decision, indicating that the distributed strategy update process has stabilized. Under this condition, the resulting operating point satisfies the definition of a Nash equilibrium, since no member can achieve a better outcome by unilaterally changing its own strategy.

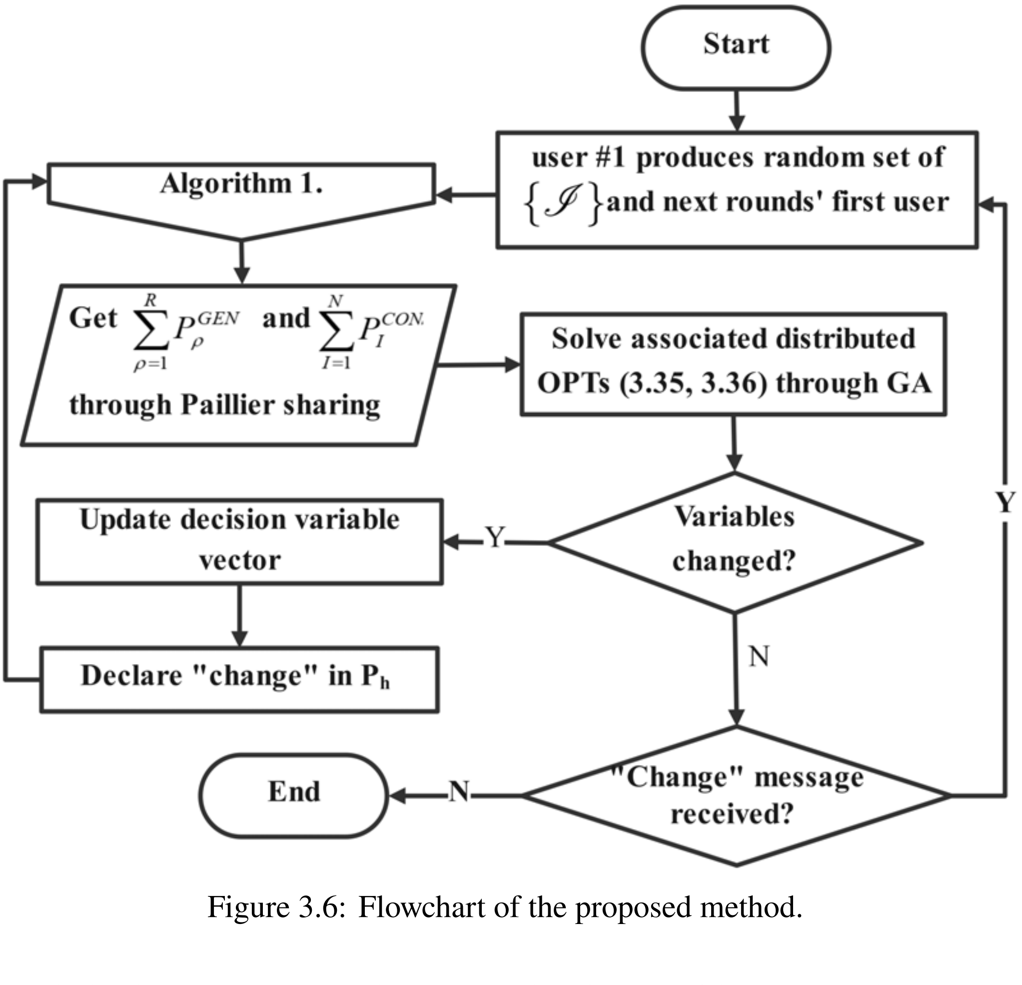

Figure 3.6: Flowchart of the proposed method.

The optimization problem described above in Figure 3.6 is solved using a Real-Coded Genetic Algorithm (RCGA) [68], which constitutes the core optimization engine of the proposed EMS framework. Once the required profiles are received through the encrypted communication channel, the local solvers embedded in the users' EMSs solve the optimization problems in (3.35) and (3.36), as depicted in Fig. 3.6. In this way, the EMS performs the optimization task

Algorithm 1 Partial Paillier ciphertext sharing

```
Require: Preset of users $\mathcal{J}$
    Input: Number of users $N \in \mathcal{J}$, users' baseline
    Output: Aggregated vector $P^{CON}$ or $P^{GEN}$
while change schedule = 1 do
    Initialization: $c_{(0)} = 1$, user $\mathcal{J}_{(1)}$ selects $p, q = \text{Prime}[min, max]$
    $l = pq$, $g \in \mathbb{Z}^*_{l^2}$, $o = \text{rand}[1, l-1]$    ▷ Public and private keys generation
    for $i = 1$ to $N$ do
        $c_{(i)} = Enc(P_{(i)}) \cdot c_{(i-1)}$    ▷ User $i$ encrypts its profile and multiplies it with the received ciphertext
    end for
    $\mathcal{J}_{(N)} \longrightarrow \mathcal{J}_{(1)}$: send $c_{(N)}$
    $\mathcal{J}_{(1)}$: $P^{CON} = \sum_{i=1}^{N} P_i = Dec(c_{(N)})$
    return $P^{CON} \& P^{GEN}$    ▷ Aggregated profile broadcast to all REC members
end while
```

locally based on the exchanged data while preserving the proposed decentralized structure.

The adopted RCGA uses an initial population of 150 individuals and a maximum of 70 generations. An elitism mechanism is incorporated so that 5% of the best individuals are preserved and directly transferred to the next generation. Crossover is then applied to 80% of the remaining population to generate new candidate solutions and enhance exploration of the search space. In addition, the solution obtained at each iteration is used as part of the initial population for the subsequent game round, introducing a form of memory that helps the GA retain information from previous iterations of the game. In order to benefit from this link between iterations of the game, a percentage of elites from each round of the game (global elites over 70 generations) are also transferred to the new round of the game. Since the problem involves bounds and linear constraints, the mutation operator is selected automatically in a way that provides feasible search directions and step lengths compatible with those constraints. In addition, rank-based fitness scaling is employed, such that individuals are ranked according to their fitness, and the score of the n^{th} ranked individual is defined as $1/|n|$. This strategy promotes selection pressure toward better solutions while maintaining population diversity during the evolutionary process.

3.6 Conclusion

This chapter established the methodological foundation of the thesis by developing the regulatory, modeling, mathematical, and algorithmic framework used in the subsequent analysis. The chapter first clarified the legal and operational context of RECs and CECs, with particular emphasis on the Italian implementation of the European framework. By reviewing the evolution from the EU directives to the Italian transposition and incentive mechanisms, it was shown that the operation of an energy community cannot be studied only from a technical perspective. Instead, the optimization problem must remain consistent with the actual settlement logic, the definition of shared energy, the role of external actors such as GSE and DSO, and the regulatory conditions that determine how incentives are obtained in practice. This regulatory grounding is essential, because the value of coordinated operation in a REC is strongly linked to the hourly matching between collective generation and collective consumption, rather than to energy production alone.

On this basis, the chapter introduced the proposed community model, in which members are represented according to their operational role as consumers, producers, or prosumers. To improve the clarity of the scheduling and settlement process, the production and consumption components of the same prosumer were modeled separately, while still belonging to the same physical user. This decomposition made it possible to represent injections and withdrawals more transparently and to integrate local storage in a way that remains consistent with the Italian regulatory treatment of generation-side energy storage systems. The demand side was further structured through a practical classification of loads into critical, shiftable, and adjustable categories, so that different forms of flexibility could be represented without sacrificing tractability. In this way, the community model was constructed to preserve both physical realism and mathematical manageability.

The mathematical formulation then translated these operational and regulatory considerations into an optimization problem. The objective was built around the core principle of the REC incentive mechanism, namely the maximization of shared energy through the temporal alignment of aggregated generation and consumption. The chapter showed that, under fixed total daily production and consumption, maximizing the shared energy is equivalent to minimizing the time-dependent mismatch between the two aggregate curves. This result provided a clear analytical justification for the structure of the proposed objective function. At the same time, the formulation incorporated the local constraints of flexible loads, user-side comfort considerations, and storage operation limits, thereby ensuring that the resulting schedules remain technically feasible and behaviorally meaningful. Consequently, the proposed optimization framework does not merely target an abstract mathematical optimum, but rather a realistic operating point compatible with both user-level flexibility and REC-level incentive logic.

A major contribution of this chapter is the justification and formulation of the distributed solution approach. Rather than relying on a centralized optimizer with full access to all private data, the chapter motivated the adoption of a decentralized architecture in which each member solves its own local problem. This design preserves user autonomy, reduces the need for intrusive data sharing, and better reflects the decentralized nature of energy communities. However, because the actions of members remain coupled through shared energy and collective operation, the problem naturally takes on a strategic structure. For this reason, the chapter introduced game theory as the analytical basis for the proposed coordination mechanism. The key concepts of players, strategies, payoffs, best responses, and equilibrium were reviewed, and the problem was positioned within a non-cooperative framework in which each member optimizes its own objective while responding to the aggregate behavior of others. The existence of equilibrium was then linked to the finite and well-defined nature of the strategy space, and the iterative distributed process was interpreted as a sequence of game rounds converging toward a Nash equilibrium.

Another central element of the methodology is the privacy-preserving information exchange mechanism. Since decentralized coordination still requires shared aggregate information, the chapter addressed the privacy risks associated with exchanging detailed user profiles inside the energy community. It was argued that direct sharing of fine-grained consumption and generation data is undesirable not only because of external cyber threats, but also because of the possibility of internal privacy leakage among legitimate members. To resolve this issue, the chapter adopted an additive partially homomorphic encryption scheme based on Paillier cryptography. The rationale for this choice was that the proposed framework only requires secure summation of individual profiles, rather than general encrypted-domain computation. Therefore, a partially homomorphic scheme was sufficient and more computationally suitable than somewhat or fully homomorphic alternatives. The chapter then described the aggregation process in which encrypted local profiles are sequentially combined and only the aggregated value is finally decrypted and broadcast, allowing the community to access the information required for coordination without disclosing individual data.

Finally, the chapter integrated these elements into a complete distributed methodology. In each iteration of the game, users receive the aggregated community information from the previous round through the Paillier-based procedure, solve their own local optimization subproblems through a Real-Coded Genetic Algorithm (RCGA), and update their strategies accordingly. This iterative process continues until the schedule changes become negligible and no participant can improve its outcome through unilateral deviation. The proposed EMS structure therefore combines privacy-preserving aggregation, decentralized optimization, and game-theoretic interaction within a unified framework. The RCGA implementation was selected to handle the nonlinear and constrained nature of the local scheduling problem, while the iterative update mechanism enables the community to move toward a stable and practically meaningful operating point.

Overall, this chapter has developed a methodology that is simultaneously regulatory-aware, technically grounded, privacy-preserving, and computationally implementable. It provides the conceptual and mathematical bridge between the policy and market context of energy communities and the algorithmic procedures required for their decentralized management. The next chapters build on this foundation to implement the proposed framework, evaluate its performance under different scenarios, and analyze the extent to which the proposed distributed game-based EMS can improve both individual and collective outcomes in the considered energy community.

Chapter 4

Results and Discussion

4.1 Main case

To evaluate the effectiveness of the proposed method, different distinct energy community scenarios were considered, each characterized by a different combination of users, PVs and wind generation resources integrated with an ESS, as summarized in Table 4.1. These scenarios were designed to represent different renewable generation conditions and resource compositions, thereby allowing the performance of the proposed framework to be examined under varying operating environments. It is worth noting that the level of collaboration reported in Table 4.1 is assumed to be inversely related to the discomfort coefficient, K_c, which was introduced in (3.21). In other words, users with a higher willingness to collaborate are modeled with lower values of K_c, which indicates that schedule modifications impose a smaller perceived inconvenience or penalty on them. Conversely, users with a more moderate level of collaboration are assigned higher discomfort coefficients, reflecting a lower tolerance toward deviations from their preferred consumption patterns. This assumption allows the model to capture the behavioral heterogeneity of community members in a simple but meaningful way, by linking their degree of flexibility to their sensitivity to load rescheduling.

In addition, the size of the optimization problem associated with each prosumer depends directly on the number of controllable assets available to that user. More specifically, the total number of decision variables for each prosumer is equal to 24 multiplied by the number of shiftable and controllable loads, plus 24 variables associated with battery charging and another 24 variables associated with battery discharging, whenever an ESS is available for that user. Accordingly, the dimensionality of each local optimization subproblem reflects both the demand-side flexibility and the storage capability of the corresponding participant. In the present study, each user is assumed to possess one adjustable load and three shiftable loads. These shiftable loads are selected from the considered set of flexible appliances.

The original case study was simulated using Messina Monte Piselli, Italy site data measured on October 6th, 2022. The optimization was performed using MATLAB on a Core i7-13700H

CPU, with an average clock speed of 4.3 GHz for the performance cores (P-cores) and 2.8 GHz for the efficiency cores (E-cores) during the process of GA optimizer. The secret sharing phase was implemented on a Raspberry Pi 4 using Python's socket library over TCP/IP, with a maximum distance of 130 km between nodes. Figure. 4.1 depicts the total PV generation and detailed consumption of the REC (by users) in the main case (Case 1) before optimization. As it is depicted, the normal behavior of the users prevents them from harvesting the maximum incentive following collective self-consumption. When applying the a general Genetic Algorithm optimizer for each user [50], with associated constraints and objective functions mentioned earlier, the users can change their operation of home appliances to maximize their own economic benefit.

Table 4.1: Communities' Scenarios

Case	Members & Consumption			Daily Production [kWh]		ESS
	Number	Collab.	[kWh]	PV	wind	[kWh]
1	10	High	60.11	41.9	0	10
2	10	High	60.11	41.9	0	0
3	30	Medium	250.65	91.4	127.3	40
4	10	High	60.11	41.9	0	Variable
5	10	Variable	60.11	41.9	0	10

This process is repeated each hour of the day with a planning horizon of 24 hours (rolling horizon). After consecutive rounds and updates, the two profiles of production and consumption almost overlap. Figure. 4.2 shows the results after the implementation of the proposed method and proves that the proposed method can establish a collaboration between the users without any central entity.

the optimized generation and consumption profile illustrated in Figure 4.2 was obtained after 6 consecutive runs of the game. The shared energy through this optimization is increased up to 41.2 kWh which covers 98% of the whole generation. A part of the optimization algorithm used to generate the profiles depicted in Figure 4.2, together with the corresponding code explanations, are presented in the following.

```
%% predefine
% prices in euros, energy in kwh

%---------------------------prices-----------------------------------
Cbuy_grid = 0.14;
Csell_grid = 0.09;
GSE_inc = 0.12;
C_comf(user) = 0.06; %[0.12 0.12 ... 0.06 0.06 0.06]; users discomfort rate
```

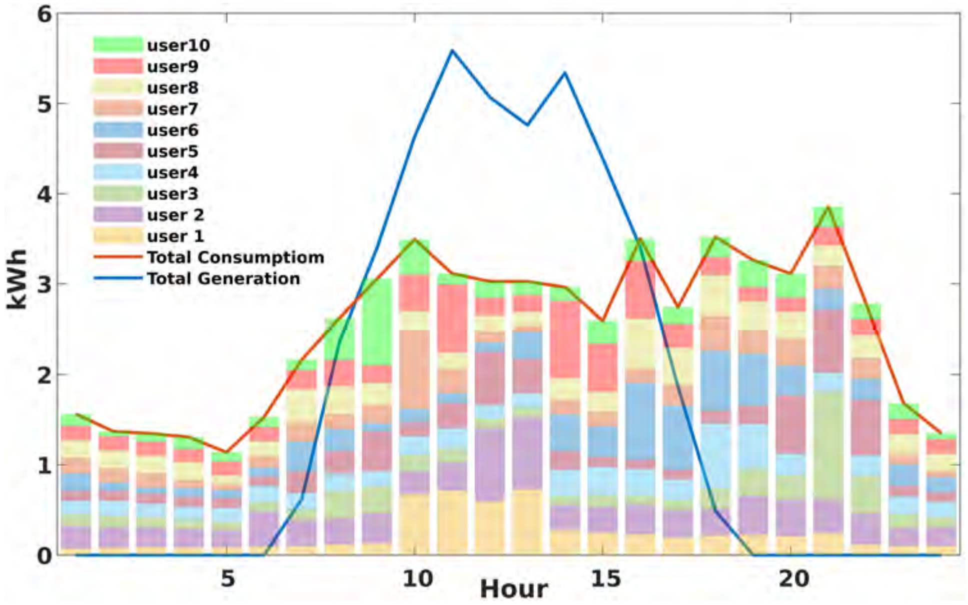

Figure 4.1: Daily generation and total consumption of users in the studied REC.

