Sustainable Energy, Grids and Networks 46 (2026) 102208

Contents lists available at ScienceDirect

Sustainable Energy, Grids and Networks

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

A scalable game-theoretic framework for secure and decentralized energy sharing in renewable energy communities

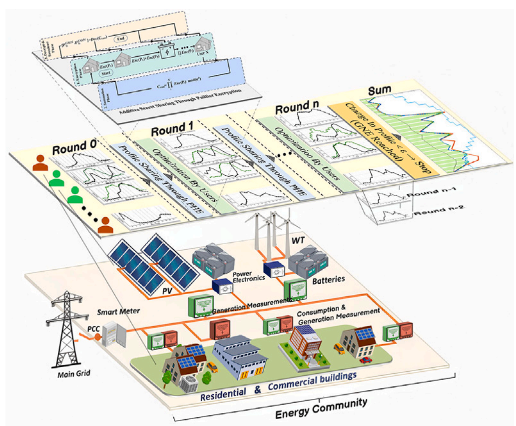
Saber Ghashghaei*, Giuseppe Sciumé, Eleonora Riva Sanseverino, Salvatore Favuzza, Mohammadreza Fakhri Moghaddam Arani

University of Palermo, Viale delle Scienze, Building 9, Palermo, 90128, Palermo, Italy

HIGHLIGHTS

- Distributed non-cooperative game-theoretic formulation for REC energy management with local load and storage optimization.
- Privacy-preserving aggregation of load and generation profiles through partial Paillier homomorphic encryption.
- Decomposition of incentive-driven optimization into consumer and producer subproblems with iterative convergence to Nash equilibrium.
- Distributed formulation scalable and suitable for low-cost devices, ensuring compatibility with large heterogeneous communities.
- High shared-energy performance and reduced grid/ESS dependence demonstrated under the Italian GSE hourly incentive scheme.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Decentralized optimization
Energy community
Game theory
Smart grid

ABSTRACT

This paper presents a secure distributed method for optimizing the operation of Renewable Energy Communities (RECs), aligning individual member benefits with collective sustainability goals. The proposed framework utilizes game theory to reach an equilibrium between users' decisions and Paillier homomorphic encryption to enable privacy-preserving collaboration among community members without relying on a central authority. By aggregating the results of distributed optimizers operating at user premises, members can select strategies that maximize their individual benefits. The aggregation of players' strategies results in a collective self-consumption behavior accompanied by rewards, and these collective actions of participants are adjusted in subsequent rounds of the game based on the strategies of others to achieve an optimal outcome. The distributed nature of this method spreads the computational workload across all users, making it suitable for implementation on low-cost devices. Thus, the method is scalable, device-agnostic, and suitable for low-cost hardware. Evaluations on different community scenarios demonstrate effective convergence to optimal energy sharing with minimal reliance on energy storage systems, confirming the method's practical viability and robustness under varying users' profiles and configurations.

* Corresponding author.
Email address: saber.ghashghaei@community.unipa.it (S. Ghashghaei).

https://doi.org/10.1016/j.segan.2026.102208
Received 27 November 2025; Received in revised form 12 March 2026; Accepted 13 March 2026

Available online 19 March 2026

1. Introduction

Centralized energy production has been a common model for decades, but the availability of renewable resources and low-cost technologies has made on-site energy generation viable. This paradigm shift has led to the emergence of Energy Communities (ECs), groups of users that cooperate in energy production and consumption, as defined in the EU Clean Energy Package (CEP) [1,2]. Renewable Energy Communities (RECs) take advantage of the distributed nature of renewable energy sources, offering benefits to end-users and utilities focusing on self-consumption and energy self-sufficiency [3]. Public involvement in green energy projects fosters sustainability, boosts the transition to clean energy systems, and drives consumers' behavior. ECs, also known as social innovation accelerants, offer lower energy prices, shared profits, and new employment opportunities, particularly in rural areas [4].

On a larger scale, ECs contribute to the decentralization of the electricity grid by promoting local energy generation. This configuration decreases the transmission losses, which are proportional to the square of the load increase. Establishing ECs also brings other technical advantages, such as improved power quality, enhanced reliability and security, improved voltage stability, and reduced gap between peak and off-peak daily energy consumption [5]. As demonstrated in prior studies [6], ECs comprising both passive and active participants contribute to enhanced energy security, grid resilience, economic gains, and climate change mitigation.

Given that an ideal EC operates as a small-scale, intelligent replica of the national grid, it can similarly be analyzed from several aspects, including cybersecurity and communication [7], energy markets and trading systems [8], optimal dispatch and advanced optimization techniques [9], control and supervisory architectures [10], etc. However, this study aims to optimize the operation of RECs' Energy Management System (EMS) by means of individual user preferences, general community goals, and government-provided incentives. In this regard, the literature has investigated several approaches, including rule-based strategies, optimization algorithms, game theory-based models, and hybrid techniques. Usually, these methods fit into two groups: centralized and decentralized schemes, each with specific benefits and drawbacks [11,12].

In this context, the research in [13] suggested a centralized EMS for RECs, thereby allowing local energy trading inside a shared pool, especially when combined with energy storage systems. Similarly, a centralized model that offers a two-phase EMS (operational and allocation phases) in a French self-consumption community is presented in [14]. Another innovative integration of a Digital Twin model with a bi-level optimization framework to centrally coordinate energy communities has been proposed in [15], where the higher level optimizes the coordination of ECs and the underlying strategies are translated into actionable instructions by the lower level. Although centralized systems provide advantages such as smooth integration with current market models, coordinated control and global optimization, superior economic efficiency, and fairness [16], they are 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, thereby reducing involvement and satisfaction [17,18].

However, hybrid methods such as [19] have been adopted to solve these deficiencies. For example, Fernandez et al. [20] introduced a bilevel optimization model that combines centralized storage with a Stackelberg game framework in which consumers aim 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. A multi-energy carrier EC has been studied in [21], where a two-stage risk-based optimization model is proposed to handle an energy management structure incorporating energy communities. Despite the merits of the proposed methods, the scalability, user preferences, and privacy of users in such schemes are overlooked. Additionally, the need for a central coordinator is still crucial.

However, decentralized strategies split the decision-making process between local agents or smart nodes, and each user can maximize their own energy consumption while working with the others, if required. The key advantage of decentralized methods is scalability, as communities can grow without limitations, not overloading a central unit [22]. 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 [23] proposed a decentralized solution involving a local energy pool to regulate electricity pricing, using a reinforcement learning approach to manage households' ESS (Energy Storage System) and enable P2P trade. 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, authors present a distributed algorithm to seek the equilibrium with several optimization techniques. While advanced energy management methods, such as energy sharing and trading platforms for users [25], bi-level management systems using Non-Cooperative Stackelberg game for aggregators [26], and AI-powered multi-agent systems [27], offer effective optimization of energy exchange and self-consumption, they generally assume centralized ownership of generation and storage by an aggregator. Additionally, a supervisory aggregator is needed for collecting consumption data and providing users with the community's load schedule (as depicted in Table 1). Furthermore, some of these methods are not practical for REC in Italy, as a bidirectional flow of energy-money between users in the same EC is not considered in regulations.

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, 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 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 [33].

This research is motivated by the fact that the most of the above-mentioned methods cannot 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 [13], there are predefined instructions and incentives for energy collective self-consumption.
- 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 necessary 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.

Table 1
Other Related works.

Ref.	Config.	Trade	Incentive	Individual	Opt. Level	Privacy	Obj.	Approach
[28]	Holacracy	P2P	No	Yes	End users	No	Convenience	MILP, GAMS
[29]	Central	-	Yes	No	EC	No	Revenues	LP, Stochastic
[30]	Central	-	No	No	EC	No	Shapley value	Game Theory
[27]	Hybrid	P2P	No	Yes	End user	Yes	Energy cost	Q-learning
[31]	Central	-	No	Yes	EC	No	Energy cost	GA
[32]	Central	-	No	Yes	EC	No	Satisfaction	Game Theory

1.1. Contribution of the paper

To address the previously mentioned issues regarding the incompatibility of different proposed methods with some REC architectures (i.e., in Italy), we expand our research carried out in [34], and propose a secure decentralized and distributed optimization framework based on Game Theory, aimed at maximizing collective self-consumption while accounting for individual advantages. In this paper, we consider more types of loads, enrich the formulation, study the effect of the presence of ESS and the effect of incentive rewards and collaboration, and endorse the scalability of the method through the empirical results. The optimization procedure addresses a series of interconnected sub-problems in successive rounds of a simultaneous game. The proposed strategy sets a trade-off between privacy and knowledge sharing, allowing all members to apply optimized decisions at an equilibrium point without disclosing their own 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 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 distributed optimization framework aligning individual user objectives with collective REC goals, enabling privacy-preserving profile aggregation through partial Paillier homomorphic encryption and eliminating the need for a central authority.
- A non-cooperative game 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 suitable for low-cost HEMS devices, ensuring scalability and significantly reducing reliance on energy storage systems, with near-optimal performance even in ESS-free scenarios.
- Direct compatibility with the Italian REC regulatory framework, including hourly GSE (the national body responsible for renewable energy and energy efficiency) energy-sharing incentives, demonstrating practical applicability in real-world policy contexts.

The rest of the paper is structured as follows: Section 2 describes the Italian regulatory framework used as a reference to implement the proposed method. In Section 3, the theoretical background of the method is presented. Section 4 is dedicated to the assessment of our proposal, and the conclusions with the highlighted aspects of the work are presented in Section 5.

2. Regulatory incentives and motivations

Italy's energy community regulation has been implemented through various legal frameworks, including the European regulation (RED II Directive) and the ARERA resolution referred to as TIAD (Testo Integrato per l'Autoconsumo Diffuso). In Italy, the national framework first implemented the European regulation (RED II Directive) by converting it into law as DL 162/19 ("Decreto Milleproroghe"), then again with DLgs 199/2021 and DLgs 210/2021. The ARERA resolution, commonly referred to as TIAD (Testo Integrato per l'Autoconsumo Diffuso), was issued on January 4, 2023, making some revisions to the previous regulations while confirming some of them, such as the definitions of the various configurations of self-consumption.Then, the CACER decree, which came into force on January 24, 2024, redefined incentives for renewable power plants.

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 hourly 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 less than 200 kW of rated size.

The RECs that use the existing power grid can include various kinds of users, such as 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 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 saved 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 hour, 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 [35]. Then, according to the definition by GSE, shared energy will be equal to the minimum value between the two mentioned terms in each 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 for the amount of energy they imported from the grid and got paid for the energy they injected into the grid [36]. 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

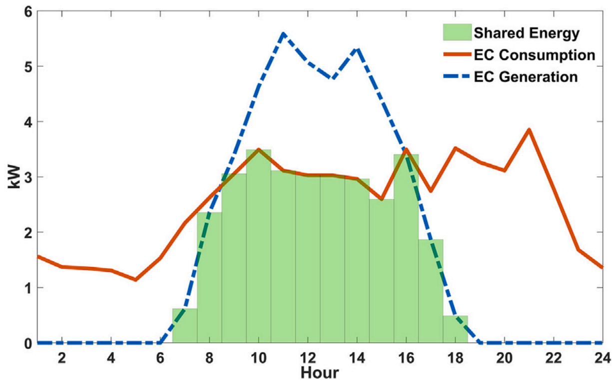


Fig. 1. Shared energy illustration defined by GSE.

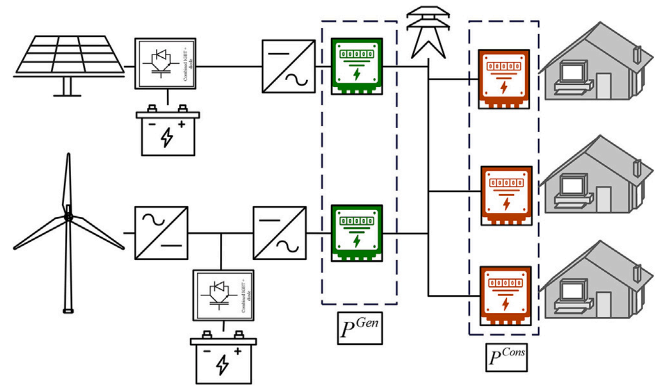


Fig. 2. Typical topology of ESS integration with generation and consumption in an EC.

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. Materials and methodology

Referring to energy sharing, defined by the GSE as the hourly minimum between the energy consumed and the energy produced by REC users (Fig. 1), 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 (1).

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

Where P_h^{GEN} and P_h^{CON} are the total energy generation and consumption of the REC in hour h. To operate the community in the most beneficial way, it's crucial to have an efficient EMS that integrates all users and elements of the community for the best solution. The main categories of centralized, decentralized, or hybrid schemes [37] represent not only differences in information network architecture and communication access models but also influence how effectively the overarching goals of the REC and its individual members are achieved. Although a centralized EMS can coordinate users and producers to achieve optimality, significant access to individual properties is needed [38]. In the centralized scheme, the members of the EC may feel restricted in applying their policies to their consumption since the central EMS objective will pursue the most economical/convenient plan for the whole REC (not for every individual).

On the other hand, if a decentralized scheme is applied to the REC management, every individual will have their own management system that will try to maximize their own benefit, possibly without sharing private data about consumption. However, in this case, coordinating members to reach an equilibrium operating point becomes challenging, as no central entity has complete information about the REC. To cover the drawbacks of each model, we are proposing a decentralized method in which members establish a simultaneous game.

3.1. Objective function

The proposed decentralized scheme has a distributed arrangement. Every member of the REC will have their own EMS for managing consumption and storage (if it exists). The Home EMS (HEMS) has access to the properties and electric appliances of its own and is connected to other HEMS in the REC. 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. So the problem expressed in (1) can be reformulated as below, introducing C_i as a fixed term of incentive for every kWh of shared energy and considering a 24-hour time horizon.

$$\mathbf{max}\left(-C_i \sum_{h=1}^{24} \left| P_h^{GEN} - P_h^{CON} \right| \right) \tag{2}$$

Given a fixed amount of produced and consumed energy (i.e., the total remains unchanged), the maxima of (1) and (2) occur at the same point. As shown in (3), the maximum benefit corresponds to the minimum of the daily consumption and generation values, where one of these terms is fully encompassed by the other during the course of the day.

$$\begin{aligned} &\mathbf{arg}\ \max(F_i) = \mathbf{arg}\ \max\left(-C_i \sum_{h=1}^{24} \left| P_h^{GEN} - P_h^{CON} \right| \right) \\ &\quad \textit{where: } F_i = \min[P_h^{GEN}, P_h^{CON}] \end{aligned} \tag{3}$$

Since the time interval is one hour, following this paper, all quantities denoted by P refer to the energy consumed or generated over a one-hour period. It is worth mentioning that the negative monetary factor $-C_i$ expresses that we dealt with the problem as a "lost opportunity" which is caused by any gap between generation and consumption. 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, the surplus can either be exported to the grid or stored in the batteries. In the topology of Fig. 2, exporting does not reduce the generation profile and therefore does not help close the gap between P_{GEN} and P_{CON}. Battery charging, instead, effectively lowers the measured generation (batteries are upstream of the metering point), bringing generation closer to consumption.