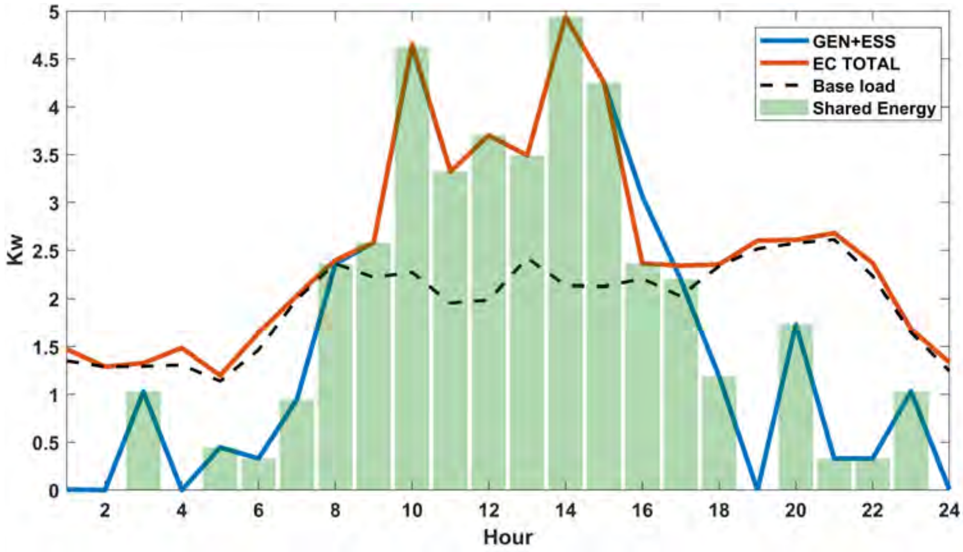

Figure 4.2: Optimized shared energy in Case 1, using the proposed method

```
Effsolar = 0.9;
% of generation. Efficiency. To change the scale of production easily

Effwind = 1;
% to change the scale of the generation;

Gensolar = (Gensolar .* Effsolar' / 1000 + Effwind' .* wind)';

%---------------------------ESS-------------------------------------------
ESS_price = 5000;    % around 5000 for 10 kwh and 140$/kwh for more
ESS_size = 10;    %kWh
```

```
ESS_lifecycle = 7000;  %cycles
ESS_num = 1;
ESS_maxrate = 5; %kw
ESS_init_Cap = 5; %kw
C_ESS = ESS_price/(2*ESS_lifecycle*eta^2)/ESS_size;   % cost of using ESS/kwh
PESS(1,:) = zeros(1,24); % assumed behaviour of battery for first round

%---------------------------GA----------------------------------------------
GAinitpop = 150;
GAmaxGen = 70;
k = 0.05;   % portion of higher-score population used as initial population
k = round(k * GAinitpop);

%---------------------------Initials of users--------------------------------
Nuser = 10;  %number of users
PROFECTTL(1,:) = sum(profh(1:Nuser,1:24));    % initial EC consumption
PROFECUSER{1}(:,:) = profh;  % initial and detailed EC consumption by user
```

Listing 4.1: Initialization of model parameters

Some of the parameters introduced and defined above change during different scenarios, such as ESS capacity, number of users, and profile of generation, etc.

After defining the required constants and system parameters, the proposed algorithm proceeds by acquiring the initial constraints and load profiles of all users. These data include operational limits, appliance characteristics, and baseline consumption patterns derived from the original (pre-optimization) scenario. Subsequently, the collected information is systematically organized into well-structured matrices and vectors compatible with MATLAB-based computation. This structured representation facilitates efficient implementation of the optimization process, enabling vectorized operations, constraint handling, and scalable analysis across multiple users within the energy community.

```
%% users optimization
for I = 1:10        % rounds of the game
    for j = 1:Nuser    % users

        user = j;
        userprof = eval(['profh' num2str(user)]);
        Crit_load(user,1:24) = userprof(2,:);
        LS1(user,1:24) = userprof(3,:);  % LS = shiftable loads
        LS2(user,1:24) = userprof(4,:);
        LS3(user,1:24) = userprof(5,:);
        LA1(user,1:24) = userprof(6,:);  % LA = adjustable load

```

```
        [~,nzero1,v1] = find(LS1(user,:)); % time slots in which loads are ON
        [~,nzero2,v2] = find(LS2(user,:));
        [~,nzero3,v3] = find(LS3(user,:));
        [~,nzero4,v4] = find(LA1(user,:));

        v1(isempty(v1)) = 0;   % replace null with zero if no such load exists
        v2(isempty(v2)) = 0;
        v3(isempty(v3)) = 0;
        v4(isempty(v4)) = 0;

        %% linear constraints
        LS1var = [ones(1,24), zeros(1,72)];              % x1 + ... + x24
        LS2var = [zeros(1,24), ones(1,24), zeros(1,48)]; % x25 + ... + x48
        LS3var = [zeros(1,48), ones(1,24), zeros(1,24)]; % x49 + ... + x72
        LA1var = [zeros(1,72), ones(1,24)];              % x73 + ... + x96

        Alin = [];
        Blin = [];
        Aeq = [LS1var; LS2var; LS3var; LA1var];
        Beq = [size(nzero1,2); size(nzero2,2); size(nzero3,2); ...
               sum(LA1(user,:))];
        % operating time slots remain equal to the pre-optimization case

        integcol = 1:72;      % integer variable columns
        lb = zeros(1,96);
        ub = [ones(1,72), max(LA1(user,:)) * ones(1,24) * 1];
        % adjustable load does not exceed the current maximum use
    end
end
```

Listing 4.2: User-side optimization loop with linear constraints

to better understand constraints coded in List 4.2, let consider a user and associated load list. three shiftable loads and one adjustable load through the 24 hours of the day,makes a a 4×24 variable space. equality and non-equality constraints expressed in a vector as follows:

$$A_{lin}x \leq B_{lin}, \tag{4.1}$$

$$A_{eq}x = B_{eq}, \tag{4.2}$$

$$lb \leq x \leq ub, \tag{4.3}$$

and for non-linear constraints, we will have the following:

$$C(x) \leq 0, C_{eq}(x) = 0 \tag{4.4}$$

Since the GA codes all variables in a vector, linear constraints should be defined as below:

$$\underbrace{\begin{bmatrix} \mathbf{1}_{1\times24} & \mathbf{0}_{1\times24} & \mathbf{0}_{1\times24} & \mathbf{0}_{1\times24} \\ \mathbf{0}_{1\times24} & \mathbf{1}_{1\times24} & \mathbf{0}_{1\times24} & \mathbf{0}_{1\times24} \\ \mathbf{0}_{1\times24} & \mathbf{0}_{1\times24} & \mathbf{1}_{1\times24} & \mathbf{0}_{1\times24} \\ \mathbf{0}_{1\times24} & \mathbf{0}_{1\times24} & \mathbf{0}_{1\times24} & \mathbf{1}_{1\times24} \end{bmatrix}}_{A_{eq}} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{96} \end{bmatrix} = \underbrace{\begin{bmatrix} \left\|\delta^*_{h,1}\right\|_0 \\ \left\|\delta^*_{h,2}\right\|_0 \\ \left\|\delta^*_{h,3}\right\|_0 \\ \sum_{l=1}^{24} \beta^*_{k_l} \end{bmatrix}}_{B_{eq}} \tag{4.5}$$

where $\left\|\delta^*_{h,j}\right\|_0$ are L_0 norm of the shiftable appliances, which denotes the number of ON state of the corresponding appliance. This constraint ensures that each of the three shiftable appliances operates for the same duration as in the baseline scenario, as well as the adjustable load, which maintains its original level of utilization. Since the maximum withdrawable power from the POD depends on the decision variables, it cannot be represented through a fixed upper-bound vector ub. Instead, this limitation constitutes a decision-dependent constraint and must be explicitly formulated as a nonlinear constraint $C(x)$. Accordingly, the feasible region is defined not only by static bounds but also by this additional functional restriction, ensuring that the aggregate power drawn at each time step does not exceed the allowable limit determined by the system conditions and decision variables.

The objective function for consumers within EC (3.35) is obtained as below.

```matlab
function z = ECcost(x)

global Cbuy_grid Csell_grid GSE_inc C_ESS C_comf
global ESS_size ESS_price ESS_cycle PESS
global profh Gensolar
global user
global PROFECTTL PROFECUSER Crit_load LS1 LS2 LS3 LA1
global I
global nzero1 v1 nzero2 v2 nzero3 v3 nzero4 v4 OPTLOAD Nuser

%% objective function for users

profEC = PROFECTTL(I,:) - PROFECUSER{I}(user,:);
% summation of all EC consumption except this user

```

```
XL1 = find(x(1:24));  %first shiftable appliance
XL2 = find(x(25:48)); %second shiftable appliance
XL3 = find(x(49:72)); %third shiftable appliance
% finding the time slots in which the variables are ON

x(XL1)      = v1;  %24 hours of appliance 1
x(XL2 + 24) = v2;  %24 hours of appliance 2
x(XL3 + 48) = v3;  %24 hours of appliance 3
% replacing ON states (binary 1) with the associated appliance power


Pshift = x(1:24) + x(25:48) + x(49:72) + x(73:96);
% programmable load (total load - critical load)


%-----------Incentive------------------------------------------
% minimize gap between generation and consumption based on "GSE incentives."

gse = -GSE_inc * abs(Gensolar + PESS(I,:) - ...
      (profEC + Crit_load(user,:) + Pshift))/Nuser;

%-----------electricity import from grid------------------------
PGbuy = Crit_load(user,:) + Pshift;

% Users are first charged for their total energy consumption,
% independent of whether it is supplied by the grid or through shared energy;
% they are then compensated by the GSE based on the amount of shared energy.

%-----------discomfort term-------------------------------------
% only demand reduction is penalized, since shifted demand will be
% supplied at another time slot

Pcomfort = profh(user,:) - (Crit_load(user,:) + Pshift);
Pcomfort = Pcomfort .* (Pcomfort > 0.01);
%Kc*(desired consumption-scheduled consumption)

%-----------selling back to grid--------------------------------

% selling is allowed only if production exceeds consumption

PGsell = (Gensolar + PESS(I,:) - ...
```

```
         (Crit_load(user,:) + Pshift + profEC)) / Nuser;
PGsell = PGsell .* (PGsell > 0);

%-----------prices---------------------------------------------
GESS     = C_ESS * abs(PESS(I,:));
Gbuy     = Cbuy_grid * PGbuy;
Gsell    = Csell_grid * PGsell;
Gcomfort = C_comf * Pcomfort;

z = sum(-sum(gse) + sum(Gbuy) + sum(Gcomfort) - sum(Gsell) );
%the objective function for consumers

end
```

Listing 4.3: User cost function of the EC optimization problem

The objective function for the ESS and generation side follows a structure similar to that of the consumer-side formulation. However, it differs in that it only includes the ESS operational cost, the revenue from energy sold to the grid, and the reward obtained from shared energy, without accounting for direct consumption costs. In addition, a specific case is considered in which the ESS is collectively owned by the members of the energy community. Under this assumption, the storage system operates for the benefit of the entire EC rather than an individual user. Therefore, a comfort-related term can be incorporated into the objective function from the ESS perspective, reflecting the impact of storage operation on the overall load adjustment and user discomfort within the whole community as a block.

Furthermore, this distributed scheme mitigates the role of the ESS, and if applied as a strategy for sizing the ESS, would also suggest a smaller ESS size by engaging users in behavior modification, which will be discussed in next subsection. Daily consumption and generation stay almost the same before and after the optimization, while the battery SOC remains at 49.9% at the end of the day (as initial state). Table 4.2 shows the results of subsequent rounds in Case 1. The results demonstrate that the proposed method is effective in increasing the energy sharing while keeping all community members at their optimum choice.

As it is depicted in Figure 4.3, for some users, a small collective change in their daily routine leads to significant self-consumption within the EC. The consumption of each user and the shifted load are represented in Table 4.3 in detail. It should be noted that the division by two is required in Equation (4.1) because, under pure load shifting, the absolute difference counts the same transferred energy twice, once at the hour from which the load is removed and once again at the hour to which that load is added. Therefore, the sum of absolute deviations represents the total upward and downward adjustments combined, rather than the actual amount of energy

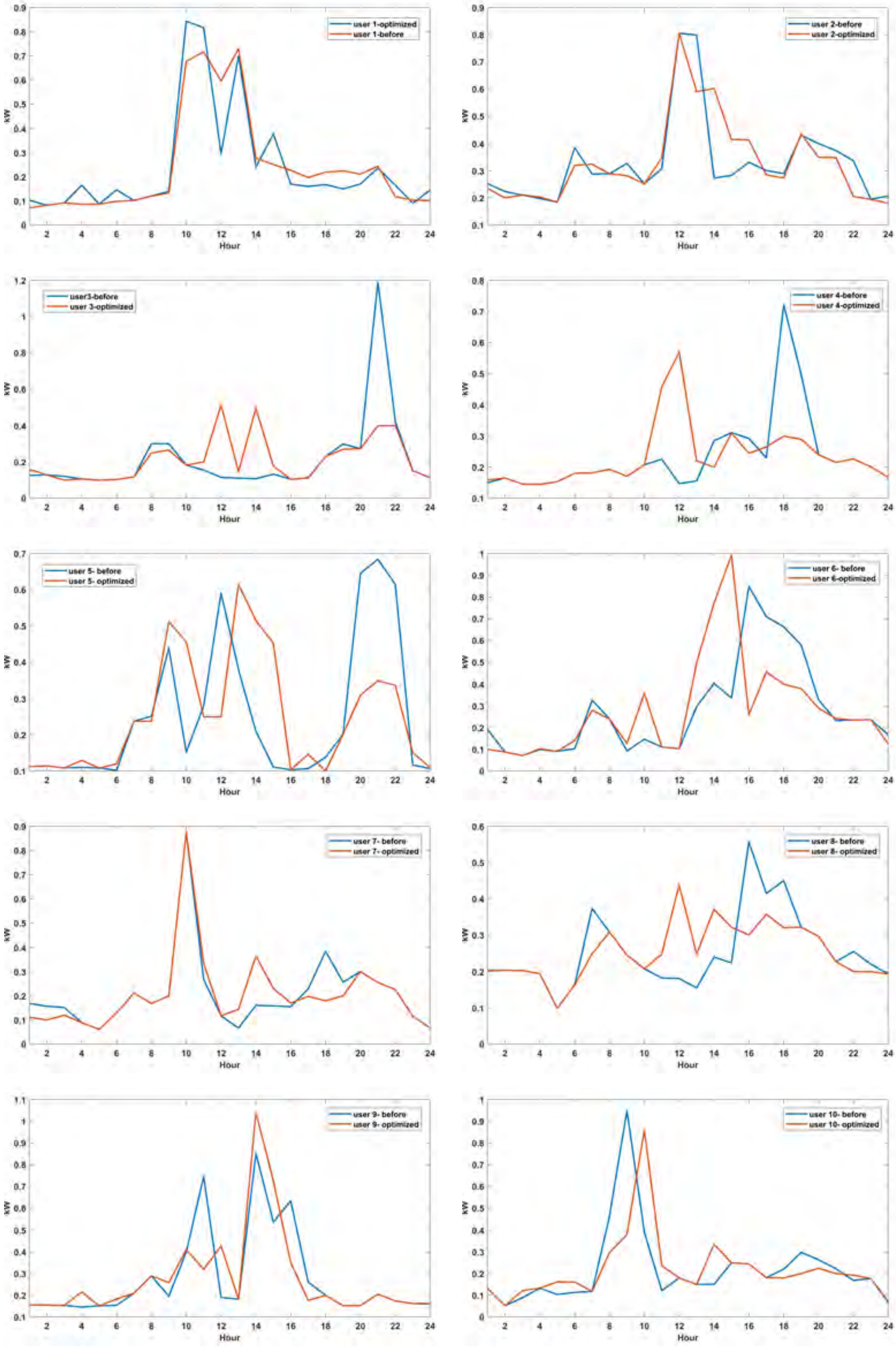

Figure 4.3: Load profiles of users.

Table 4.2: Shared energy along the rounds of the game-Case 1

Iteration	0	1	2	3	4	5	6
%Shared Energy	71.6	95	90.2	92.8	88	93.5	98.3
ESS Usage (kWh)	0	8.7	8	8.2	7.5	7.9	6.6

Max Optimization Solving Time	23.4 s
Max ciphertext Sharing Time	0.8 s
Worst-case Time to Reach the Equilibrium	140.4 s

that has been rescheduled.

$$\text{Shifted Energy}(\%) = 100 \cdot \frac{\frac{1}{2}\sum_{h=1}^{24}\left|P_h^{\text{new}} - P_h^*\right|}{\sum_{h=1}^{24} P_h^*} \tag{4.6}$$

Table 4.3: Actual consumption and shifted consumption

User	1	2	3	4	5	6	7	8	9	10
Daily consumption (Kwh)	5.8	8	5.1	5.6	6	6.7	5	6.1	6.6	5.2
Shifted load (%)	11.3	7.9	18.5	13.6	22.7	22.6	8.8	10.5	11.9	17.8

In addition, the state of the battery, including the actual power interaction with EC and SOC is expressed in Figure 4.4. It is represented that in this case, the battery follows constraints such as minimum and maximum SOC, power, and final SOC, which is essential for a sustainable operation.

4.2 ESS

To further assess the effectiveness and generality of the proposed framework, a second scenario is considered in which the ESS is completely removed from the energy community. While storage is commonly regarded as a key enabler for enhancing self-consumption and energy sharing, its installation is often associated with significant investment costs, operational complexity, and maintenance requirements. Therefore, evaluating the performance of the proposed method in the absence of ESS is essential to demonstrate its applicability in more constrained and realistic settings where such infrastructure may not be available. Moreover, by excluding ESS from the model, other similar methods might not be able to set up a game since the players are restricted to being ESS or RES [22] while our proposed solution is able to capture the advantages of EC without ESS perfectly.

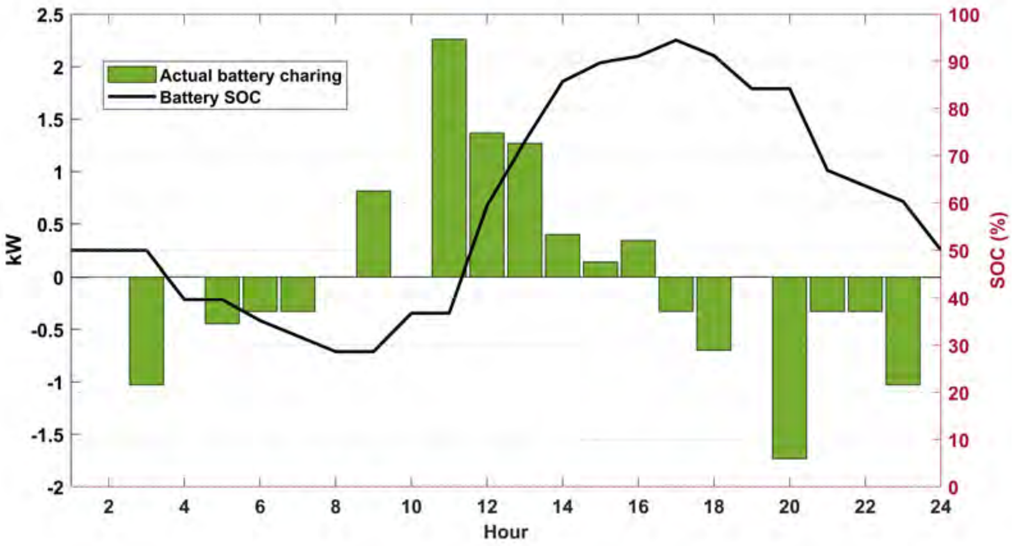

Figure 4.4: Battery status in optimized Case 1

In this scenario, the optimization relies solely on demand-side flexibility, where users adjust their consumption profiles through shiftable and controllable loads in response to local generation patterns. By aligning consumption with the temporal availability of renewable generation, the method aims to reduce the mismatch between production and demand, thereby increasing the amount of energy that can be shared within the community. Also, in wider applications of the proposed method, a small ESS may enable RECs to propose negawatts (if it is valued in the market mechanism) [102]. This setup isolates the contribution of behavioral and scheduling strategies from that of physical storage, allowing a clearer understanding of how much improvement can be achieved through decentralized coordination alone.

The shared energy and collective users' consumption profile in Case 2 is represented in Fig. 4.5

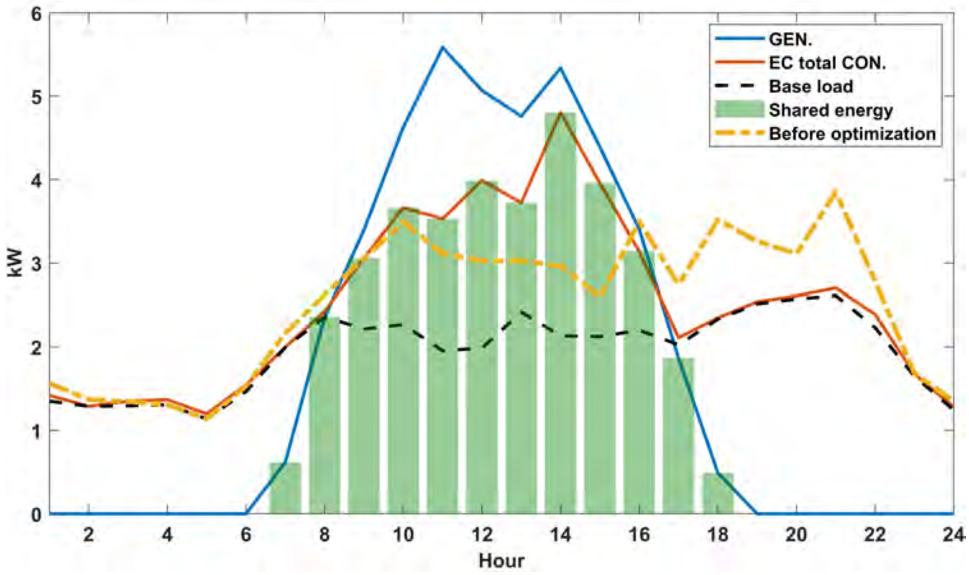

Figure 4.5: Optimized shared energy in Case 2 (without ESS)

The results obtained from this configuration show that, even without the support of ESS, the proposed approach is capable of enhancing the shared energy among users. Although the absolute level of shared energy may be lower compared to scenarios with storage (Table 4.4), the relative improvement over the baseline (non-optimized) case remains significant as demonstrated in Fig.4.5. This indicates that intelligent load management and decentralized decision-making can play a substantial role in improving the operational efficiency of energy communities, even in the absence of storage infrastructure. It should be noted that, in this scenario, a portion of the total demand is composed of base loads that must be supplied at all times and are not subject to modification. Since the base load profile is fixed and cannot be shifted or curtailed, it does not contribute to the flexibility of the system and therefore cannot be adjusted to better match the generation profile. As a consequence, only the flexible portion of the demand, namely the shiftable and controllable loads, can be rescheduled in response to local generation. This limitation directly constrains the maximum amount of energy that can be effectively aligned with renewable production. In the present case, the total energy associated with flexible loads, together with the portion of base load that coincides with local generation, amounts to 36 kWh. This value represents the upper bound of energy that can be effectively aligned with and potentially covered by local generation and the percentage in Table 4.4.

Table 4.4: Shared energy along the rounds of the game-Case 2

Iteration	1	2	3	4	5	6	7	8	9	10
Shared Energy (%)	94.9	92.7	93.5	95.1	93.2	96.4	95.6	96.4	97.4	97.8
Total Shifted Load (Kwh)	7	5.7	6.1	6	6.1	5.7	6.1	5.7	5.7	5.6
Max Optimization Solving Time										22.1 s
Max Ciphertext Sharing Time										0.8 s
Worst-case Time to Reach the Equilibrium										228.2 s

Furthermore, by comparing Case 1 (with ESS) and Case 2 (without ESS), where all other conditions and parameters are kept identical, it becomes possible to explicitly quantify the contribution of users. This comparative analysis not only decouples the additional benefits brought by ESS, such as temporal energy shifting and enhanced flexibility, but also clarifies the extent to which the proposed method can operate effectively without it. Such a comparison provides valuable insight into the trade-offs between infrastructural investment and algorithmic coordination, and supports the adaptability of the proposed framework to different levels of technological deployment within energy communities. This analysis is intentionally designed to decouple the performance of the proposed method from the presence of an ESS and to isolate the contribution of users' behavior. By removing the ESS from the scenario, the objective is not to replicate a fully optimized infrastructure, but rather to evaluate how much improvement can be achieved solely through users' participation, flexibility, and coordination within the energy community. this analysis demonstrates that while ESS can further improve system performance, the proposed method remains effective even in its absence, making it suitable for a wider range of practical applications of EC where storage integration is limited or not economically feasible.

4.3 convergence of the method

One of the primary concerns in the proposed decentralized framework is the convergence of individual decisions toward a stable and optimal collective outcome. This challenge arises from the intrinsic information limitations of the system, where each participant does not have access to the individual decisions of others and can only observe aggregated outcomes from previous iterations of the game. As a result, decision-making is based on partial and delayed information, which may affect the stability of the overall process. A representative issue emerges when, at a given hour,for example, local generation exceeds consumption. In such a situation, the aggregated signal indicates an opportunity for increasing demand to better utilize the available generation. However, since all users observe the same aggregated information and act independently, a large number of participants may simultaneously decide to shift their loads to that specific hour. This uncoordinated yet correlated behavior leads to the creation of a new demand peak, despite the absence of direct communication among users. Such dynamics can be interpreted as a form of collective or “herding” behavior induced by shared signals[7].

When this phenomenon occurs repeatedly among multiple players as the iterations of the game proceed, it can lead to oscillatory dynamics in the system. In particular, users continuously shift their loads from previously congested hours to less-utilized ones. However, because many users follow the same logic, the previously underutilized hours become congested in subsequent iterations, while the formerly congested periods become underutilized again [76]. This cyclical pattern may result in a “ping-pong” or oscillatory behavior, where the system fails to settle into a stable equilibrium and instead fluctuates between different operating points. If not properly addressed, such oscillations may prevent the algorithm from converging to a well-defined solution. This issue is evident in Figure 4.6

These periodic oscillations, which prevent users from converging to an agreed collective consumption pattern, can also be observed in the heatmap in Figure 4.7

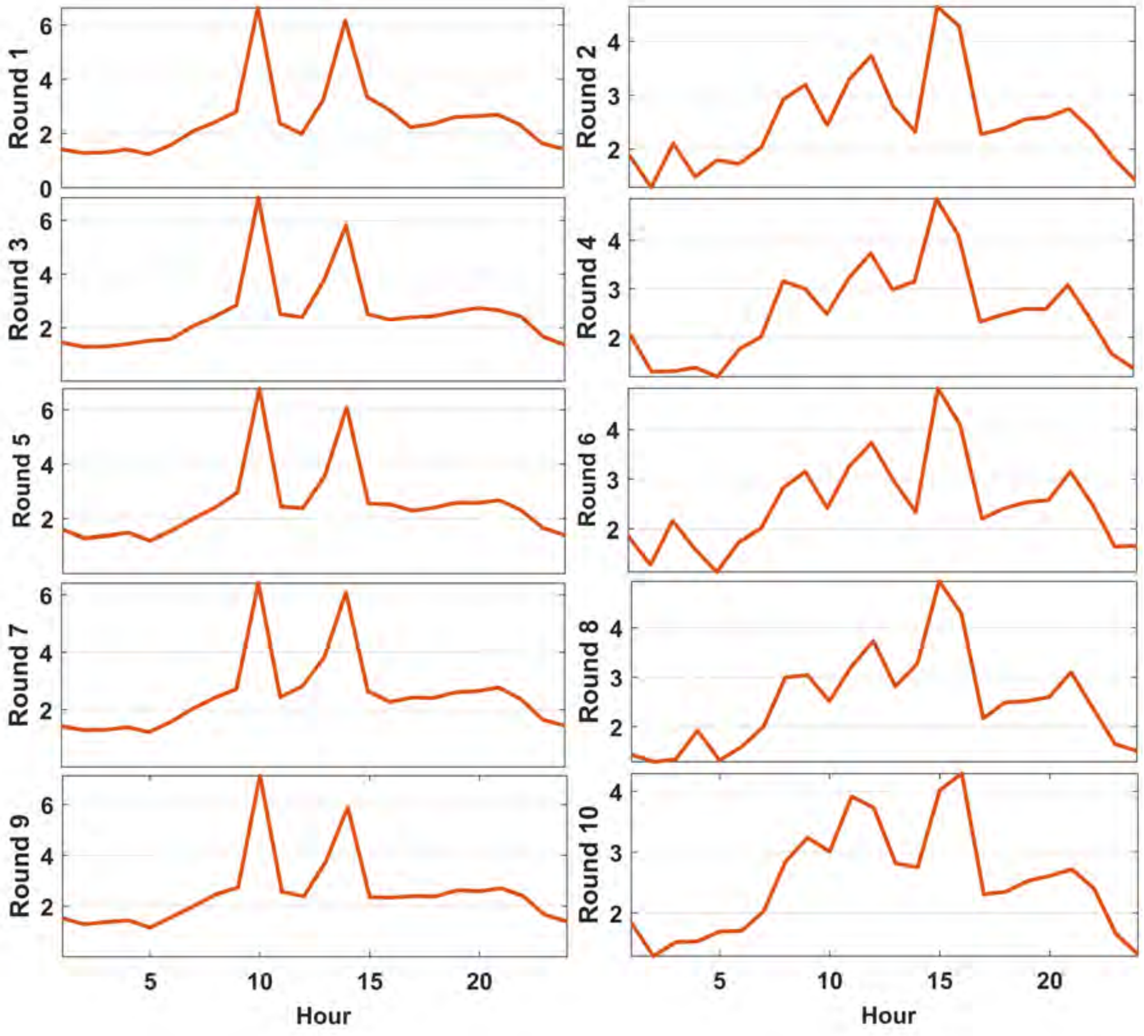

Figure 4.6: oscillatory pattern along rounds of the game.

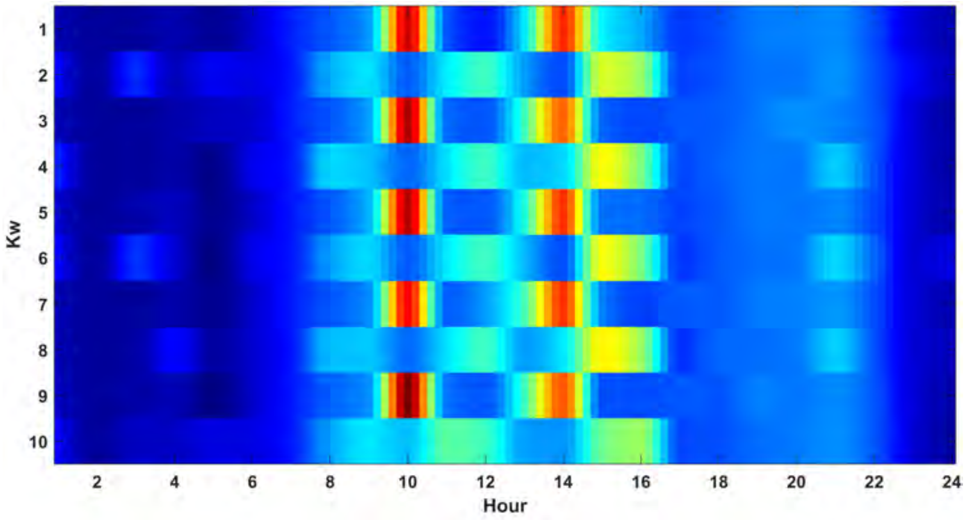

Figure 4.7: non-converging oscillations of collective consumption along the rounds of the game.

To mitigate this issue, several strategies can be considered. One effective approach is the introduction of randomization mechanisms in the decision process. This consideration has partially motivated the adoption of a GA framework, where stochastic elements such as mutation and crossover inherently introduce diversity in the search process, and optimizers have a set of hours to choose from instead of one. These mechanisms help break synchronized decision patterns among users and reduce the likelihood of collective oscillations.

Another solution is a probabilistic decision-making mechanism. Instead of selecting a single optimal time slot in a deterministic manner, each user assigns a probability distribution over feasible time intervals based on the corresponding objective values. By using a softmax and under its formulation, time slots with lower cost retain higher selection probabilities, while suboptimal alternatives remain accessible with non-zero probability. Consequently, users distribute their load adjustments across multiple time intervals rather than converging to a single point. From a game-theoretic perspective, this approach shifts the system from a pure-strategy equilibrium to a mixed-strategy equilibrium, in which users adopt probabilistic strategies. This reduces the correlation among individual decisions and mitigates herd behavior without requiring centralized coordination or information sharing.

However, A simpler yet effective mechanism is adopted in this work to mitigate the risk of synchronized behavior and resulting congestion. Specifically, we consider a worst-case scenario in which all users simultaneously attempt to compensate for the mismatch between generation and consumption at a particular hour. Such behavior, if unrestricted, would lead to overcompensation and the creation of a new peak, thereby destabilizing the convergence to the equilibrium point. To address this issue, a proportional allocation rule is utilized. At each iteration, the total mismatch between generation and consumption at a given hour is calculated and then evenly distributed among all users. Accordingly, each user is allowed to contribute only up to a predefined share, defined as the total imbalance divided by the number of users. This constraint prevents excessive and synchronized load shifting, ensuring that no single time slot becomes congested due to collective action.

In the initial stage, users adjust their load profiles to compensate for the mismatch, but only within the limits of their assigned share. However, due to individual constraints, such as inflexible loads or the power of the block of shiftable load, not all users may be able to fully utilize their allocated portion. As a result, a residual imbalance may remain after each iteration. This remaining mismatch is then carried over to subsequent iterations of the game, where the same proportional allocation rule is applied again. In each round, users are repeatedly given the opportunity to contribute within their limits, gradually reducing the gap between generation and consumption. Through this iterative process, the imbalance is progressively diminished, and the system converges toward a stable operating point.

The efficiency of the proposed solution on Case 2 is illustrated in Figure 4.8, where the convergence of the method is evident as the iterations of the game proceed. In this figure, the last two rows of the heatmap, which are associated with 10^{th} and 9^{th} rounds of the game, reveal a negligible difference.

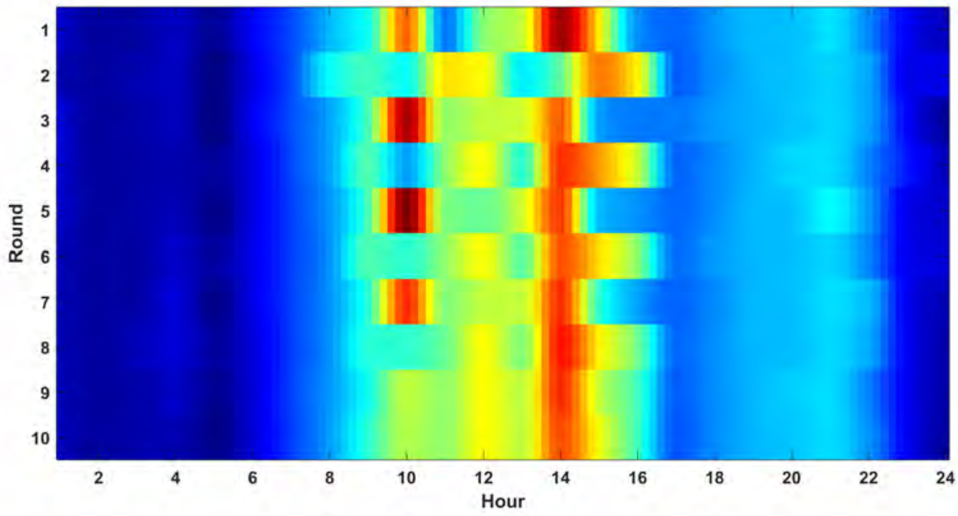

Figure 4.8: converging oscillations of collective consumption along the rounds of the game through proposed solution.