A third option is load shifting: increasing demand at hour h implies a reduction at another hour where consumption exceeds generation, thus reducing mismatches in both periods. Since the optimization evaluates the full 24-hour horizon, it often favors this redistribution over relying only on battery charging.

Accordingly, the priority becomes firstly self-consumption, then battery charging, and at last grid export, although this hierarchy may change if export prices or incentives increase significantly. When the minimum amount between two terms (P^{GEN} or P^{CON}) moves toward its maximum, it gets closer to the above curve (generation or consumption curve, depending on the situation). Therefore, seeking to minimize the distance between these two terms follows the same target as (1).

However, this equivalent optimization does not match the original optimization (1). The reason is the prevalent topology, which deploys batteries on the generation side and results in the presence of decision variables in both P^{GEN} and P^{CON} (Fig. 2). Since the objective function is to decrease the gap, in an unconstrained problem, (2) tries to minimize the disparity in the daily profile. However, it does so without distinguishing whether this is achieved by increasing the minimum or decreasing the maximum of P^{GEN} and P^{CON}, even though each approach leads to a different outcome. Nevertheless, this issue can be mitigated through the proposed distributed optimization by separating the generation and consumption sides of the optimization problem.

In our energy community, we posit the inclusion of prosumers and renewable energy resources (specifically wind and solar), collectively owned by the entire community. The electrical load within this community is categorized into three types: base (or critical), shiftable loads, and adjustable loads (with discrete changes). The total consumption of a generic user in a day will thus be defined as follows:

$$P_d^{con} = \sum_{h=1}^{24} \left(P_h^b + P_h^{SH} + P_h^{ADJ} \right) \tag{4}$$

where P_h^b, P_h^{SH}, and P_h^{ADJ} are hourly base, shiftable, and adjustable loads. Variables are defined as $\delta \in \{0,1\}$, expressing the decision variable for shiftable loads (ON/OFF), and $\beta \in \{0, \Delta, 2\Delta, \dots, 1\}$ for the discrete percentage of adjustable load. With given P_h^{sh} and P_h^{adj} as the energy consumption of the j^{th} shiftable load and the k^{th} adjustable load respectively, (4) can be rewritten as follows:

$$P_d^{con} = \sum_{h=1}^{24} \left(P_h^b + \sum_{j=1}^{S} \delta_{h,j} P_j^{sh} + \sum_{k=1}^{A} \beta_{h,k} P_k^{adj} \right) \tag{5}$$

in which $j \in \{1, \dots, S\}$ and $k \in \{1, \dots, A\}$ denote a set of shiftable and adjustable loads and h represents the hour of the day. The consumption of the whole community is equal to the sum of (5) across all N users of the community (i) where $i \in \mathcal{I} \triangleq \{1, \dots, N\}$.

$$P_d^{CON} = \sum_{i=1}^{N} P_d^{con} = \sum_{i=1}^{N} \sum_{h=1}^{24} \left(P_h^b + \sum_{j=1}^{S} \delta_{h,j} P_j^{sh} + \sum_{k=1}^{A} \beta_{h,k} P_k^{adj} \right) \tag{6}$$

In the above equation and in the following, d subscript 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 other side, the production of the community is represented by the summation of the power generated by small-scale plants. In this article, we only consider PV and wind resources since they are the prevailing sources in RECs [39]. The generation entities of REC, including RES (PV and wind) and storage, will provide energy according to (7)

$$P_d^{GEN} = \sum_{r=1}^{R} P_d^{gen} = \sum_{r=1}^{R} \sum_{h=1}^{24} \left(P_{r,h}^{RES} + ds_{r,h}^d Ps_r^d - ds_{r,h}^c Ps_r^c \right) \tag{7}$$

where $r \in \mathfrak{R} \triangleq \{1, \dots, R\}$ represents a set of RES and integrated ESS. 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. The problem (2), by substituting (6) and (7), can be written as (8):

$$\max \left(-C_i \sum_{h=1}^{24} \left| \begin{array}{l} \sum_{r=1}^{R} \left(P_{r,h}^{RES} + ds_{r,h}^d Ps_r^d - ds_{r,h}^c Ps_r^c \right) - \\ \sum_{h=1}^{24} \left(P_h^b + \sum_{j=1}^{S} \delta_{h,j} P_j^{sh} + \sum_{k=1}^{A} \beta_{h,k} P_k^{adj} \right) \end{array} \right| \right) \tag{8}$$

However, the total economic benefit depends on other factors besides incentives too. In addition, other terms including grid interactions (F_G), battery degradation cost per kWh of usage (F_{ESS}), users' discomfort due to load shifting (F_L), must be taken into account as represented below.

$$\max \left(F_R + F_G - F_{ESS} - F_L \right) \tag{9}$$

$$F_{ESS} = \sum_{h=1}^{24} \sum_{r=1}^{R} \left(d_{h,r}^d + d_{h,r}^c \right) Cs_r Ps_r^{d,c} \tag{10}$$

$$F_G = \sum_{h=1}^{24} Cg_h^+ P_h^{CON} - Cg_h^- Pg_h^- \tag{11}$$

$$F_L = \sum_{h=1}^{24} \sum_{i=1}^{N} Kc \left(P_{h,i}^{con^*} - P_{h,i}^{con} \right) \left(\mathbf{1}_{\left(P_{h,i}^{con^*} \leq P_{h,i}^{con} \right)} \right) \tag{12}$$

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 lifetime (in cycles) and price of the battery [40]. Cg_h^+, Cg_h^-, and Pg_h^- are the prices of buying and selling transactions with the grid, and the sold power, respectively. Also K_c is a penalty factor to map users' discomfort into monetary terms, and $P_{h,i}^{con^*}$ 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 [41]. It should be noted that in our case, we only consider "reduced consumption" as a form of user discomfort. Since total daily consumption is assumed to remain constant, any reduction in consumption at a given hour necessarily implies an increase in consumption at another hour, and we only count it once in the hour where reduced consumption has occurred, which is mathematically modeled and applied to (12) by using the indication function.

3.2. Constraints

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

$$P_d^{con^*} = \sum_{h=1}^{24} \left(P_h^b + \sum_{j=1}^{S} \delta_{h,j} P_j^{sh} + \sum_{k=1}^{A} \beta_{h,k} P_k^{adj} \right) \tag{13}$$

$$\overline{P^{con}} \geq \left(P_h^b + \sum_{j=1}^{S} \delta_{h,j} P_j^{sh} + \sum_{k=1}^{A} \beta_{h,k} P_k^{adj} \right) \qquad \forall h \in \{1, \dots, 24\} \tag{14}$$

Where $\overline{P^{con}}$ is the maximum withdrawal power of users and $P_d^{con^*}$ is the daily desired consumption of the user, in this way the total optimized energy consumption must equal the initially specified desired energy. Shiftable loads of each user after optimization are expected to be fed throughout the day as well as their initial desired profiles, as expressed by (15):

$$\sum_{h=1}^{24} \delta_{h,j} = \sum_{h=1}^{24} \delta_{h,j}^* \tag{15}$$

In which δ^* is the desired hourly on/off state of each appliance. In addition, the number of ON states for adjustable loads is restricted according to users' preferences to avoid the optimizer accumulating all adjustable loads into one timeslot. Preferences can be applied to the algorithms through the HEMS panel installed in each user's property.