In addition, this convergence can be distinguished perfectly in Figure 4.9 where the last two EC consumption profiles show remarkable similarity, which proves the convergence of the method to the agreed schedule, namely, the equilibrium of the game.

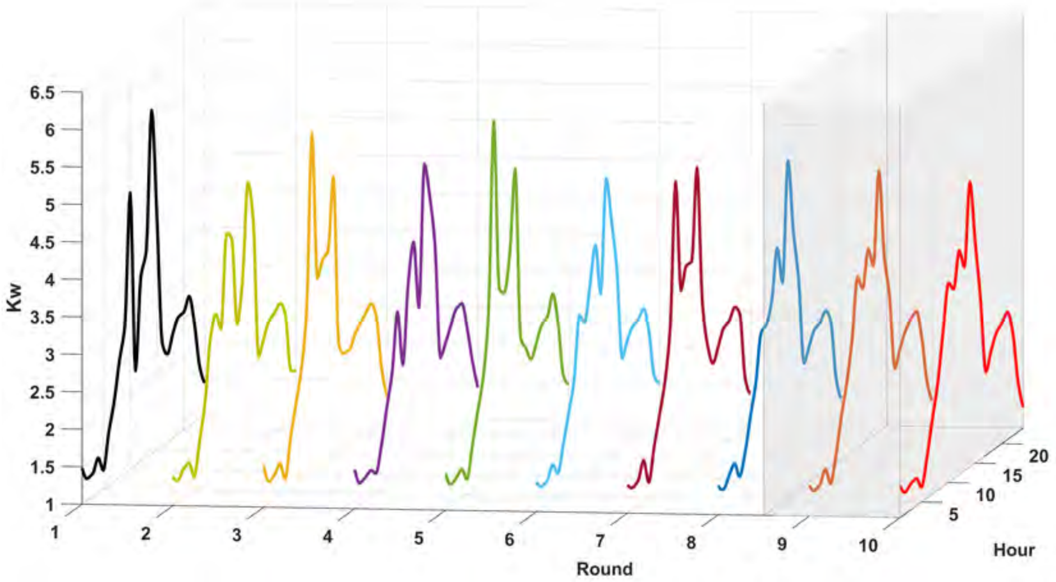

Figure 4.9: converging oscillations of collective consumption along the rounds of the game.

In addition to algorithmic solutions, there exists a natural moderating factor in practical implementations, namely the heterogeneity in user responsiveness. In real-world settings, not all users respond identically to optimization signals. While the current analysis focuses on the behavior of idealized optimizers, actual users may exhibit varying degrees of willingness or ability to adjust their consumption. Some users may choose not to follow the suggested load shifting strategies due to comfort preferences or behavioral constraints. This diversity in user behavior acts as a damping factor, reducing the likelihood of perfectly synchronized actions and consequently mitigating oscillatory effects. It is important to note that this aspect of heterogeneous user participation will be further investigated in subsequent sections, where different levels of user collaboration and discomfort coefficients are considered. Such extensions are expected to provide a more realistic assessment of convergence properties and system stability in practical energy community settings.

4.4 Reduced ESS

In this case study, the effect of reducing battery capacity on the performance of the proposed method is investigated. In the previous analyses, two reference conditions were examined, namely a case with a 10 kWh battery and a case without any battery. However, an important practical question still remains: to what extent can battery installation be reduced while still preserving a satisfactory level of self-consumption and energy sharing within the community. Addressing this question is essential, since the economic and technical feasibility of energy communities depends not only on their ability to improve renewable energy utilization, but also on the amount of storage capacity required to achieve such improvements. However, response to this question is not only a matter of EC configuration and information of loads and generation, but also the pattern of load and generation is one of the key factors to answer this question. As discussed earlier, the deployment of battery energy storage systems is closely linked to the availability of strategic raw materials, particularly lithium. Since the supply of these materials is often concentrated in a limited number of countries, their price and accessibility may be strongly affected by geopolitical tensions, supply-chain disruptions, and political constraints [90]. For this reason, large-scale reliance on battery storage may introduce a new form of dependency into the energy transition, even though batteries themselves are widely regarded as one of its enabling technologies. From this perspective, reducing the storage requirement without significantly compromising system performance becomes a meaningful objective.

Accordingly, in energy transition planning, it is desirable to promote solutions that remain as independent and resilient as possible. In the context of energy communities, which are considered a promising pathway toward a decentralized and participatory energy transition, excessive dependence on storage systems may weaken long-term robustness and affordability. Therefore, any method capable of reducing the reliance of such communities on batteries, through improved coordination and management of users, can contribute to a more self-sufficient and resilient design. In other words, the more effectively user flexibility and collective coordination are exploited, the less the community must depend on storage capacity alone to achieve efficient operation. Based on this motivation, the present scenario evaluates the performance of the proposed method under a variety of battery sizes. The objective is to demonstrate that, even when storage is available in a smaller capacity, the proposed framework can still maintain an effective level of load management, self-consumption enhancement, and energy sharing. This method is still able to fully exploit the battery's potential and makes effective use of the available capacity, despite the battery having no prior knowledge of users' current consumption patterns.

Table 4.5: ESS Scenarios

Case	ESS Specifications			ESS Contribution to Convergence		
	Size (Kwh)	Power (Kw)	Price (€)	Round	ESS Usage (Kwh)	Shared energy (Kwh)
4.1	5	3	2500	4	4	37.8
4.2	7	4.2	3000	8	5.8	39.5
4.3	2×5	3, 4	2500, 3500	9	8.3	41.1
4.4	20	12	8500	3	9.6	41.8

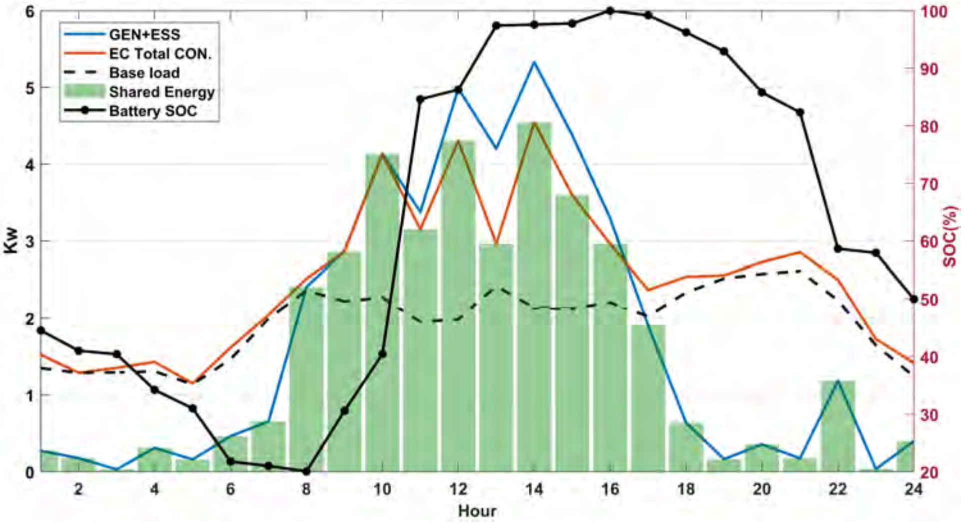

Figure 4.10: Battery status in Case 4.1 with ESS = 5 kWh

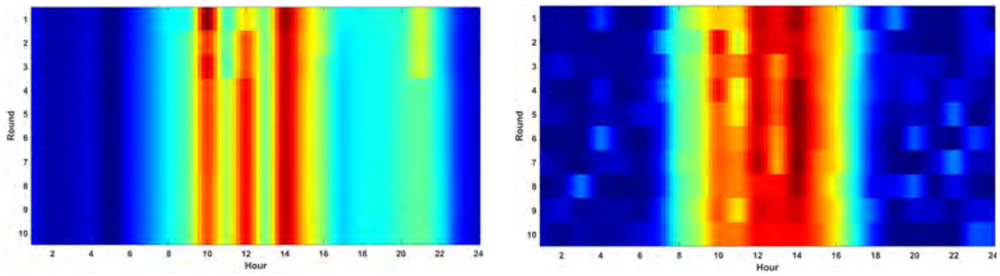

Figure 4.11: convergence of method in Case 4.1 with ESS = 5Kwh. (a) Consumption and (b) Generation

As can be seen in Figure 4.10, the generation curve cannot completely adapt to the consumption curve. The reason is the size of the ESS, where the available energy from

RES between hours 10:00 to 16:00 is much higher than the empty capacity of the battery, and in the optimization, the ESS is prohibited from being charged more than its nominal capacity. Therefore, the excess energy that couldn't be stored and used in other hours of the day, can be seen from hours 11:00 to 16:00. This excess energy is valued in the Italian market and can be sold back to the grid. It is worth noting that the minor variations observed in the heatmap Figure 4.11 do not lead to significant changes in the amount of shared energy. A careful comparison of Figures 4.10 and 4.11, particularly when examined simultaneously, reveals that during time intervals where consumption dominates generation (from 10:00 to 16:00), the exact timing of battery discharge has a negligible impact on the shared energy. In other words, as long as the generation profile does not exceed the consumption level, the shared energy remains effectively unchanged regardless of when the battery is discharged within that interval. For instance, distributing approximately 50% of the battery discharge across the hours between 18:00 and 24:00 yields similar results in terms of shared energy, provided that generation does not surpass demand during these periods. This observation highlights that, under consumption-dominant conditions and a fixed price of electricity during the day, unless one curve does not take over the other one, the timing of energy release from storage is less critical than the total amount of energy supplied.

However, the shared energy is increased in the Case 4.2 with 7kWh, but still it can be seen that the limited free capacity of the battery prevents the method from perfectly capturing the potential shared energy, which is possible to reach. The same obstacle that existed in the case of the 5kWh ESS, can be noticed in Figure 4.13. The excess energy beyond consumption from hours 10 to 16 amounts to 11.45 kWh. Part of this energy is absorbed through load shifting strategies, while another part is stored in the battery system. Any residual amount beyond these two mechanisms is surplus energy that is depicted in the figure 4.12

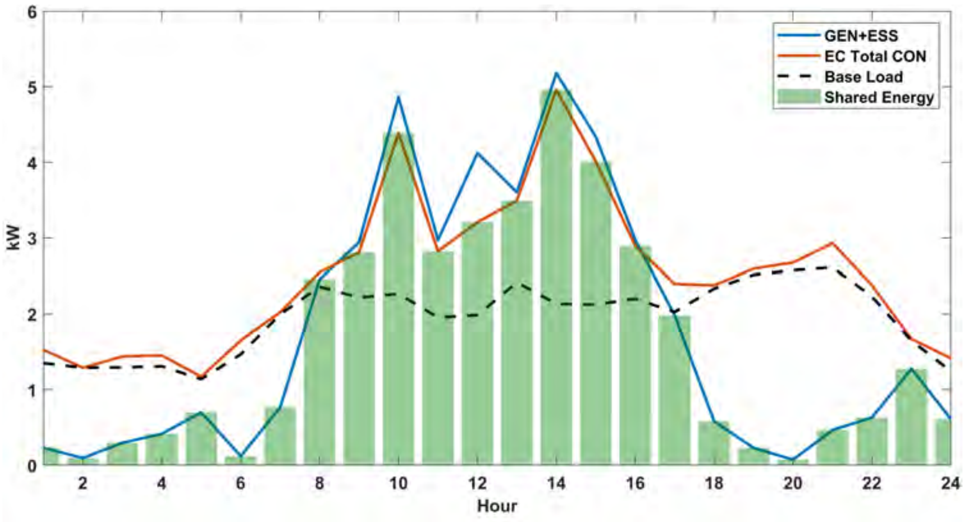

Figure 4.12: Optimized Shared Energy in Case 4.2 with ESS = 7Kwh

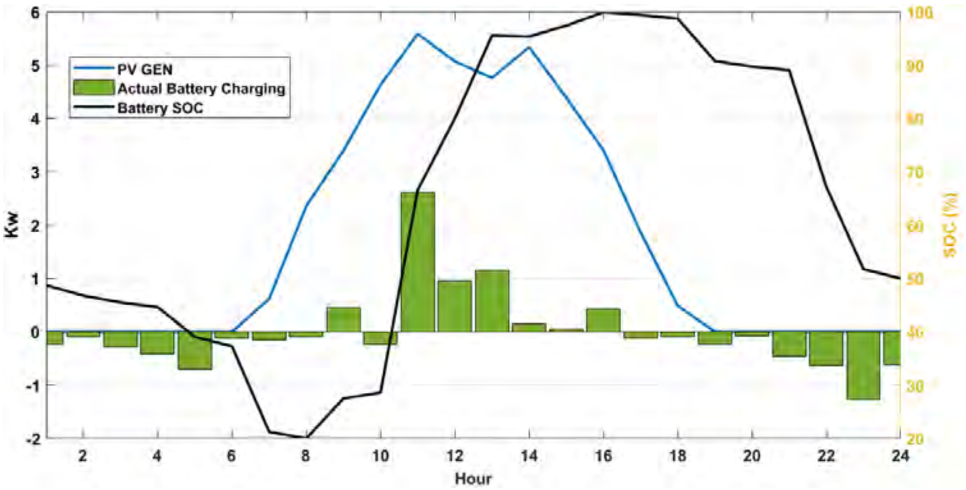

Figure 4.13: Battery status in Case 4.2 with ESS = 7 kWh

A key distinction of Case 4.3 lies in the presence of two independent battery systems owned by two different users. In the previous cases, the storage system was assumed to be fully shared among all members of the energy community, and its operation was optimized based on a collective objective function that incorporated the overall discomfort cost of the community. In contrast, this case considers two separate storage units, each controlled by an independent players who does not have access to the decisions of the other. This scenario reflects a more realistic setting in which users, in addition to their controllable loads, contribute their privately owned battery systems to the community. Rationally, each user defines their own preferences, costs, and operational priorities for their storage device, which are embedded in their individual optimization problem.

From a system perspective, achieving an equilibrium operating point becomes more challenging under this decentralized structure. In the previous configurations, the generation-side optimization was only influenced by its own decisions, meaning that the resulting production profile was solely determined by a single decision-making entity. Consequently, any oscillatory behavior in the system was limited to the interaction between total demand and generation, effectively forming a two-player dynamic. However, in the present case, an additional layer of complexity is introduced. Not only does the interaction between aggregated consumption and generation persist, but the generation profile itself becomes subject to fluctuations induced by the independent and potentially conflicting decisions of the two storage systems. Since each battery operates based on its own objective and without coordination, their charging and discharging actions can introduce internal oscillations within the generation curve. This leads to a multi-agent dynamic in which both consumption and generation are influenced by decentralized decision-making processes, ultimately making convergence to a stable equilibrium more difficult and potentially slower. If this issue is not addressed on the generation side, similarly to how it was mitigated on the consumption side, the resulting behavior exhibits oscillations. As illustrated in Figure 4.14, repetitive fluctuations are clearly observed in the generation profile.