$$\underline{\beta_{k_i}} \leq \beta_{k_i} \leq 1 \tag{16}$$

$$\|\beta_{k_i}\|_0 \geq \underline{\|\beta_{k_i}^*\|_0} \tag{17}$$

$$\sum_{h=1}^{24} \beta_{i,h,k_i} P_{i,h,k_i} = \sum_{h=1}^{24} P_h^{adj^*} \tag{18}$$

Where $\underline{\|\beta_{k_i}^*\|_0}$ is the minimum desired number of ON states of adjustable loads in a day. For the generation side in this study, we assume that

RES are set to harvest the maximum energy available, and the decision variable will only control the charging and discharging of batteries. We allow the batteries to have three feasible states (charging, discharging, and idle) by limiting their status and charging/discharging power to the maximum rate according to (19):

$$ds^c_{r,h}Ps^c_r \le \overline{Ps^c_r}, \quad ds^d_{r,h}Ps^d_r \le \overline{Ps^d_r}, \quad ds^d_{r,h} + ds^c_{r,h} \le 1 \tag{19}$$

$\overline{Ps^c_r}$ and $\overline{Ps^d_r}$ are maximum charging and discharging power flows. 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 (22)

$$\underline{SoC_r} \le SoC_{r,h} \le \overline{SoC_r} \tag{20}$$

$$SoC_{r,h} = SoC_{r,h-1} + \frac{\left(Ps^c_r\eta^c_r ds^c_{r,h} - Ps^d_r ds^d_{r,h}/\eta^d_r\right)}{\overline{C_r}} \tag{21}$$

$$ds^c_{r,h}Ps^c_{r,h} \le \sum_{r=1}^{R} P^{pv}_{r,h} - P^{CON}_h \tag{22}$$

$\underline{SoC_r}$, $\overline{SoC_r}$, and $\overline{C_r}$ denote the minimum and maximum allowable state of charge (SoC), and the battery capacity, respectively. Finally, the SoC should be in an acceptable range of its initial SoC when the planning horizon concludes.

$$0.9SoC_{r,h=1} \le SoC_{r,h=24} \le \min\left[1.1SoC_{r,h=1}, 1\right] \tag{23}$$

3.3. Secure distributed scheme and game theory

As mentioned earlier in Section 3.1, optimization carried out at each user's premise aims to optimize the consumption curve with the decision variables (δ, β) and generation profile with (ds^c and ds^d). We define the 'loss of opportunity' of gaining incentives for self-consumption as the distance between the two curves, one for producers and one for consumers. This arrangement simplifies the management of variables. Moreover, on each side of consumption and generation, we separate the components of the equation into those arising from the "user's own decisions" and those resulting from the "decisions of other players". Excluding others' decisions in each consumer's optimization and each producer's (ESS) optimization results in (24) and (25) respectively:

$$\begin{aligned} P^{CON}_h &= \sum_{i=1}^{N}\left(P^b_{i,h} + \sum_{j=1}^{S} P^{SH}_{i,h} + \sum_{k=1}^{A} P^{ADJ}_{i,h}\right), \quad i \in \mathscr{I} \triangleq \{1,\dots,n,\dots,N\} \\ &= \sum_{I=1}^{N} P^{con}_{I,h} + \left(P^b_{n,h} + \sum_{j=1}^{S}\delta_{n,h,j}P^{sh}_{n,j} + \sum_{k=1}^{A}\beta_{n,h,k}P^{adj}_{n,k}\right), \quad \forall I \in \mathscr{I}\backslash\{n\} \end{aligned} \tag{24}$$

$$\begin{aligned} P^{GEN}_h &= \sum_{r=1}^{R}\left(P^{pv}_{r,h} + ds^c_{r,h}P^c_{r,h} - ds^d_{r,h}P^d_{r,h}\right), \quad r \in \mathfrak{R} \triangleq \{1,\dots,m,\dots,R\} \\ &= \sum_{\rho=1}^{R} P^{gen}_{\rho,h} + \left(P^{pv}_{m,h} + ds^c_{m,h}P^c_{m,h} - ds^d_{m,h}P^d_{m,h}\right), \quad \forall \rho \in \mathfrak{R}\backslash\{m\} \end{aligned} \tag{25}$$

Where n and m are every individual consumer and producer whose self-optimization is running on their premises, I and ρ are the sets of communities' members (consumers and producers), excluding n and m, respectively. Having formulated (24) and (25), the problem (9) can be customized for consumers and producers as (26) and (27) respectively.

$$\max \sum_{h=1}^{24}\left(\begin{aligned} &-Ci\left|P^{GEN}_h - \left(\sum_{I=1}^{N}P^{con}_{I,h} + P^b_{n,h} + \sum_{j=1}^{S}\delta_{n,h,j}P^{sh}_{n,j} + \sum_{k=1}^{A}\beta_{n,h,k}P^{adj}_{n,k}\right)\right| \\ &+ Cg^-_{n,h}Pg^-_{n,h} - Cg^+_{n,h}Pg^{con}_{n,h} - Kc_n(P^{con^*}_{n,h} - P^{con}_{n,h}) \end{aligned}\right) \tag{26}$$

$$\max \sum_{h=1}^{24}\left(\begin{aligned} &-C_i\left|P^{CON}_h - \left(\sum_{\rho=1}^{R}P^{RES}_{R,h} + Ps_{R,h} + (ds^d_{m,h}Ps^d_{m,h} - ds^c_{m,h}Ps^c_{m,h}\right)\right| \\ &-(ds^d_{m,h}Ps^d_{m,h} + ds^c_{m,h}Ps^c_{m,h})Cs_m \end{aligned}\right) \tag{27}$$

It is worth noting that if a member is a prosumer who engages in both energy consumption and production, then both optimization problems are applied to its associated components. The problem for each entity consists of two components: one reflecting others' collective actions and one containing its own decision variables. This problem contains a set of features such as

1. Multiple decision-makers: where REC contains a variety of users who can decide about their consumption.
2. Strategic interdependence: which describes how the consequences of every user's decision also affect the global aim of the REC, and the outcome for each player depends not only on their own decisions but also on the decisions of others.
3. Known outcomes: the summation of strategies results in a defined outcome that can be evaluated.
4. Rational behavior: meaning that each player is assumed to act rationally and make decisions to guarantee the best outcome for themselves.
5. Payoff: which is relevant to the prize associated with a certain outcome, such as the offered incentives or price of consumption on the bill.

These characteristics make our issue an appropriate candidate for resolution via a game-theoretic method to achieve an optimum operational state [42]. At this stage, we employ a non-cooperative, game-theoretic method, wherein each entity autonomously optimizes its associated subproblem based exclusively on the decision variables it is permitted to access and manage. The remaining components of the problem caused by the actions of others are substituted with existing or shared information.