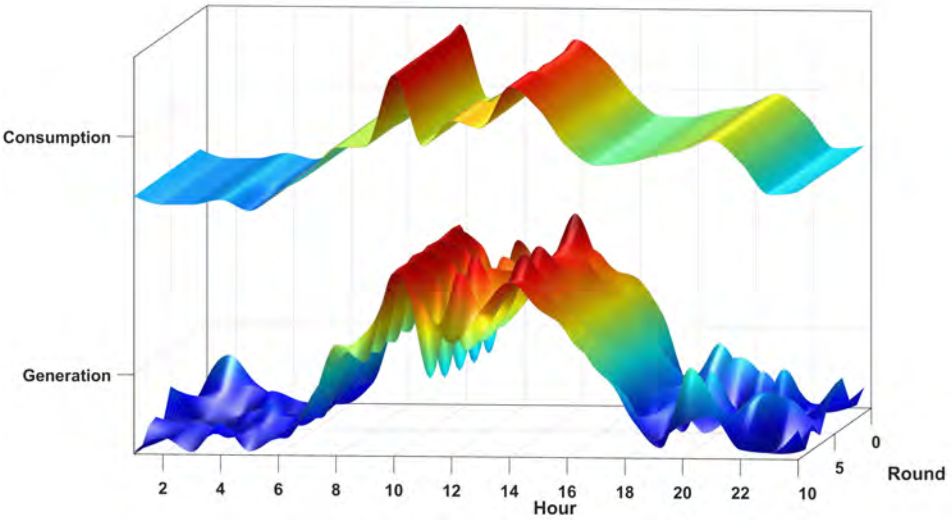

Figure 4.14: unconstrained fluctuations in generation in Case 4.3 with two separated ESS

However, with the same compensation expressed earlier for consumption, the generation curve will also converge to the summation of optimal answers obtained by both ESS during the optimization process. The shared energy is increased to 41.1 kWh, which is equal to 98% of the shareable energy. Figure 4.15 shows the ESS SOCs and convergence of both consumption and generation in Case 4.3

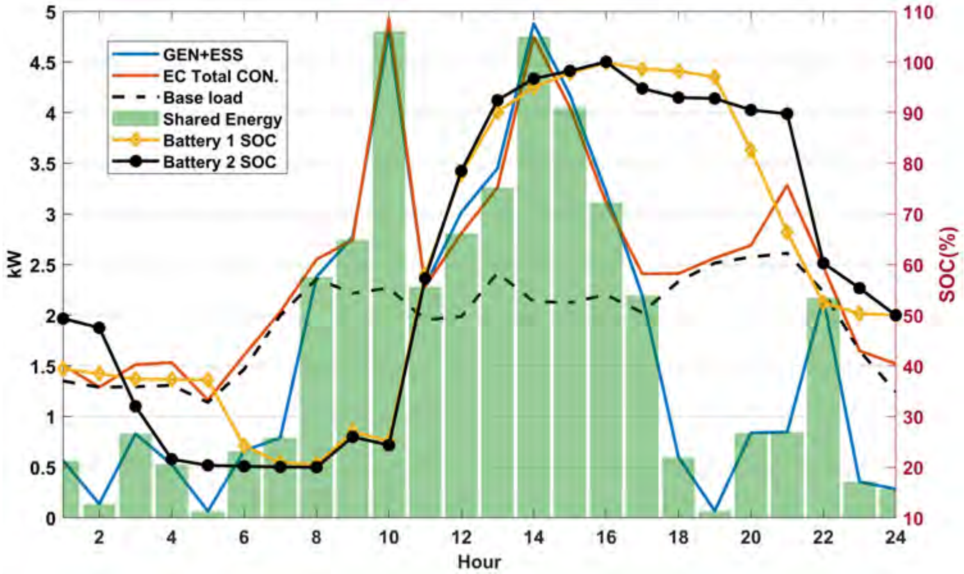

Figure 4.15: Optimized Shared Energy and battery SOC in Case 4.3 with two 5kWh ESS

Now it can be seen that with enough empty capacity in ESS, they can perfectly absorb the excess energy during hours 10:00 to 16:00, reaching from 25% on nominal capacity to 100%

To provide a more comprehensive assessment of the role of ESS, Case 4.4 considers a larger storage unit with a capacity of 20 kWh, allowing the impact of increased storage capacity on energy sharing to be evaluated. It is evident that, due to the higher amount of stored energy available at the beginning of the simulation, ESS can discharge more energy at first. However, it is important to emphasize that the energy provided by ESS should be compensated by generation at the end of the day. Therefore, the total amount of shared energy in Table 4.5 will not change remarkably. Figure 4.16 depicts shared energy and battery status in Case 4.4 during the day.

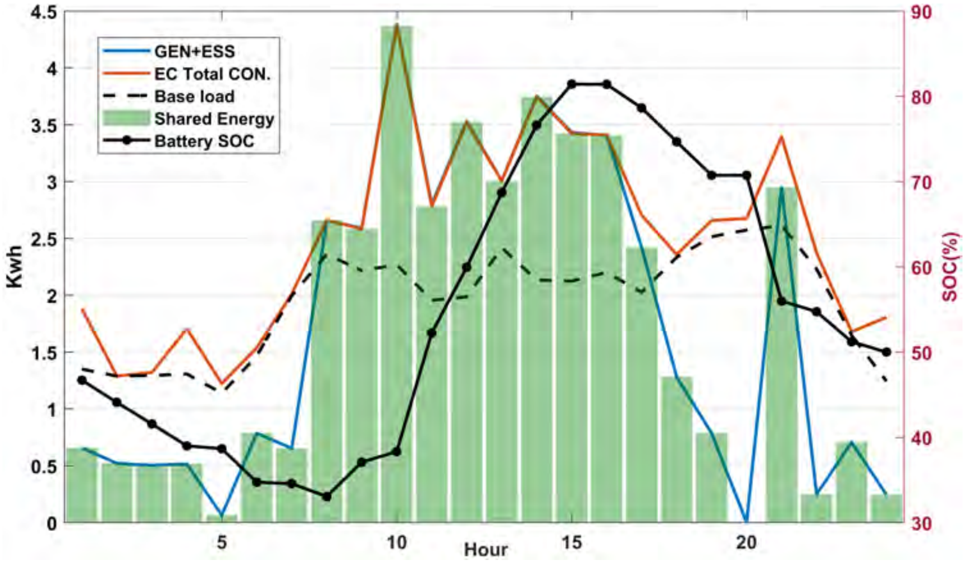

Figure 4.16: Optimized Shared Energy and battery SOC in Case 4.4 with ESS = 20 kWh

This section would indicate that, owing to the improved coordination among users provided by the proposed approach, the same operational benefits do not necessarily require large storage installations. Consequently, the results of this scenario can provide evidence that better management and coordination is highly important enough to be compared with battery capacity, leading to a more economical, resilient, and less resource-dependent energy community design.

4.5 Scalability of method and performance under different load/generation profile

EC can range from a limited number of participants to several thousands. Consequently, any proposed EMS must ensure scalability and convergence toward an equilibrium operating point independently of the number of users and the heterogeneity of their load and generation profiles. Although centralized EMS approaches can theoretically achieve global optimality, their applicability becomes increasingly limited as the dimensionality of the decision space grows, particularly when the problem formulation involves Mixed-Integer Nonlinear Programming (MINLP). This limitation becomes more pronounced when heterogeneous users are involved, and when intermittent renewable sources such as wind generation are integrated. Under these conditions, the aggregated generation and consumption profiles exhibit significant temporal misalignment, with peaks occurring at different hours of the day. With new overall production and consumption curves, the peaks of consumption and generation occur at totally different hours of the day (Figure 4.17). Studying Case 3 with a remarkable disparity between generation and consumption in hours of the day, and 30 users leading to 2880 variables (24 h × 4 appliances × 30 users) which is 3 times greater than Cases 1 and 2, imposes more time required for a solution. In the normal case before optimization, as seen in Figure 4.17, shared energy amounts to 168 kWh while energy mismatch is equal to 132 kWh. In this scenario, under constant generation and consumption profiles, the shared energy can increase up to 218.7 kWh, which corresponds to the total generated energy.

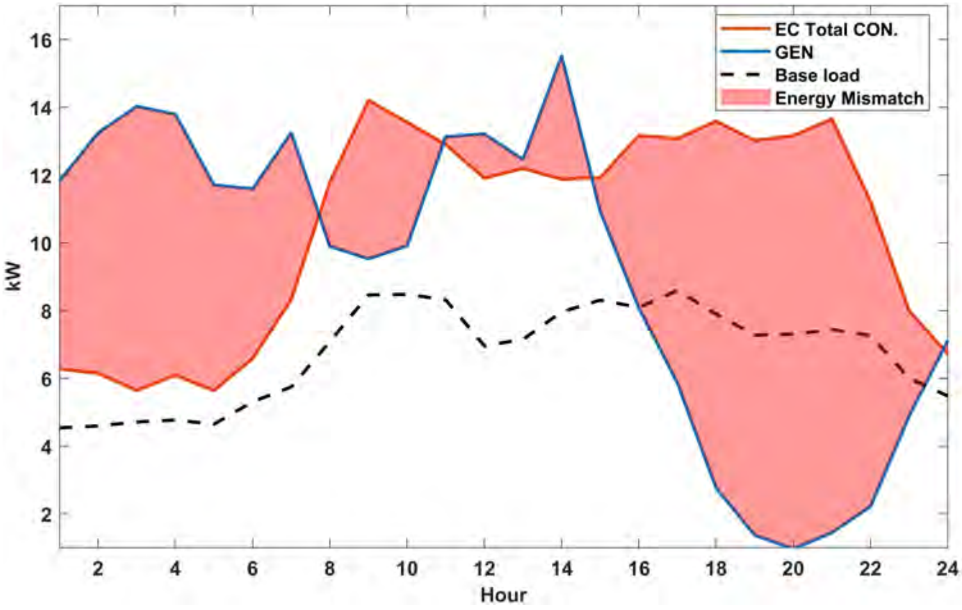

Figure 4.17: normal consumption and generation in Case 3

In a centralized framework, solving such a large-scale optimization problem would require substantial computational effort depending on the optimizer. For comparison, let's consider the same GA was supposed to be adopted for that in the central schema. In GAs and evolutionary algorithms in general, the dominant computational burden arises from the evaluation of the fitness function [45]. Therefore, the number of fitness function evaluations is commonly used as a proxy for computational complexity. In this study, the fitness function is defined based on the mismatch between generation and consumption, where both generation and consumption are functions of decision variables. In a centralized formulation, this leads to coupled decision variables. This coupling significantly increases the computational burden of evaluating the fitness function, as changes in one variable propagate through both terms.

The computational complexity of a GA is often approximated as:

$$O(n.g.C(m)) \tag{4.7}$$

where temporarily n is the size of the population, g denotes number of generations and $C(m)$is the complexity of evaluating the fitness function, which itself is a function of an individual's size (m) [66, 3]. Even under a relaxed assumption where the fitness evaluation cost scales linearly with the number of decision variables ($O(m)$), the overall complexity becomes:

$$O(n.g.m) \tag{4.8}$$

However, this simplification hides a critical issue. Increasing the individual size m without adjusting the population size n typically leads to loss of diversity and premature convergence. To maintain adequate exploration of the solution space, it is reasonable to assume that the population size scales with the individual size, such as $n = k.m$ where k is a scale ratio depending on different sources. With another relaxation, considering the augmentation relation as $log(m)$ (as one of the most optimistic known ratio), the equation in 4.8 yields:

$$O(n \cdot g \cdot m) = O(log(m) \cdot g \cdot m) = O(g \cdot m\, log(m)) \tag{4.9}$$

which denotes a linearithmic relation between computation complexity and individual size. The complexity grows with other relations between n and m, i.e., $O(g \cdot m^2)$ growth of computational complexity under a linear relation between population size and individual size. For example, moving from Case 1 to Case 3 (with 30 users) results in approximately 9 times higher computational cost, which contradicts the fundamental scalability requirements of RECs, where new members may join progressively over time.

In contrast, the proposed distributed approach significantly alleviates this issue. Since each user solves a local optimization problem with a fixed number of decision variables (depending on devices), the effective problem size per optimizer remains constant and independent of the total number of users. The results in Table 4.6 confirm that the total computation time of the proposed method is comparable to Case 1.

Table 4.6: Shared energy along the rounds of the game in Case 3

Iteration	1	2	3	4	5	6
Shared Energy (%)	88.8	94.5	94.6	96.6	96.7	97.9
Total Shifted Load (kWh)	24	28.4	30.8	33.1	31.6	33.6
Max Optimization Solving Time						24.7 s
Max Ciphertext Sharing Time						2.6s
Worst-case Time to Reach the Equilibrium						161.2 s

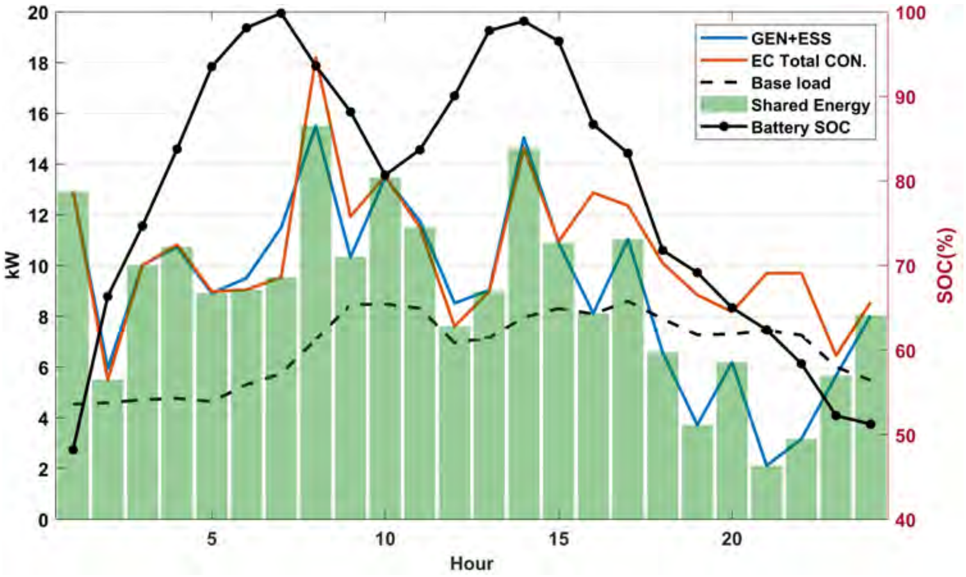

Figure 4.18: Optimized Shared energy and battery SOC in Case 3

Interestingly, in this case, the convergence time remains comparable to that of Case 1, despite the EC population increasing by a factor of three. It's worth noting that the only procedure that takes more time in this case is the interaction between users as expressed in Algorithm 1.

4.6 Grid Interactions

Beyond promoting citizens' participation in energy systems and facilitating access to affordable and low-carbon electricity, an ideal EC is expected to operate with a high degree of autonomy by maximizing the utilization of local renewable energy resources and minimizing its dependency on the upstream utility grid. This objective is typically achieved through coordinated EMSs that aim to align local generation and consumption. From an operational perspective, the interaction between an EC and the main grid can be quantified through the net exchanged power at each time interval h defined as:

$$P_h^{\text{grid}} = P_h^{GEN} - P^{CON} \tag{4.10}$$

Although exporting energy back to the grid is economically incentivized in Italy, in several countries such as Canada, regulators impose strict limitations on reverse power flow [80]. This is primarily due to the technical challenges it introduces in distribution networks, including voltage rise along feeders, desensitization and potential miscoordination of protection systems, and an increase in short-circuit current levels that may approach or exceed safe operating limits [60]. The formulation of the problem expressed in Equations (3.3) and (4.10), together implicitly minimizes the positive and negative interactions with the grid. This formulation not only provides a self-sufficient EC but also limits back injection of power into the grid. By pursuing this objective, ECs contribute to the formation of stable and semi-autonomous sub-regions within the power system. Such regions are capable of sustaining their operation under abnormal conditions, including grid outages, cascading failures, or large-scale disruptions [64]. In this context, ECs play a key role in enabling advanced grid support mechanisms such as Special Protection Schemes (SPS), including controlled islanding strategies [59]. The decentralized nature of EC operation further enhances system resilience, which has become a critical requirement in modern power systems exposed to increasing threats from extreme weather events, cyber-physical attacks, and other contingencies [42]. By reducing dependency on centralized infrastructure and enabling localized decision-making, ECs improve the ability of the grid to withstand and recover from such disturbances. As illustrated in Figures 4.19, 4.20, and 4.21, the adoption of the proposed method significantly reduces the interaction between the EC and the utility grid across all examined cases. This reduction is not only limited to energy imports but also extends to exports. In particular, excessive backfeeding, i.e., injecting surplus power into the grid, is substantially mitigated in the optimized scenarios (see Table 4.7).