Given that the proposed method requires only an aggregated representation of others' behaviors, this information can be securely obtained and shared across the REC using privacy-preserving techniques such as Paillier homomorphic encryption that allows summation operations on ciphertexts [43,44] as will be explained further. As a result of the partial homomorphism characteristic of Paillier encryption, some mathematical operations are directly feasible on ciphertexts without the need to decrypt them. Therefore, the confidentiality of the user profiles will be ensured by this method. Our proposed secret sharing procedure entails a randomly chosen initial member selecting a set of random numbers satisfying specific requirements. Once the public and private keys are generated, the user encrypts their own load/generation profile with known public keys, and subsequently passes it to another member. Each subsequent member follows this process, adding their own profile to the ciphertext (by multiplying the received ciphertext by their own-encrypted ciphertext) and passing the multiplication of encrypted messages to another member until all participants have contributed their data and it is returned to the initial user. The initial user who possesses the private key decrypts the product of ciphertexts, and the resultant value will represent the aggregation of the collective consumptions and productions of users, which will be broadcast to all as depicted in Fig. 3.

$$l = p.q\begin{cases} \forall d \in \mathbb{Z}, (1 < d < p) \Rightarrow (p \mod d \ne 0) \\ \forall d \in \mathbb{Z}, (1 < d < q) \Rightarrow (q \mod d \ne 0) \end{cases} \tag{28}$$

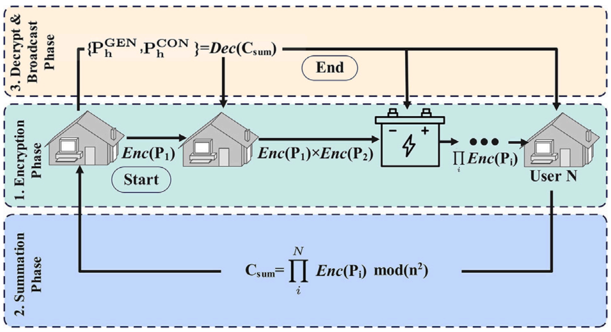


Fig. 3. Partial Paillier encryption in the proposed method.

By choosing g from the set $Z^*_{l^2}$ (relatively prime to l^2) the public keys (l, g) are available for encryption of message M as follow (derived from [44])

$$c = Enc(M) = g^M \cdot o^l \mod l^2 \tag{29}$$

where o is a random number between 1 and l, and c the ciphertext assosiated to message M. In Paillier encryption, the homomorphic property ensures that the product of two ciphertexts corresponds to the sum of their respective plaintexts modulo l. This is because each ciphertext is structured as (29), and multiplying two such ciphertexts yields the summation of plaintext messages after decryption, as proved in (30), demonstrating Paillier's additive homomorphism.

$$c_1 \cdot c_2 = g^{M_1+M_2} \cdot (o_1 o_2)^l \mod l^2 = Enc(M_1 + M_2) \tag{30}$$

Subsequently, all profiles are encrypted into ciphertexts using public keys, which are then aggregated by multiplying the ciphertexts using an additive secret sharing scheme. After all users have added their value to the resulting ciphertext, the first user, who possesses the corresponding private key, decrypts the aggregated profiles through (31) [44]

$$M_{sum} = \left(\frac{c_{sum}^{\lambda} \mod (l^2) - 1}{l} \right) .\mu \mod l \tag{31}$$

where the private keys of μ and λ are calculated as follows:

$$\lambda = \text{lcm}(p-1, q-1), \mu = \left(\frac{(g^{\lambda} \mod l^2) - 1}{l} \right)^{-1} \mod l \tag{32}$$

It should be noted that the term 'inverse' here refers specifically to the modular inverse.

3.4. Equilibrium of the game

Running the distributed optimization subproblems by each node is one "round" or "iteration" of a game. After each round, members are informed about the summation of others' actions in the previous round. In the distributed scheme, where the game has been established, the lack of a central optimizer for all users causes the members to change their decisions once they get informed about others' behavior, which happens at the end of each iteration, and they may try to maximize their own benefit in the next round according to the others' behavior. This process continues until no other node tends to change its decision variable, or in other words, an equilibrium state occurs, which will be discussed further. The flowchart in Fig. 4 explains the whole process where a random list of users is generated by the first user and the total consumption and generation of the EC in the previous iteration are obtained through the sharing of Paillier ciphertexts and then decrypted and broadcast by the first user (Algorithm 1). In the next step, each user solves its own optimization problem and declares if there is any change in its load schedule.

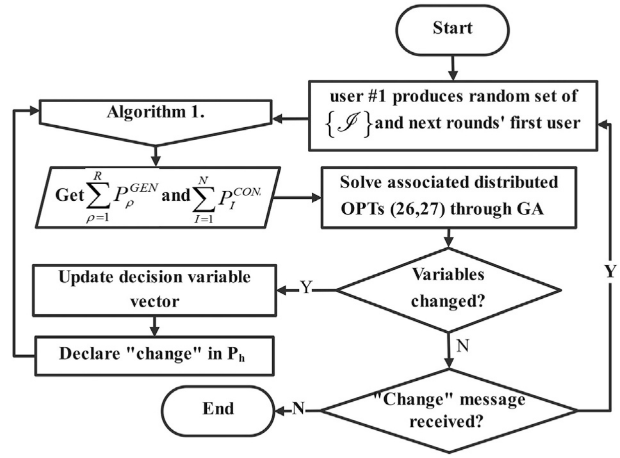


Fig. 4. Flowchart of the proposed method.

Once a "change" message is broadcast from any user, the same procedure is repeated as a new iteration of the game. This process continues until no member further changes its decision, meaning that the schedule updates fall below a predefined threshold and become negligible. At this point, no participant can improve its outcome through further optimization, and a Nash equilibrium is reached.

The optimization problem described above is solved using a Real-Coded Genetic Algorithm (RCGA) [45], 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 (26) and (27), as depicted in Fig. 4. In this way, the EMS performs the optimization task 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 was 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 $1/\sqrt{|n|}$. This strategy promotes selection pressure toward better solutions while maintaining population diversity during the evolutionary process.

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

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.

Algorithm 1 Partial Paillier ciphertext sharing.

Require: Preset of users $\mathscr{I}$
  Input: Number of users $N \in \mathscr{I}$, users' baseline
  Output: Aggregated vector P^{CON} or P^{GEN}
while change schedule $= 1$ **do**
  Initialization: $c_{(0)} = 1$, user $\mathscr{I}_{(1)}$ 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
  $\mathscr{I}_{(N)} \rightarrow \mathscr{I}_{(1)}$: send $c_{(N)}$
  $\mathscr{I}_{(1)}$: $P^{CON} = \sum_{i=1}^{N} P_i = Dec(c_{(N)})$
  return P^{CON} & P^{GEN} ▷ Aggregated profile broadcast to all REC members
end while

Every game with a finite number of players choosing from finite compact strategies has at least one Nash Equilibrium [46]. Thus the game G has an equilibrium point. □

Let G represent this game with $\mathscr{I}$ as a set of players, and $\mathbb{S}$ as the 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 ($\mathcal{S}_{-i}$: $-i \triangleq \mathscr{I} \setminus \{i\}$).

$$G = \langle N, (\mathbb{S}_i)_{i \in \mathscr{I}}, (U_i)_{i \in \mathscr{I}} \rangle \tag{33}$$

according to the Nash Equilibrium definition, in one round of the game, $\mathcal{S}^* = (\mathcal{S}^*_1, \ldots, \mathcal{S}^*_N)$ will be the pure strategy Nash Equilibrium if (34) is true for all $i \in \mathscr{I}$ and all $\mathcal{S}_i \in \mathbb{S}_i$ [47]

$$U_i(\mathcal{S}^*_i, \mathcal{S}^*_{-i}) \geqslant U_i(\mathcal{S}_i, \mathcal{S}^*_{-i}))\tag{34}$$

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.

$$\mathcal{S}^*_i = \underset{\mathcal{S}_i}{\text{argmax}}\, U_i(\mathcal{S}_i, \mathcal{S}^*_{-i}) \text{ [47]} \tag{35}$$

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 $\mathcal{S}^*_i$.

4. Results and discussion

To assess the proposed method, we assumed two scenarios of a community with a single 10 kW PV installation, one with a single 15 kW PV, and a hybrid RES including a 20 kW PV and a small wind turbine in the other scenario, as expressed in Table 2. It is worth mentioning that the level of collaboration as shown in Table 2, is inversely related to the discomfort factor (K_c). Users who are more collaborative tend to have lower K_c values, meaning that changes in load impose less cost or inconvenience on them compared to moderately collaborative users. The number of variables for each Prosumer is equal to 24 times the number of shiftable and controllable loads, plus 24 variables for charging and 24 for discharging of the battery (if a battery is available for that user). We considered one adjustable load and three shiftable loads for each user, selected from the set of shiftable appliances, namely the vacuum cleaner, dishwasher, washing machine, boiler, and electric bicycle. 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. Fig. 5 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 a general Genetic Algorithm optimizer for each user [48], with associated constraints and objective functions mentioned earlier, the users can change their operation of home appliances to maximize their own economic benefit. 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. Fig. 6 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.

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

Table 2
Communities' scenarios.

Case	Members & Consumption			Daily Production [kWh]		ESS [kWh]
	Number	Collab.	[kWh]	PV	wind	
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	20	Medium	151.25	55.8	88	30

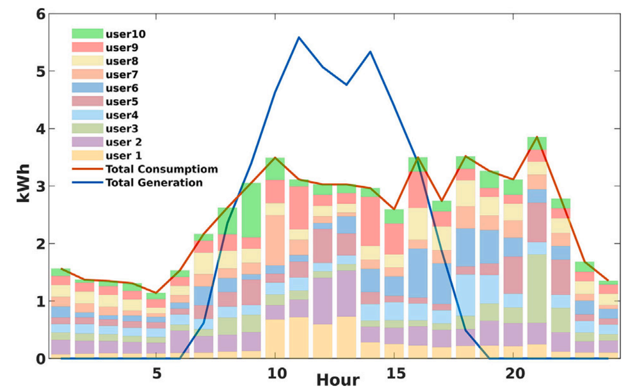


Fig. 5. Daily generation and total consumption of users in the studied REC.

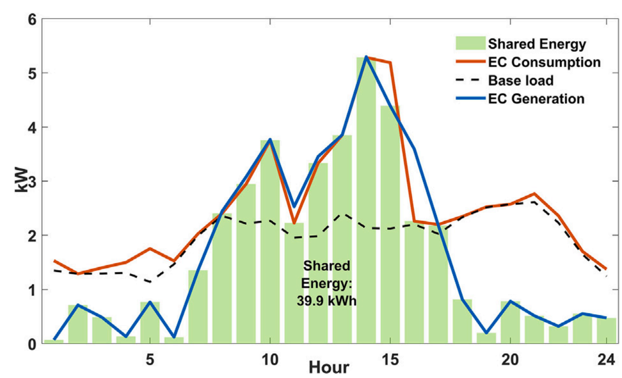


Fig. 6. Optimized shared energy in case 1, using the proposed method.

Table 3
Shared energy along the rounds of the game-Case 1.

Iteration	0	1	2	3	4	5	6	7
%Shared Energy	72.5	95.2	93	92.6	90.7	95.1	90	95.4
ESS Usage (kWh)	9	9	9.3	9	9	9	9.3	9.2
Max Optimization Solving Time								20.2 s
Max ciphertext Sharing Time								0.8 s
Worst-case Time to Reach the Equilibrium								147 s

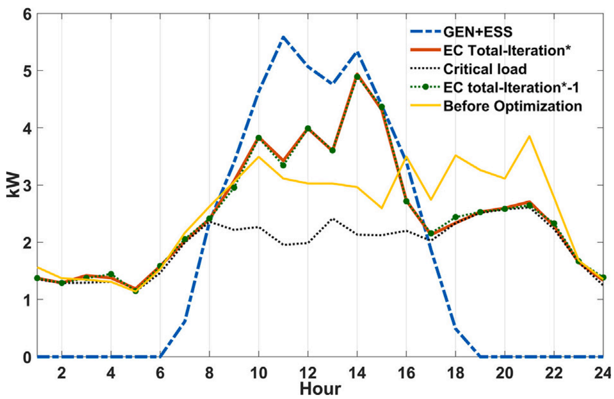


Fig. 7. Optimized shared energy in case 2 (without ESS).

almost the same (1% error) before and after the optimization, while the Battery SOC remains at 50,21% at the end of the day (as initial state). Table 3 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.

4.1. Mitigating role of ESS

Modification of users' behavior by rescheduling their usage profile can compensate for the role of ESS adoption [49]. Through user collaboration, even smaller storage systems can effectively manage the balance between energy generation and consumption, thereby addressing concerns associated with the use of large bulk storage systems in large energy communities. 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)[50]. By comparing the scenarios in Cases 1 and 2, where the only variable changed is the use of ESS, the efficiency of the proposed method in reducing the reliance on bulk ESS can be validated. 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 [51] while our proposed solution is able to capture the advantages of EC without ESS perfectly. It is worth mentioning that the algorithm is set to feed the base load unconditionally (24.1 kWh). Therefore, the maximum possible energy to be shared is limited to 36 kWh. The proposed method, as illustrated in Fig. 7, improves the shared energy, without utilizing ESS, to 35.2 kWh, which covers 97.6% of possible shared energy compared to the initial case shown in Fig. 5 (regardless of the detailed consumption by users). In addition, negligible differences between the consumption in the iteration where equilibrium occurred and the iteration before endorse the convergence of the method.

4.2. Scalability of method and performance under different load/generation profiles

REC's size can vary from a few members to thousands. Therefore, the proposed method should be capable of converging to an equilibrium point regardless of the REC's size and profiles. Despite the efficiency of central EMSs, they appear incapable once the decision variables grow (especially when MINLP problems are to be solved). Also, other users with semi-industrial load profiles (frequently shiftable loads), and wind generation may be added to the REC. With new overall production and consumption curves, the peaks of consumption and generation occur at totally different hours of the day (Fig. 8). Studying Case 3 with a remarkable disparity between generation and consumption in hours of the day, and 30 users leading to 2880 variables (3 times greater than Cases 1 and 2), demonstrates that the maximum solving time is almost the same as Case 1 (Table 4) and the only procedure that takes more time is the interaction between users as expressed in Algorithm 1. However, in general, the method reaches the equilibrium even faster than Case 1. It should be noted that in this case, the industrial loads with semi-fixed profiles and also base loads, restrict the algorithm from reaching a higher percentage of energy sharing.

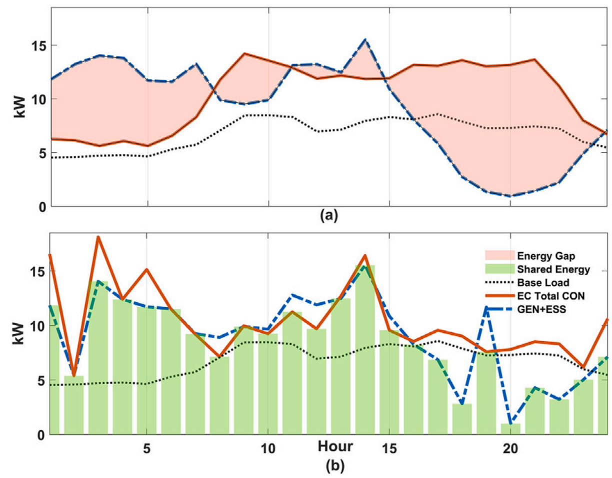


Fig. 8. Shared energy in case 3 (a) original scenario, (b) optimized profile.

Table 4
Result of the game in case 3.