Table 4.7: Grid Interactions

Case	Imported (kWh)	Backfeeded (kWh)	Change from original case	
			Imported	Backfeeded
1	18.9	0.7	30.11 (−37.2)%	11.89 (−94.1%)
2	24.9	6.7	30.11 (−17.3%)	11.89 (−43.6%)
3	36.74	4.51	82.47(−55.5%)	50.56(−91.1%)

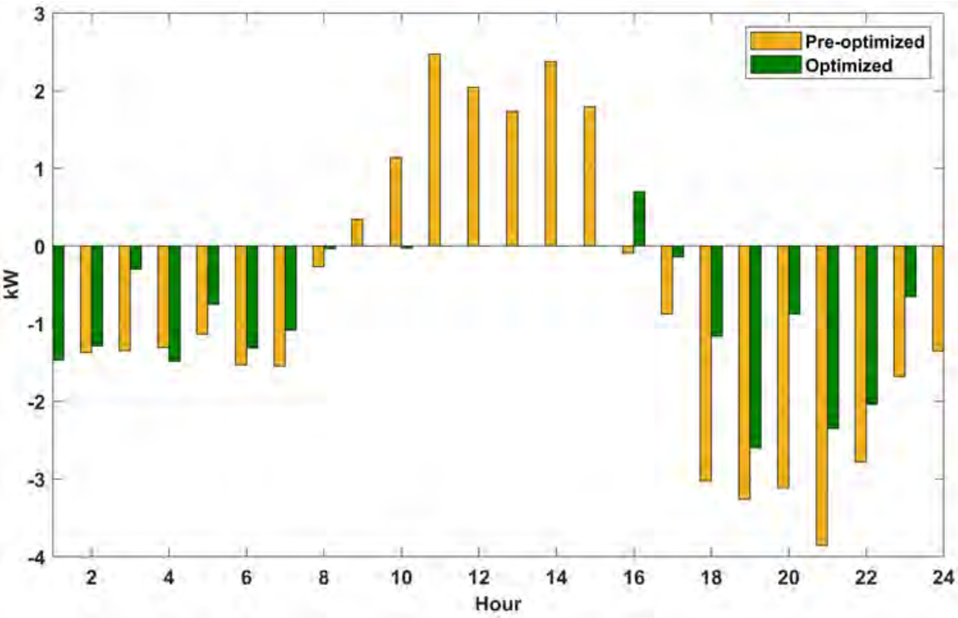

Figure 4.19: EC and Grid interactions in Case 1

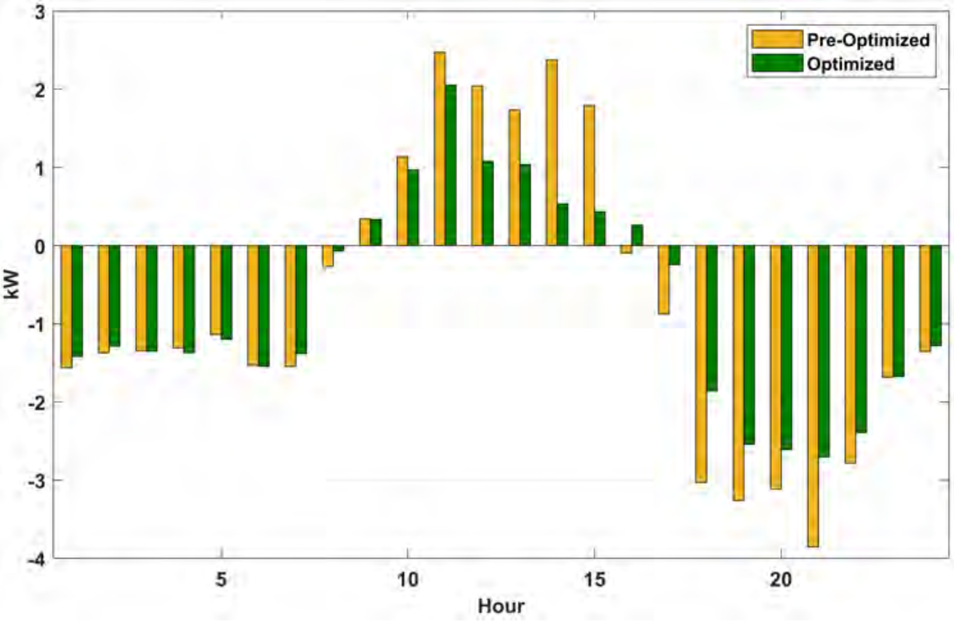

Figure 4.20: EC and Grid interactions in Case 2

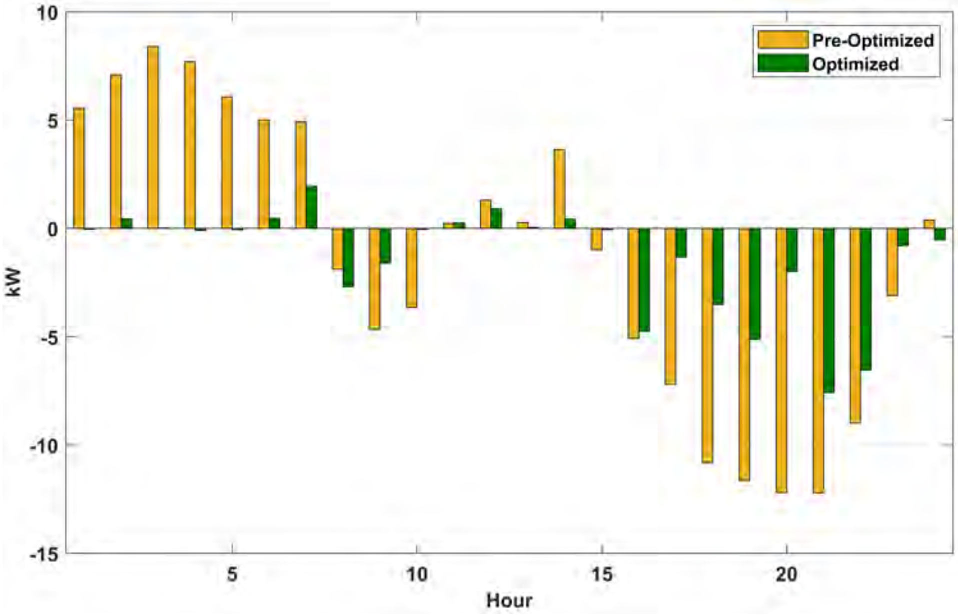

Figure 4.21: EC and Grid interactions in Case 3

4.7 Collaboration effect

Achieving high levels of self-sufficiency in an EC, as well as maximizing the incentives obtained through GSE, does not come without trade-offs. In particular, any modification of users' consumption patterns, such as postponing shiftable loads or reducing the operating levels of adjustable loads, introduces an implicit cost to the users. This cost is not directly monetary but reflects the discomfort or inconvenience experienced when deviating from preferred consumption behavior. In optimization problems related to demand side management, this imposed inconvenience is typically modeled through a discomfort or dissatisfaction factor, which can take various mathematical forms and weighting structures depending on the application [36]. These formulations aim to quantify the extent to which users are willing to alter their consumption in exchange for economic or operational benefits.

In this work, a different perspective from prioritizing is adopted. From the viewpoint of the energy community, any deficit between the desired and actual consumption at a given time interval is interpreted as a source of user dissatisfaction. Unlike centralized approaches in the literature, where a central controller assigns priorities to different loads, this framework delegates the prioritization process entirely to the users. That is, each user autonomously determines how to allocate their available energy across competing loads. For instance, at a specific time slot, a user may decide whether to defer a high-priority appliance or instead postpone multiple lower-priority loads to ensure that the most critical demand is satisfied. This endogenous prioritization reflects a more realistic behavioral model, where users retain full control over their consumption decisions rather than adhering to externally imposed scheduling rules. Accordingly, from the EC's perspective, the primary objective is to deliver the total amount of energy requested by each user, while the internal allocation of that energy remains the user's responsibility. Any shortfall in meeting the desired consumption level directly translates into user discomfort.

It is important to note that modeling dissatisfaction in monetary terms is inherently heterogeneous across users. Different individuals exhibit varying levels of flexibility. Some users may be highly willing to adjust their consumption patterns, while others may associate high cost with even minor deviations. Therefore, assigning a diverse dissatisfaction coefficient across all users would lead to more realistic representations of behavior. Moreover, if the perceived dissatisfaction cost exceeds the economic incentives provided (e.g., through energy sharing or GSE rewards), no load shifting will occur. In such cases, the optimization process will naturally converge to the original consumption profile, as any deviation would result in a net loss for the user. This highlights the critical balance between incentives and user flexibility in demand response programs. In addition to dissatisfaction parameters, other economic factors, such as electricity purchase prices and battery degradation costs, also influence the final scheduling decisions and the extent of load shifting.

In this section, the impact of dissatisfaction coefficients on the overall performance of the energy community is investigated. Particular emphasis is placed on heterogeneous user behavior, where different users are characterized by distinct dissatisfaction parameters. This assumption provides a more realistic representation of real-world communities, where uniform behavior across all participants is highly unlikely. An even more refined modeling approach considers intra-user variability, where a single user may assign different levels of importance to consumption at different times of the day. For example, midday loads may be significantly more critical for some users, while others may prioritize evening consumption. Incorporating such temporal heterogeneity further enhances the realism of the model.

Table 4.8: Different discomfort coefficient in Case 4

Collaboration	Number of users with K_c = 14¢	12¢	10¢	6¢	Average Shared Energy (kWh)
High	0	1	3	6	34.9
Moderate	1	2	2	5	33.6
Low	3	2	0	5	32.8
Negligible	5	3	1	1	31.9

For a clearer assessment of the impact of user collaboration, ESS is excluded in this scenario. By removing ESS from the analysis, the interactions between shared energy and collaboration are decoupled from storage-related effects. This allows the observed outcomes to be attributed solely to the collaborative behavior of users, without any interference arising from storage operation. As a result, the study isolates the pure contribution of coordination among participants, enabling a more transparent evaluation of how collective load adjustments and cooperative strategies influence shared energy. This setup ensures that any improvement in performance can be directly linked to collaboration mechanisms, rather than being amplified or masked by the presence of energy storage.

The results indicate that the willingness of participants plays a critical role in the overall performance of energy communities. Even with the most efficient and well-designed energy management systems, limited user engagement can significantly constrain achievable benefits. In other words, the effectiveness of any optimization framework is inherently dependent on the extent to which users are willing to adapt their consumption behavior and actively participate in coordinated strategies. This observation highlights that technical efficiency alone is not sufficient to ensure successful operation. The human factor, namely user acceptance, responsiveness, and flexibility, becomes a determining element in realizing the full potential of energy communities. If participants are reluctant to engage with demand-side programs or adjust their usage patterns, the system will not be able to exploit available flexibility, regardless of the sophistication of the underlying algorithm.

Therefore, alongside the development of effective management methods, it is essential to design appropriate motivation and incentive mechanisms. These mechanisms should be structured to align individual benefits with community objectives, encouraging users to participate actively and consistently. A successful energy community requires a balanced integration of advanced technical solutions and well-designed behavioral incentives.

4.8 Simultaneous vs. sequential games

In game theory, a basic distinction is made between simultaneous and sequential games, depending on how and when players make their decisions. In simultaneous games, all players act at the same time, without knowing what others are currently choosing. Each player, therefore, makes a decision based on expectations about others' behavior, trying to maximize their own payoff under this uncertainty. This type of formulation is commonly used to represent decentralized systems in which agents act independently but are still linked through shared outcomes. In contrast, sequential games assume that decisions are made one after another. In this case, players who move later can observe the actions of those who moved before them and adjust their strategies accordingly. This creates a natural hierarchy in the decision process, where earlier actions influence later responses. The appropriate solution concept here is the subgame perfect equilibrium, which ensures that players behave optimally at every stage of the game.

From a modeling perspective, the difference between these two structures mainly lies in information, timing, and convergence. Simultaneous games require solving a system where all decisions are interdependent, often leading to a fixed-point problem. Sequential games, on the other hand, can often be analyzed step by step, since later decisions are explicitly conditioned on earlier ones. As a result, simultaneous formulations tend to rely on iterative solution methods, while sequential ones are typically handled through backward reasoning. However, a key aspect of this study is not only the distinction between simultaneous and sequential games, but more importantly, how these two structures influence the convergence of decisions. In simultaneous games, all players make their decisions at the same time. The only information available to each player is typically the outcome of the previous iteration. As a result, players react to outdated aggregate information, which often leads to oscillatory behaviors, previously referred to as ping-pong responses. In such cases, players continuously overcompensate for each other's actions and change their decisions, causing the system to fluctuate rather than stabilize. However, these oscillations are gradually damped by the constraints imposed on users (such as power limits, comfort constraints, and feasibility conditions). Over successive iterations, the magnitude of these oscillations decreases, and the system eventually converges to a stable solution, which corresponds to the equilibrium. An important advantage of this framework is that it preserves privacy and fairness among users, as no participant has priority over others and all decisions are made symmetrically. In addition, load/generation profiles can be shared among users and involved in mathematical operations without any need for decryption.

In contrast, in sequential games, users make decisions one after another, and each user has access to the updated aggregate information resulting from the decisions of previous users. This structure introduces an inherent ordering effect. Users who act earlier in the sequence typically have greater flexibility and a wider range of feasible options, allowing them to select more convenient or preferred operating points (as can be seen for early users in Figure 4.22).

On the other hand, users who act later may benefit from updated system conditions, but they may also lose access to certain favorable choices that have already been taken. For example, in an energy community where certain time slots (such as nighttime consumption periods) are highly preferred, early decision-makers can allocate these slots according to their preferences, while later users may be forced to adjust to less favorable alternatives. Despite this potential imbalance, sequential games offer an important advantage where they naturally mitigate the oscillatory behavior observed in simultaneous settings. Since each user makes decisions based on the most recent aggregate information, rather than outdated data, the system evolves more smoothly [96]. At each step, users partially correct the mismatch between generation and consumption, leading to a gradual reduction in system imbalance. In this process, later users effectively act as compensators, refining the decisions made by earlier users. As a result, the overall system tends to converge more quickly, and large fluctuations between iterations are significantly reduced. At the end of the cycle, aggregated EC consumption or generation will be passed to the first user again, who can further refine their decision if residual imbalance still exists and if constraints allow.

Figure 4.22 illustrates how gradually the load profile of the EC changes as it is passed to users to optimize their schedule and update the total load curve. In this schema, all community reach equilibrium just in the first iteration (starting from user one and ending with user ten). It should be emphasized that in this schema, sharing constraints are not needed to prevent oscillation of decisions since users now have access to the most updated load curve once it's their time to reschedule their loads.

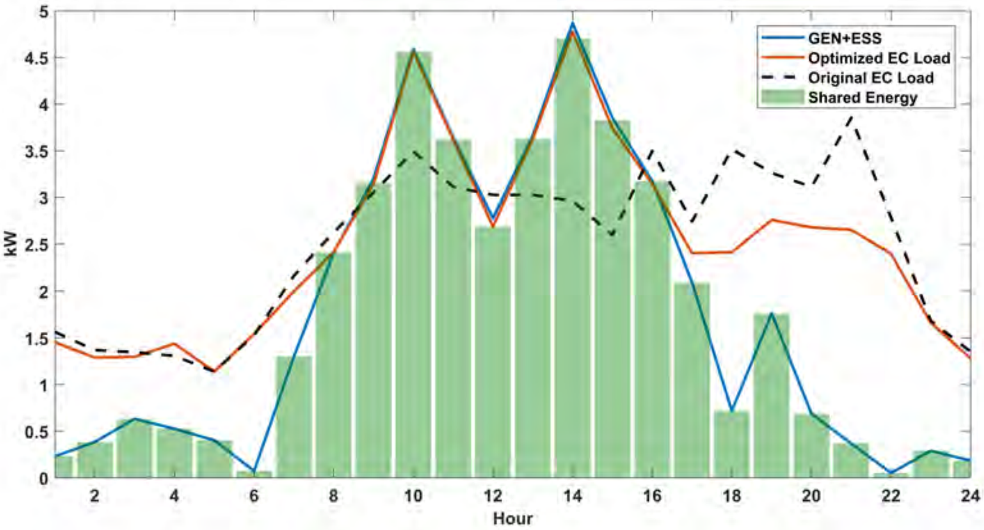

Figure 4.23: normal consumption and generation in Case 3

From a fairness perspective, the sequential structure may initially appear biased toward early players. However, this concern can be mitigated by introducing randomized user ordering. By uniformly random selection of the sequence of users in each round, and with reference to the

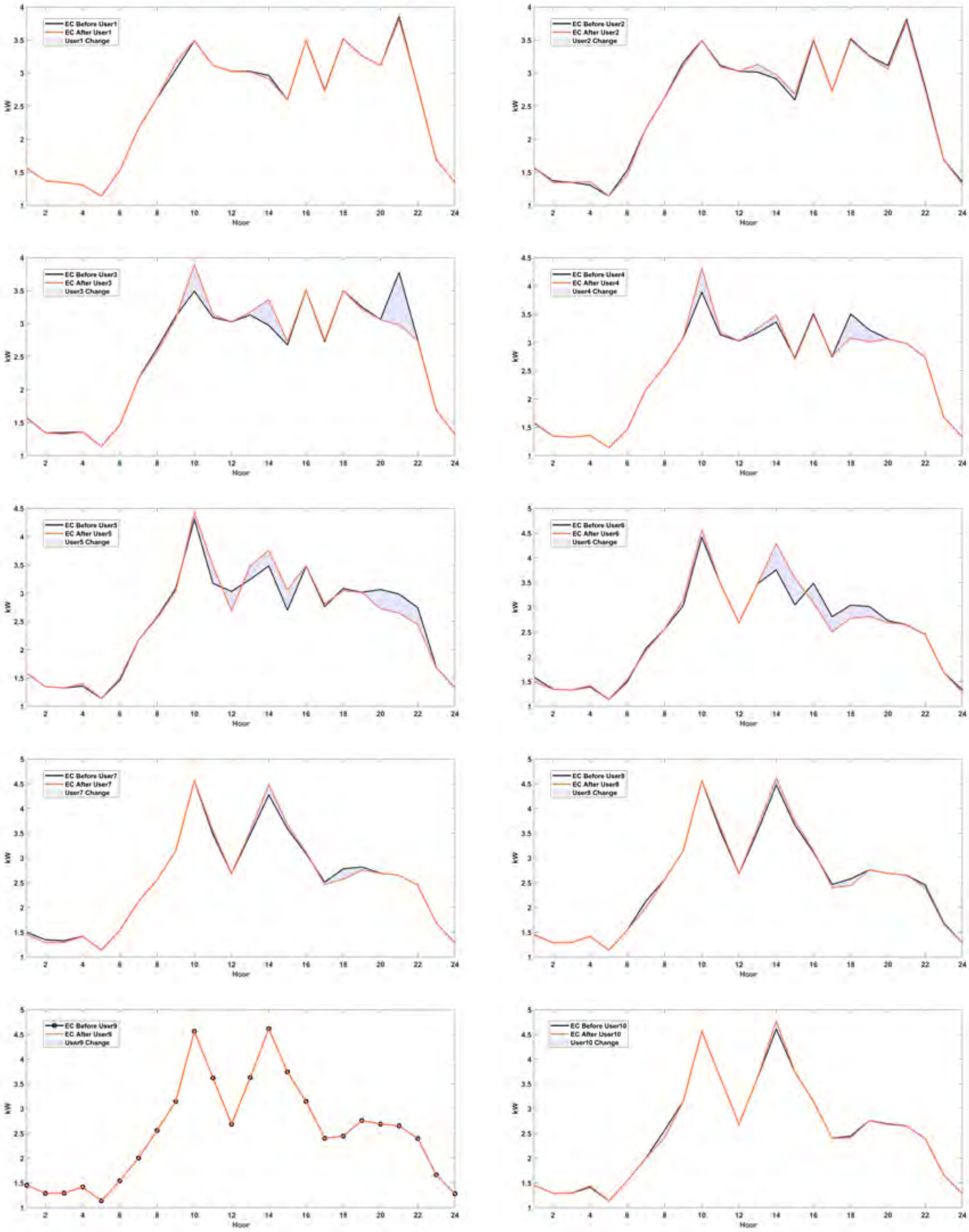

Figure 4.22: Sequential formation of the optimized EC load schedule

law of large numbers, it can be argued that in the long run all users will have equal opportunities in the decision process [74]. Therefore, while short-term advantages may exist, the overall mechanism remains fair over time. Another important concern relates to privacy preservation. In the simultaneous framework, users typically share their data through secure secret sharing methods, such as homomorphic Paillier encryption, ensuring that only aggregated information is revealed without exposing individual load profiles. However, in the sequential setting, after each user performs optimization, the aggregate load curve must be updated. This creates a potential privacy risk where by comparing the aggregate load before and after a user's decision, it may be possible to infer that user's individual contribution.

This issue can be mitigated through controlled information sharing. Specifically, at each step, only the user whose turn it is receives access to the aggregate load profile. After optimization, the updated aggregate is passed privately to the next user in the sequence, without being disclosed to others. In this way, no user has access to both the pre- and post-optimization aggregate of another user, preventing the extraction of individual load profiles. For example, if user 1 performs optimization, only user 2 receives the updated aggregate, and user 2 cannot distinguish which portion of the load originates from the initial system and which portion results from user 1's decision. This sequential and private update mechanism helps preserve user privacy while maintaining the advantages of sequential decision-making.

4.9 Discussion of Results

The results presented in this section and in [49] provide a comprehensive evaluation of the proposed decentralized energy management framework under various operating conditions and system configurations. By explicitly incorporating user flexibility, behavioral preferences, and distributed decision-making, the framework successfully balances individual objectives with community-level performance. The findings consistently demonstrate that the proposed approach significantly enhances shared energy within the energy community while effectively reducing the mismatch between local generation and consumption profiles. One of the most important observations is the robustness of the proposed method with respect to system scaling. As the size of the energy community increases, the convergence behavior remains stable and comparable to smaller-scale cases. This indicates that the distributed structure of the algorithm inherently mitigates the computational and coordination challenges typically associated with centralized optimization approaches. Despite the substantial increase in the number of decision variables and interactions among participants, the system converges reliably to an equilibrium point without exhibiting severe oscillatory behavior.

Furthermore, the analysis highlights the role of energy storage systems in improving overall performance. While larger storage capacities lead to higher levels of shared energy, the results reveal that this improvement is primarily driven by the availability of reserved capacity rather than enhanced coordination among users. Consequently, the proposed framework demonstrates the ability to extract significant value even in scenarios with limited or no storage resources by intelligently reshaping demand profiles. Another key outcome is the substantial reduction in power exchanges with the upstream grid. By aligning consumption patterns with local renewable generation, the framework promotes self-consumption and minimizes backfeeding, which is critical for maintaining grid stability and reducing operational complexity. This behavior directly supports the development of more resilient and self-sufficient energy communities, capable of operating with reduced dependency on external energy sources.

Taken together, the results confirm that the proposed decentralized approach provides a scalable, privacy-preserving, and practically implementable solution for energy community management. It effectively captures user behavior, ensures convergence, and delivers measurable improvements in both technical and operational performance metrics. These characteristics make the framework well-suited for real-world deployment, particularly in the context of modern power systems where flexibility, resilience, and user participation play an increasingly important role.

Chapter 5

Conclusion

This thesis has addressed one of the most critical challenges in modern power systems, which is the design of an efficient, scalable, and privacy-preserving energy management framework for energy communities (ECs). As the global energy paradigm shifts from centralized fossil-fuel-based systems toward decentralized, renewable-based infrastructures, the role of coordinated local energy management becomes increasingly important. Energy communities, as collective entities of prosumers, provide a promising pathway toward achieving sustainability, resilience, and user participation. However, their practical deployment introduces significant technical challenges, particularly in terms of coordination, scalability, data privacy, and regulatory compliance. This work has aimed to systematically tackle these challenges through a novel, secure, and distributed optimization framework.

The proposed approach is built upon a decentralized and non-cooperative game-theoretic formulation, where each community member independently optimizes its energy consumption and storage behavior while interacting with others through aggregated information. Unlike centralized methods, which require full access to users' private data and suffer from scalability limitations, the proposed framework enables autonomous decision-making at the user level while still achieving a coordinated system-level objective. This is accomplished through an iterative best-response mechanism that converges to a Nash equilibrium, ensuring that no participant has an incentive to unilaterally deviate from the final solution. A key contribution of this thesis lies in the integration of privacy-preserving mechanisms into the energy management process. By employing partially homomorphic encryption techniques, specifically additive encryption schemes, the framework allows users to contribute to global system metrics without revealing their individual consumption or generation profiles. Only aggregated information is disclosed, ensuring that sensitive user data remains protected throughout the optimization process. This addresses one of the major barriers to the real-world adoption of distributed energy management systems, where concerns regarding data privacy and cybersecurity are increasingly prominent.

From a modeling perspective, the thesis introduces a comprehensive formulation that captures the heterogeneity of user behavior through different categories of loads, including critical, shiftable, and adjustable demands. The incorporation of discomfort costs associated with deviations from preferred consumption patterns allows the model to realistically represent user preferences and flexibility. Furthermore, the separation of consumption and storage decision variables mitigates the inherent coupling between generation and consumption, particularly in systems where energy storage is installed upstream of the point of measurement. This decomposition significantly simplifies the optimization problem while preserving its physical accuracy. The results obtained from extensive simulations provide strong evidence of the effectiveness of the proposed framework. Across various scenarios, including different community sizes, load profiles, and storage capacities, the method consistently demonstrates significant improvements in shared energy and reductions in the mismatch between generation and consumption. One of the most important findings is that the solving time of the algorithm does not increase as the size of the energy community increases substantially. This confirms the scalability of the approach and highlights its suitability for large-scale deployments.

Another important insight concerns the role of energy storage systems within energy communities. While the presence of storage enhances the level of shared energy and reduces grid dependency, the results indicate that effective management of users can increase the self-sufficiency of EC even with a smaller ESS or lack of a storage system. This observation has important implications for the design and planning of energy communities, suggesting that investment in flexibility and coordination mechanisms can be as important as, or even more important than, increasing storage capacity. The analysis also highlights the ability of the proposed framework to significantly reduce interactions with the upstream utility grid. By aligning consumption patterns with local renewable generation, the system minimizes both energy imports and exports, thereby reducing transmission losses, mitigating grid congestion, and enhancing local self-sufficiency. This behavior is particularly valuable in the context of modern power systems, where the integration of distributed energy resources introduces new challenges for grid stability and operation.

In addition to technical performance, this thesis has also considered the regulatory and practical context of energy communities, particularly within the European and Italian frameworks. By aligning the optimization objectives with existing incentive mechanisms, such as shared energy definitions and local consumption policies, the proposed method ensures compatibility with real-world implementations. This regulatory awareness is essential for bridging the gap between theoretical models and practical deployment.

Despite its contributions, this work also opens several avenues for future research. First, the current formulation assumes a deterministic environment with known generation and consumption profiles. Extending the model to incorporate uncertainty, for example through stochastic optimization or robust frameworks, would enhance its applicability in real-world scenarios. second, while the proposed encryption scheme ensures privacy, it introduces computational overhead that may become significant in very large systems; therefore, exploring more efficient secure distributed computation techniques and encryption (such as Distributed Key Generation (DKG)) remains an important direction. Moreover, the behavioral aspects of users represent another important dimension for future investigation. While this thesis incorporates discomfort costs to model user preferences, more advanced approaches, such as learning-based models or adaptive preference estimation, could provide a more accurate representation of user behavior.

In conclusion, this thesis has demonstrated that a secure and distributed approach to energy management in energy communities is not only feasible but also highly effective. By combining game theory, optimization, and privacy-preserving techniques, the proposed framework achieves a balance between individual autonomy and collective efficiency. The results confirm that decentralized coordination can deliver performance comparable to centralized solutions while overcoming their fundamental limitations in scalability and privacy. As energy systems continue to evolve toward more decentralized and participatory structures, such approaches will play a crucial role in enabling the next generation of sustainable and resilient power systems

Bibliography

[1] Décret du 2 mai 2019 ... en vue de favoriser le développement des communautés d'énergie renouvelable, September 2019.

[2] *Proceedings of the 1st Workshop on BLOckchain for Renewables INtegration (BLORIN 2022)*. IEEE, 2022. Available on IEEE Xplore.

[3] Rewayda Razaq Abo-Alsabeh and Abdellah Salhi. The genetic algorithm: A study survey. *Iraqi Journal of Science*, 63(3), 2022.

[4] Abbas Acar, Hidayet Aksu, A Selcuk Uluagac, and Mauro Conti. A survey on homomorphic encryption schemes: Theory and implementation. *ACM Computing Surveys (Csur)*, 51(4):1–35, 2018.

[5] Samson Ademola Adegoke, Yanxia Sun, Adesola Sunday Adegoke, and Damilola Ojeniyi. Optimal placement of distributed generation to minimize power loss and improve voltage stability. *Heliyon*, 10(21):e39298, 2024.

[6] Peyman Afzali, Arash Rajaei, Masoud Rashidinejad, and Hossein Farahmand. Peer-to-peer energy trading among prosumers in energy communities based on preferences considering holacracy structure. *IEEE Transactions on Engineering Management*, 71:7756–7767, 2024.

[7] Hossein Akhavan-Hejazi, Zahra Baharlouei, and Hamed Mohsenian-Rad. Challenges and opportunities in large-scale deployment of automated energy consumption scheduling systems in smart grids. In *2012 IEEE Third International Conference on Smart Grid Communications (SmartGridComm)*, pages 270–275, 2012.

[8] Thamer Alquthami, Ahmad H Milyani, Muhammad Awais, and Muhammad B Rasheed. An incentive based dynamic pricing in smart grid: A customer's perspective. *Sustainability*, 13(11):6066, 2021.

[9] M. R. Amin. *Self-synchronized converter for fast synchronization between low voltage microgrid and inverter connection*. PhD thesis, Universiti Tun Hussein Onn Malaysia, 2023.

[10] Charles H. Anderton and John R. Carter. *Fundamentals of Game Theory*, page 53–66. Cambridge University Press, 2009.

[11] ARERA – Autorità di Regolazione per Energia Reti e Ambiente. Delibera 04 agosto 2020, 318/2020/R/eel: Regolazione delle partite economiche relative all'energia elettrica condivisa da un gruppo di autoconsumatori di energia rinnovabile che agiscono collettivamente in edifici e condomini oppure condivisa in una comunità di energia rinnovabile. ARERA "Atti e provvedimenti" webpage, August 2020. Data pubblicazione sul sito ARERA: 05 agosto 2020.

[12] Shahab Bahrami, M. Hadi Amini, Miadreza Shafie-Khah, and João P. S. Catalão. A decentralized renewable generation management and demand response in power distribution networks. *IEEE Transactions on Sustainable Energy*, 9(4):1783–1797, 2018.

[13] Adela Bâra and Simona-Vasilica Oprea. Enabling coordination in energy communities: A digital twin model. *Energy Policy*, 184:113910, 2024.

[14] Martin Bichler. *Game-Theoretical Basics*, page 11–29. Cambridge University Press, 2017.

[15] Sami Saeed Binyamin, Sami Abdullah Ben Slama, and Bassam Zafar. Artificial intelligence-powered energy community management for developing renewable energy systems in smart homes. *Energy Strategy Reviews*, 51:101288, 2024.

[16] Bernd Bonfert. 'we like sharing energy but currently there's no advantage': Transformative opportunities and challenges of local energy communities in europe. *Energy Research & Social Science*, 107:103351, 2024.

[17] Chiara Bordin, Harold Oghenetejiri Anuta, Andrew Crossland, Isabel Lascurain Gutierrez, Chris J Dent, and Daniele Vigo. A linear programming approach for battery degradation analysis and optimization in offgrid power systems with solar energy integration. *Renewable energy*, 101:417–430, 2017.

[18] BP p.l.c. bp Energy Outlook 2025. Energy outlook report, BP, 2025. Accessed: 2025-12-17.

[19] A. U. A. Caramizaru. Energy communities: An overview of energy and social innovation. In *EUR 30083 EN*. Publications Office of the European Union, Luxembourg, 2020.

[20] F Ceglia, P Esposito, E Marrasso, and M Sasso. From smart energy community to smart energy municipalities: Literature review, agendas and pathways. *Journal of Cleaner Production*, 254:120118, 2020.

[21] Lu Chen, Qingshan Xu, Yongbiao Yang, Hui Gao, and Weixiao Xiong. Community integrated energy system trading: a comprehensive review. *Journal of Modern Power Systems and Clean Energy*, 10(6):1445–1458, 2022.

[22] Adriana Chiş and Visa Koivunen. Coalitional game-based cost optimization of energy portfolio in smart grid communities. *IEEE Transactions on Smart Grid*, 10(2):1960–1970, 2019.

[23] Co2mmunity Project. Sprakebüll – a pioneering energy community in north frisia, germany. https://co2mmunity.eu/wp-content/uploads/2019/02/Factsheet-Sprakeb Factsheet, INTERREG Co2mmunity Project.

[24] S. Cui and J.-W. Xiao. Game-based peer-to-peer energy sharing management for a community of energy buildings. *International Journal of Electrical Power & Energy Systems*, 123:106204, Dec 2020.

[25] Shichang Cui, Yan-Wu Wang, and Jiang-Wen Xiao. Peer-to-peer energy sharing among smart energy buildings by distributed transaction. *IEEE Transactions on Smart Grid*, 10(6):6491–6501, 2019.

[26] Barbara Curli, Edoardo Ferrero, Mario Perugini, and Elisa Ruozzi. What drives the development of community energy in europe? the importance of the national energy systems. *Energy Res. Soc. Sci*, 13:136–147, 2020.

[27] M. L. Di Silvestre, M. G. Ippolito, E. R. Sanseverino, G. Sciumè, and A. Vasile. Energy self-consumers and renewable energy communities in italy: New actors of the electric power systems. *Renewable and Sustainable Energy Reviews*, 151:111565, Nov 2021.

[28] Marialaura Di Somma, Mohammad Dolatabadi, Alessandro Burgio, Pierluigi Siano, Domenico Cimmino, and Nicola Bianco. Optimizing virtual energy sharing in renewable energy communities of residential users for incentives maximization. *Sustainable Energy, Grids and Networks*, 39:101492, 2024.

[29] DMEA Wholesale Energy Markets and Environmental Sustainability Directorate. Regulation of economic transactions relating to electricity shared by a group of renewable energy self-consumers acting collectively in buildings and condominiums or shared in a renewable energy community, 2020.

[30] Sobhan Dorahaki, Masoud Rashidinejad, Seyed Farshad Fatemi Ardestani, Amir Abdollahi, and Mohammad Reza Salehizadeh. An integrated model for citizen energy communities and renewable energy communities based on clean energy package: A two-stage risk-based approach. *Energy*, 277:127727, 2023.

[31] Elektrizitätswerke Schönau (EWS) eG. Die Geschichte der Stromrebellen – EWS Schönau. https://www.ews-schoenau.de/ews/geschichte/, n.d. Accessed: 2025-12-22.

[32] Energy Collective Project Consortium. The energy collective: Final report. Technical report, Energiforskning.dk, 2021. Final technical report for the Energy Collective project; consumer-centric electricity markets and energy sharing among prosumers.

[33] European Commission. Commission approves €5.7 billion Italian State aid scheme under the Recovery and Resilience Facility to support renewable energy communities and self-consumers. Press release IP/23/5787, European Commission, Brussels, November 2023.

[34] European Parliament and Council of the European Union. Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources (recast), 2018. Official Journal: OJ L 328, 21.12.2018, pp. 82–209. ELI: dir/2018/2001/oj.

[35] European Parliament and Council of the European Union. Directive (EU) 2019/944 of the European Parliament and of the Council of 5 June 2019 on common rules for the internal market for electricity and amending Directive 2012/27/EU (recast), 2019. Consolidated text: 16 July 2024. CELEX: 02019L0944-20240716.

[36] Ricardo Faia, Pedro Faria, and Zita Vale. Optimal energy management with discomfort calculation in residential buildings considering load shifting and home battery storage system. *Sustainable Energy, Grids and Networks*, 41:101624, 2025.

[37] XM Fan, XH Li, YM Ding, J He, and M Zhao. Demand response scheduling algorithm for smart residential communities considering heterogeneous energy consumption. *Energy and Buildings*, 279:112691, 2023.

[38] Federal Ministry for Economic Affairs and Energy (BMWi). Renewable energy sources act (eeg 2017). Official PDF publication, 2017. English translation of the German Renewable Energy Sources Act (Erneuerbare-Energien-Gesetz).