Converged Iteration	Shared Energy	ESS Usage (kWh)	Users With Industrial Profile	GSE Incentive
2	94.7%	32.2	4	0.12 €/kWh
Max Optimization Solving Time				21 s
Max ciphertext Sharing Time				2.5 s
Worst-Case Time to Reach the Equilibrium				47.1 s

4.3. Convergence of decisions

Consecutive runs of the game for Case 4, which has been depicted in Fig. 9, illustrate the collective load profiles that reflect the decisions of players. In this case, the two consumption and generation profiles almost overlap each other, resulting in shared energy reaching up to 99.2% of the total consumption within just 8 interactions. As observed, the similarity of profiles between the last two iterations explains the concept of equilibrium and endorses the convergence of players' decisions toward this point. In addition to the strategic convergence observed over successive game iterations, the alignment between energy consumption and generation achieved through the ESS is noteworthy, as depicted in Fig. 10.

4.4. Grid interactions

Besides fostering citizens' participation across energy systems for cheaper and green energy, an ideal EC also aims to reduce its interaction with the utility grid as much as possible by using local renewable energy sources and advanced energy management systems. ECs contribute to

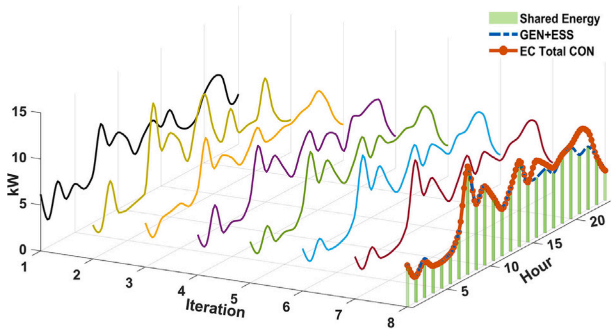


Fig. 9. Case 4: Profile of the users in 8 iterations.

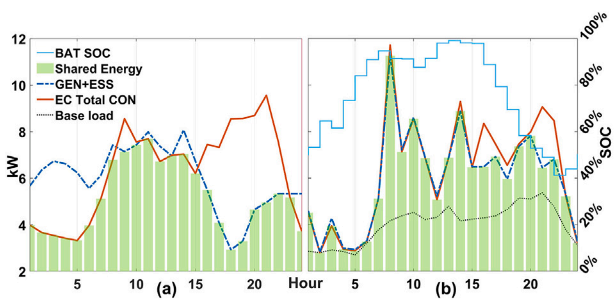


Fig. 10. Shared energy in case 4: (a) original scenario, (b) optimized profile.

forming stable and self-sufficient sub-regions that can maintain stability even during grid outages, cascaded blackouts, or disruptions [52] and enable Special Protection Schemes (SPS) such as controlled islanding of coherent regions [53]. This decentralized approach to energy management of ECs also improves the resiliency of the system during natural disasters and threats which is a necessity of modern power systems [54]. As illustrated in Fig. 11, adoption of the proposed method decreases the ECs' interaction with grid significantly in all cases. Furthermore, backfeeding the power into the grid, which can complicate grid management, voltage regulation, and protection schemes, is minimized in optimized cases (Table 5).

5. Conclusion

This paper has presented a study on REC and its role in green and sustainable energy. In this regard, we have proposed a distributed game theory method that enables users to collaborate with each other to maximize the REC reward. The efficiency and compatibility of the method have been evaluated with Italian government incentives for REC.

The proposed distributed method based on Game Theory attempted to ensure the privacy of users by omitting the central entity data storage. By sharing load and generation profiles through partial Paillier encryption, no personal data is revealed, while users are still able to access the summation profile of REC obtained from sequentially multiplied ciphertexts. By reformulating the GSE incentive as a minimization problem and decomposing it according to node type, the proposed distributed scheme allows users to align global REC objectives with their local goals. This fragmentation of the optimization through Game Theory principles eliminates the need for powerful devices to be implemented. Moreover, since the problem is independent of the number of users, the growth of the energy community does not require upgrading the existing computational infrastructures, which confirms the scalability of the proposed method. To conclude, a notable advantage of this work is its ability to enhance collaboration among users, thereby reducing reliance on ESS, resulting in a critical benefit for many energy communities that may face constraints in deploying bulk batteries.

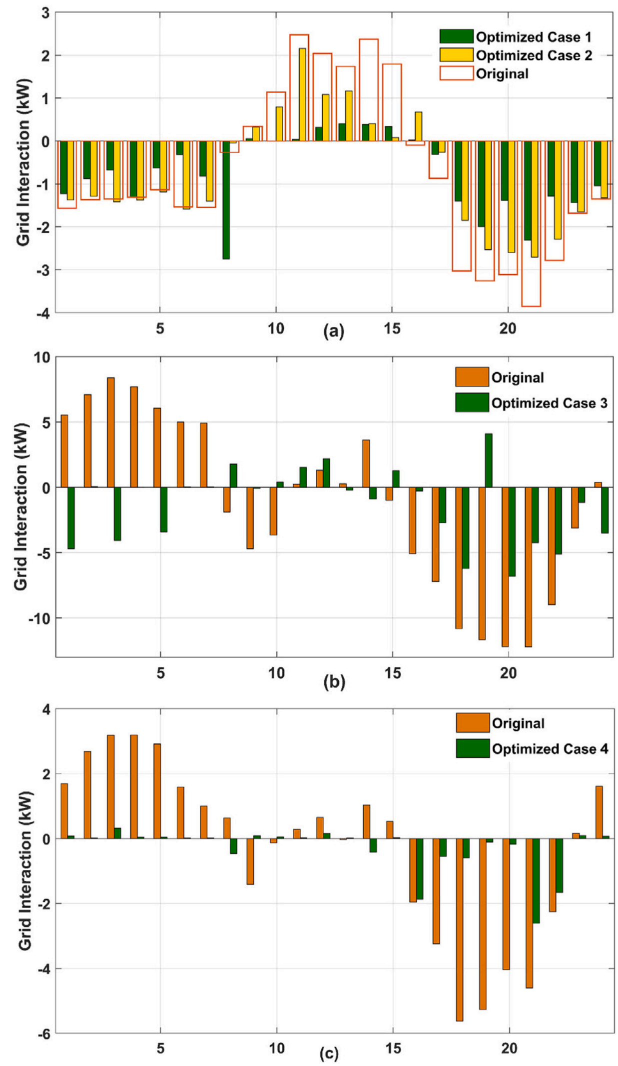


Fig. 11. EC and grid interactions in (a) Cases 1&2, and (b) case 3, and (C) case 4.

Table 5
Grid interactions.

Case	Imported (kWh)	Backfeeded (kWh)	Change from original case	
			Imported	Backfeeded
1	19.8	1.55	−34.2%	−86.9%
2	24.9	6.6	−17.2%	−44.5%
3	43.3	11.45	−47.6%	−77.3%
4	8.43	1.06	−70.4%	−96.2%

The proposed method demonstrates a significant cost reduction and enhanced scalability under identical conditions (without ESS), outperforming [30], which achieves a 12% cost saving with the Game Theory approach. When ESS is included, it achieves a comparable cost reduction while offering superior privacy, autonomy, and independence from centralized data requirements relative to [27]. Another study limited to just two types of loads [31], evaluated two optimized scenarios, with and without ESS, and achieved household energy cost reductions of 24.3% and 11.8%, respectively. In comparison, our proposed method with the inclusion of adjustable loads in addition to shiftable and basic loads, achieves reductions of 32% and 16.9% under the same conditions. Although we attempted to compare the proposed method with the most closely related studies, the results cannot be fully generalized in all aspects, as the underlying community models are not identical.

Other factors that significantly influence the outcomes include countries' specific definitions and regulations of energy communities, the allowance of intra-community trading, the modeling of user discomfort, the formulation of incentives, and the reward mechanisms used to value self-consumption. In addition, the modeling of uncertainty in generation and consumption is a key factor affecting comparability, which we plan to address in future work.