[39] Mark Fenwick, Wulf A Kaal, and Erik PM Vermeulen. Regulation tomorrow: what happens when technology is faster than the law. *Am. U. Bus. L. Rev.*, 6:561, 2016.

[40] E. Fernandez, M. J. Hossain, K. Mahmud, M. S. H. Nizami, and M. Kashif. A bi-level optimization-based community energy management system for optimal energy sharing and trading among peers. *Journal of Cleaner Production*, 279:123254, Jan 2021.

[41] D. Fioriti, T. Ferrucci, and D. Poli. Fairness and reward in energy communities: game-theory versus simplified approaches. In *2023 IEEE International Conference*

on Environment and Electrical Engineering and 2023 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), pages 1–6. IEEE, 2023.

[42] Mahmoud Fotuhi-Firuzabad. Guest editorial: Reliability and resilience modelling, assessment, and enhancement of modern power systems with proliferation of grid-edge resources. *IET Generation, Transmission & Distribution*, 18:n/a–n/a, 12 2023.

[43] Drew Fudenberg. *Game theory*. MIT press, 1991.

[44] Kaiye Gao, Tianshi Wang, Chenjing Han, Jinhao Xie, Ye Ma, and Rui Peng. A review of optimization of microgrid operation. *Energies*, 14(10):2842, 2021.

[45] Eduard Garcia-Villegas, Alejandro Lopez-Garcia, and Elena Lopez-Aguilera. Genetic algorithm-based grouping strategy for ieee 802.11ah networks. *Sensors*, 23(2), 2023.

[46] María-Victoria Gasca, Rémy Rigo-Mariani, Vincent Debusschere, and Yousra Sidqi. Fairness in energy communities: Centralized and decentralized frameworks. *Renewable and Sustainable Energy Reviews*, 208:115054, 2025.

[47] Gestore dei Servizi Energetici (GSE S.p.A.). Configurazioni per l'autoconsumo diffuso, n.d. Webpage under "Comunità energetiche e autoconsumo"; includes guidance on CACER/REC and groups of self-consumers.

[48] Gestore Servizi Energitici. Servizio di scambio sul posto, 2019.

[49] Saber Ghashghaei, Giuseppe Sciumé, Eleonora Riva Sanseverino, Salvatore Favuzza, and Mohammadreza Fakhri Moghaddam Arani. A scalable game-theoretic framework for secure and decentralized energy sharing in renewable energy communities. *Sustainable Energy, Grids and Networks*, 46:102208, 2026.

[50] David E Golberg. Genetic algorithms in search, optimization, and machine learning. *Addion wesley*, 1989(102):36, 1989.

[51] Luis Gomes and Zita Vale. Costless renewable energy distribution model based on cooperative game theory for energy communities considering its members' active contributions. *Sustainable Cities and Society*, 101:105060, 2024.

[52] Emi Minghui Gui and Iain MacGill. Typology of future clean energy communities: An exploratory structure, opportunities, and challenges. *Energy Research & Social Science*, 35:94–107, 2018. Energy and the Future.

[53] H. Habibzadeh, C. Kaptan, T. Soyata, B. Kantarci, and A. Boukerche. Smart city system design. *ACM Computing Surveys*, 52(2):1–38, Mar 2020.

[54] Yiliang Han, Yuanyuan Wang, Liqiang Wu, Haokang Feng, Xuguang Wu, and Ruifeng Li. Survey of privacy-preserving data aggregationm schemes in smart grid. *Journal of King Saud University Computer and Information Sciences*, 37(9):263, 2025.

[55] R Hanna. Community renewables innovation lab. energy transition platform policy briefing. *Spiral. Imperial. Ac. Uk*, 22, 2017.

[56] Mohammad Sadegh Javadi, Ali Esmaeel Nezhad, Pedro H.J. Nardelli, Matthew Gough, Mohamed Lotfi, Sérgio Santos, and João P.S. Catalão. Self-scheduling model for home energy management systems considering the end-users discomfort index within price-based demand response programs. *Sustainable Cities and Society*, 68:102792, 2021.

[57] Christine Jost, Ha Lam, Alexander Maximov, and Ben Smeets. Encryption performance improvements of the paillier cryptosystem. *Cryptology ePrint Archive*, 2015.

[58] Marc Joye. On-line/off-line dcr-based homomorphic encryption and applications. In *Cryptographers' Track at the RSA Conference*, pages 115–131. Springer, 2023.

[59] Sadegh Kamali, Turaj Amraee, and Mahmud Fotuhi-Firuzabad. Controlled islanding for enhancing grid resilience against power system blackout. *IEEE Transactions on Power Delivery*, 36(4):2386–2396, 2021.

[60] M. Karimi, H. Mokhlis, K. Naidu, S. Uddin, and A.H.A. Bakar. Photovoltaic penetration issues and impacts in distribution network – a review. *Renewable and Sustainable Energy Reviews*, 53:594–605, 2016.

[61] Lorna Kiamba, Lucelia Rodrigues, Julian Marsh, Eldar Naghiyev, Mark Sumner, Lee Empringham, Liliana De Lillo, and Mark Gillott. Socio-economic benefits in community energy structures. *Sustainability*, 14(3):1890, 2022.

[62] Binod Prasad Koirala, Elta Koliou, Jonas Friege, Rudi A Hakvoort, and Paulien M Herder. Energetic communities for community energy: A review of key issues and trends shaping integrated community energy systems. *Renewable and Sustainable Energy Reviews*, 56:722–744, 2016.

[63] Jatinder Kumar and Ashutosh Kumar Singh. A secure paillier cryptosystem based privacy-preserving data aggregation and query processing models for smart grid. *Cluster Computing*, 27(6):7389–7400, 2024.

[64] Julien Lemaire, Rui Castro, and Fátima Montemor. Empowering remote and off-grid renewable energy communities: Case studies in congo, australia, and canada. *Energies*, 17(19), 2024.

[65] Gaoqi Liang, Steven R Weller, Junhua Zhao, Fengji Luo, and Zhao Yang Dong. The 2015 ukraine blackout: Implications for false data injection attacks. *IEEE transactions on power systems*, 32(4):3317–3318, 2016.

[66] Fernando G Lobo, David E Goldberg, and Martin Pelikan. Time complexity of genetic algorithms on exponentially scaled problems. In *Proceedings of the 2nd annual conference on genetic and evolutionary computation*, pages 151–158, 2000.

[67] Tim Meehan. New approach to transmission planning links renewable energy zones to major load centers via longer, high-voltage transmission. *NREL*, 2024.

[68] Zbigniew Michalewicz. *Genetic algorithms+ data structures= evolution programs*. springer science & business media, 1996.

[69] Ministero dell'Ambiente e della Sicurezza Energetica (MASE). Comunità energetiche, firmato il decreto che modifica la disciplina degli incentivi, May 2025. News/press webpage on the MASE portal announcing signature of the decree updating incentives for renewable energy communities (CER) and self-consumption configurations.

[70] Ministry of Energy. Annual statistical report. https://isn.moe.gov.ir/getattachment/684f2f59-4fb7-4552-8d2a-226fe2f8df30/ Accessed: 2025-12-13.

[71] Francesco Demetrio Minuto and Andrea Lanzini. Energy-sharing mechanisms for energy community members under different asset ownership schemes and user demand profiles. *Renewable and Sustainable Energy Reviews*, 168:112859, 2022.

[72] Chris Mooney. Half of earth's glaciers could melt even if key warming goal is met, study says. *The Washington Post*, January 5 2023. Accessed: 2025-12-17.

[73] Bruno Mota, Pedro Faria, and Zita Vale. Energy cost optimization through load shifting in a photovoltaic energy-sharing household community. *Renewable Energy*, 221:119812, 2024.

[74] Rajeev Motwani and Prabhakar Raghavan. Randomized algorithms. *ACM Computing Surveys (CSUR)*, 28(1):33–37, 1996.

[75] A. D. Mustika, R. Rigo-Mariani, V. Debusschere, and A. Pachurka. A two-stage management strategy for the optimal operation and billing in an energy community with collective self-consumption. *Applied Energy*, 310:118484, Mar 2022.

[76] Mahmood Muttaqee, Greg Stelmach, Chad Zanocco, June Flora, Ram Rajagopal, and Hilary S Boudet. Time of use pricing and likelihood of shifting energy activities, strategies, and timing. *Energy Policy*, 187:114019, 2024.

[77] John F Nash Jr. Equilibrium points in n-person games. *Proceedings of the national academy of sciences*, 36(1):48–49, 1950.

[78] Loai Nasrat, Mona Zedan, Al-Attar Ali, and Gaber Shabib. Review on energy trading of community-based projects around the world. In *2022 23rd International Middle East Power Systems Conference (MEPCON)*, pages 1–8. IEEE, 2022.

[79] Mikko Nykyri, Salla Annala, Pertti Silventoinen, et al. Review of demand response and energy communities in serious games. *IEEE Access*, 10:91018–91026, 2022.

[80] Ontario Energy Board. Guidance - protection philosophy for der connections. Technical report, Ontario Energy Board, November 2020. Accessed: 2026-04-14.

[81] Pascal Paillier. Public-key cryptosystems based on composite degree residuosity classes. In *International conference on the theory and applications of cryptographic techniques*, pages 223–238. Springer, 1999.

[82] Lucas Pereira, Jonathan Cavaleiro, and Luísa Barros. Economic assessment of solar-powered residential battery energy storage systems: The case of madeira island, portugal. *Applied Sciences*, 10(20), 2020.

[83] Ignacio J Pérez-Arriaga et al. *Regulation of the power sector*, volume 61. Springer, 2013.

[84] Ziang Qiu, Xibin Zhang, and Yang Zhang. Empowering energy security: The impact of geopolitical risks on green total factor energy efficiency. *Energy Economics*, page 108924, 2025.

[85] B. Rajasekhar, N. Pindoriya, W. Tushar, and C. Yuen. Collaborative energy management for a residential community: A non-cooperative and evolutionary approach. *IEEE Transactions on Emerging Topics in Computational Intelligence*, 3(3):177–192, Jun 2019.

[86] Iromi Ranaweera, Ole-Morten Midtgård, Magnus Korpås, and Hossein Farahmand. Control strategies for residential battery energy storage systems coupled with pv systems. In *2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)*, pages 1–6. IEEE, 2017.

[87] Ram C. Rao. Game theory, overview. In Kimberly Kempf-Leonard, editor, *Encyclopedia of Social Measurement*, pages 85–97. Elsevier, New York, 2005.

[88] Repubblica Italiana. Decreto Legislativo 8 novembre 2021, n. 210 — Art. 14 (Clienti attivi e comunità energetiche dei cittadini). Normattiva (Il portale della legge vigente), January 2026. Attuazione della Direttiva (UE) 2019/944 (mercato interno dell'energia elettrica).

[89] Repubblica Italiana. Decreto Legislativo 9 gennaio 2026, n. 5: Attuazione della direttiva (UE) 2023/2413 del Parlamento europeo e del Consiglio, del 18 ottobre 2023, che modifica la direttiva (UE) 2018/2001, il regolamento (UE) 2018/1999 e la direttiva n. 98/70/CE per quanto riguarda la promozione dell'energia da fonti rinnovabili e che abroga la direttiva (UE) 2015/652 del Consiglio, January 2026. Gazzetta Ufficiale, Serie Generale n. 15, 20/01/2026. Codice redazionale: 26G00018. Entrata in vigore: 04/02/2026.

[90] Thea Riofrancos. The security–sustainability nexus: Lithium onshoring in the global north. *Global Environmental Politics*, 23(1):20–41, 02 2023.

[91] Masood Rizvi, Bhanu Pratap, and Shashi Bhushan Singh. Optimal energy management in a microgrid under uncertainties using novel hybrid metaheuristic algorithm. *Sustainable Computing: Informatics and Systems*, 36:100819, 2022.

[92] David R Rounce, Regine Hock, Fabien Maussion, Romain Hugonnet, William Kochtitzky, Matthias Huss, Etienne Berthier, Douglas Brinkerhoff, Loris Compagno, Luke Copland, et al. Global glacier change in the 21st century: Every increase in temperature matters. *Science*, 379(6627):78–83, 2023.

[93] D. Said. A survey on information communication technologies in modern demand-side management for smart grids: Challenges, solutions, and opportunities. *IEEE Engineering Management Review*, 51(1):76–107, Mar 2023.

[94] Dhaou Said. A survey on information communication technologies in modern demand-side management for smart grids: Challenges, solutions, and opportunities. *IEEE engineering management review*, 51(1):76–107, 2022.

[95] S.A.T.B.A. Renewable energy and energy efficiency organization (satba). https://www.satba.gov.ir/en/investmentpowerplants/guaranteedfeedintariffsfits-Guaranteed-Feed-in-Tari n.d. Accessed: 2025-12-03.

[96] Giuseppe Sciumé, Francesco Montana, Eleonora Riva Sanseverino, and Gaetano Zizzo. A game theory-based edge device for renewable energy communities optimal management. *Sustainable Energy, Grids and Networks*, page 102034, 2025.

[97] Adi Shamir. How to share a secret. *Communications of the ACM*, 22(11):612–613, 1979.

[98] A. Shrestha et al. Peer-to-peer energy trading in micro/mini-grids for local energy communities: A review and case study of nepal. *IEEE Access*, 7:131911–131928, 2019.

[99] South Tyrol Energy Association (SEV). Power. https://www.sev.bz.it/en/south-tyrolean-energy/power/35-100.html, n.d. Accessed: 2025-12-28.

[100] A Suwa and A Sando. Geothermal energy and community sustainability. *Grand Renewable Energy, Pacific*, 2018.

[101] G. S. Thirunavukkarasu, M. Seyedmahmoudian, E. Jamei, B. Horan, S. Mekhilef, and A. Stojcevski. Role of optimization techniques in microgrid energy management systems—a review. *Energy Strategy Reviews*, 43:100899, Sep 2022.

[102] Wayes Tushar, Tapan K. Saha, Chau Yuen, David Smith, Peta Ashworth, H. Vincent Poor, and Subarna Basnet. Challenges and prospects for negawatt trading in light of recent technological developments. *Nature Energy*, 5(11):834–841, 2020.

[103] Wayes Tushar, Tapan Kumar Saha, Chau Yuen, David Smith, and H. Vincent Poor. Peer-to-peer trading in electricity networks: An overview. *IEEE Transactions on Smart Grid*, 11(4):3185–3200, 2020.

[104] European Union. Directive (eu) 2018/2001 of the european parliament and of the council of 11 december 2018 on the promotion of the use of energy from renewable sources (recast). *Official Journal of the European Union*, 2018:82–209, 2018.

[105] European Union. Directive (eu) 2019/944 on common rules for the internal market for electricity and amending directive 2012/27/eu. *Official Journal of the European Union*, page 18, 2019.

[106] U.S. Energy Information Administration. Levelized costs of new generation resources in the annual energy outlook 2022. https://www.eia.gov/outlooks/aeo/electricity$_g eneration/, March2022. \quad Accessed : 2026 - 02 - 10.$

[107] Karlijn L Van den Broek. Household energy literacy: A critical review and a conceptual typology. *Energy Research & Social Science*, 57:101256, 2019.

[108] Jianxiao Wang, Feng Gao, Yangze Zhou, Qinglai Guo, Chin-Woo Tan, Jie Song, and Yi Wang. Data sharing in energy systems. *Advances in Applied Energy*, 10:100132, 2023.

[109] David E Whitehead, Kevin Owens, Dennis Gammel, and Jess Smith. Ukraine cyber-induced power outage: Analysis and practical mitigation strategies. In *2017 70th Annual conference for protective relay engineers (CPRE)*, pages 1–8. IEEE, 2017.

[110] Nick Wilkinson. *Game Theory*, page 459–518. Cambridge University Press, 2022.

[111] Linfang Yan, Xia Chen, Yin Chen, and Jinyu Wen. A hierarchical deep reinforcement learning-based community energy trading scheme for a neighborhood of smart households. *IEEE Transactions on Smart Grid*, 13(6):4747–4758, 2022.

[112] Fikret K Yegül. Baths and bathing in classical antiquity. *(No Title)*, 1992.

[113] G. G. G. E. Yiasoumas. A review of energy communities: Definitions, technologies, data management. In *2022 2nd International Conference on Energy Transition in the Mediterranean Area (SyNERGY MED)*, pages 1–6. IEEE, 2022.

[114] Georgios Yiasoumas, Lazar Berbakov, Valentina Janev, Alessandro Asmundo, Eneko Olabarrieta, Andrea Vinci, Giovanni Baglietto, and George E Georghiou. Key aspects and challenges in the implementation of energy communities. *Energies*, 16(12):4703, 2023.

[115] Y. Zahraoui et al. Energy management system in microgrids: A comprehensive review. *Sustainability*, 13(19):10492, Sep 2021.

[116] S. Zhou, Z. Hu, W. Gu, M. Jiang, and X.-P. Zhang. Artificial intelligence based smart energy community management: A reinforcement learning approach. *CSEE Journal of Power and Energy Systems*, 2019.

[117] S. Zhou, F. Zou, Z. Wu, W. Gu, Q. Hong, and C. Booth. A smart community energy management scheme considering user dominated demand side response and p2p trading. *International Journal of Electrical Power & Energy Systems*, 114:105378, Jan 2020.