To improve the methodology to adapt to the real situation with humanistic behavior, we will consider the game with a set of probabilities of strategies to address uncertainties stemming from both others' decisions and the variability inherent in RES. In addition to the secret sharing phase, optimization will be implemented on the edge device too. To further strengthen user privacy and reduce reliance on a rotating dealer for key generation, we plan to investigate distributed key generation schemes for Paillier encryption.

CRediT authorship contribution statement

Saber Ghashghaei: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Giuseppe Sciumé:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Data curation. **Eleonora Riva Sanseverino:** Supervision, Project administration, Methodology, Formal analysis, Conceptualization. **Salvatore Favuzza:** Supervision, Resources, Project administration, Investigation, Data curation. **Mohammadreza Fakhri Moghaddam Arani:** Validation, Supervision, Methodology.

Declaration of competing interest

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

Data availability

Data will be made available on request.

References

[1] 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), Off. J. Eur. Union 2018 (2018) 82–209.

[2] European Union, Directive (EU) 2019/944 on common rules for the internal market for electricity and amending directive 2012/27/EU, Off. J. Eur. Union (2019) 18.

[3] D. Fioriti, T. Ferrucci, 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), IEEE, 2023, pp. 1–6, https://doi.org/10.1109/EEEIC/ICPSEurope57605.2023.10194696

[4] 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), IEEE, 2022, pp. 1–6.

[5] M.R. Amin, Self-Synchronized Converter for Fast Synchronization Between Low Voltage Microgrid and Inverter Connection, (Ph.D. thesis), Universiti Tun Hussein Onn Malaysia, 2023.

[6] M.L. Di Silvestre, M.G. Ippolito, E.R. Sanseverino, G. Sciumè, A. Vasile, Energy self-consumers and renewable energy communities in italy: new actors of the electric power systems, Renew. Sustain. Energy Rev. 151 (2021) 111565, https://doi.org/10.1016/j.rser.2021.111565

[7] D. Said, A survey on information communication technologies in modern demand-side management for smart grids: challenges, solutions, and opportunities, IEEE Eng. Manag. Rev. 51 (1) (2023) 76–107, https://doi.org/10.1109/EMR.2022.3186154

[8] L. Chen, Q. Xu, Y. Yang, H. Gao, W. Xiong, Community integrated energy system trading: a comprehensive review, J. Mod. Power Syst. Clean Energy 10 (6) (2022) 1445–1458, https://doi.org/10.35833/MPCE.2022.000044

[9] G.S. Thirunavukkarasu, M. Seyedmahmoudian, E. Jamei, B. Horan, S. Mekhilef, A. Stojcevski, Role of optimization techniques in microgrid energy management systems—a review, Energy Strat. Rev. 43 (2022) 100899, https://doi.org/10.1016/j.esr.2022.100899

[10] Y. Zahraoui, et al., Energy management system in microgrids: a comprehensive review, Sustainability 13 (19) (2021) 10492, https://doi.org/10.3390/su131910492

[11] F.D. Minuto, A. Lanzini, Energy-sharing mechanisms for energy community members under different asset ownership schemes and user demand profiles, Renew. Sustain. Energy Rev. 168 (2022) 112859, https://doi.org/10.1016/j.rser.2022.112859, https://www.sciencedirect.com/science/article/pii/S1364032122007419.

[12] E.M. Gui, I. MacGill, Typology of future clean energy communities: an exploratory structure, opportunities, and challenges, Energy Res. Soc. Sci. 35 (2018) 94–107, energy and the Future. doi:https://doi.org/10.1016/j.erss.2017.10.019, https://www.sciencedirect.com/science/article/pii/S221462961730347X.

[13] S. Zhou, F. Zou, Z. Wu, W. Gu, Q. Hong, C. Booth, A smart community energy management scheme considering user dominated demand side response and p2p trading, Int. J. Electr. Power Energy Syst. 114 (2020) 105378, https://doi.org/10.1016/j.ijepes.2019.105378

[14] A.D. Mustika, R. Rigo-Mariani, V. Debusschere, A. Pachurka, A two-stage management strategy for the optimal operation and billing in an energy community with collective self-consumption, Appl. Energy 310 (2022) 118484, https://doi.org/10.1016/j.apenergy.2021.118484

[15] A. Bâra, S.-V. Oprea, Enabling coordination in energy communities: a digital twin model, Energy Policy 184 (2024) 113910.

[16] M.-V. Gasca, R. Rigo-Mariani, V. Debusschere, Y. Sidqi, Fairness in energy communities: centralized and decentralized frameworks, Renew. Sustain. Energy Rev. 208 (2025) 115054.

[17] G. Yiasoumas, L. Berbakov, V. Janev, A. Asmundo, E. Olabarrieta, A. Vinci, G. Baglietto, G.E. Georghiou, Key aspects and challenges in the implementation of energy communities, Energies 16 (12) (2023) 4703.

[18] B. Bonfert, 'we like sharing energy but currently there's no advantage': transformative opportunities and challenges of local energy communities in Europe, Energy Res. Soc. Sci. 107 (2024) 103351.

[19] L. Yan, X. Chen, Y. Chen, J. Wen, A hierarchical deep reinforcement learning-based community energy trading scheme for a neighborhood of smart households, IEEE Trans. Smart Grid 13 (6) (2022) 4747–4758.

[20] E. Fernandez, M.J. Hossain, K. Mahmud, M.S.H. Nizami, M. Kashif, A bi-level optimization-based community energy management system for optimal energy sharing and trading among peers, J. Clean. Prod. 279 (2021) 123254, https://doi.org/10.1016/j.jclepro.2020.123254

[21] S. Dorahaki, M. Rashidinejad, S.F. Fatemi Ardestani, A. Abdollahi, M.R. 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 (2023) 127727, https://doi.org/10.1016/j.energy.2023.127727, https://www.sciencedirect.com/science/article/pii/S0360544223011210.

[22] S. Bahrami, M.H. Amini, M. Shafie-Khah, J.P.S. Catalão, A decentralized renewable generation management and demand response in power distribution networks, IEEE Trans. Sustain. Energy 9 (4) (2018) 1783–1797, https://doi.org/10.1109/TSTE.2018.2815502

[23] S. Zhou, Z. Hu, W. Gu, M. Jiang, X.-P. Zhang, Artificial intelligence based smart energy community management: a reinforcement learning approach, CSEE J. Power Energy Syst. (2019), https://doi.org/10.17775/CSEEJPES.2018.00840

[24] S. Cui, J.-W. Xiao, Game-based peer-to-peer energy sharing management for a community of energy buildings, Int. J. Electr. Power Energy Syst. 123 (2020) 106204, https://doi.org/10.1016/j.ijepes.2020.106204

[25] S. Cui, Y.-W. Wang, J.-W. Xiao, Peer-to-peer energy sharing among smart energy buildings by distributed transaction, IEEE Trans. Smart Grid 10 (6) (2019) 6491–6501, https://doi.org/10.1109/TSG.2019.2906059

[26] B. Rajasekhar, N. Pindoriya, W. Tushar, C. Yuen, Collaborative energy management for a residential community: a non-cooperative and evolutionary approach, IEEE Trans. Emerg. Top. Comput. Intell. 3 (3) (2019) 177–192, https://doi.org/10.1109/TETCI.2018.2865223

[27] S.S. Binyamin, S.A. Ben Slama, B. Zafar, Artificial intelligence-powered energy community management for developing renewable energy systems in smart homes, Energy Strateg. Rev. 51 (2024) 101288, https://doi.org/10.1016/j.esr.2023.101288, https://www.sciencedirect.com/science/article/pii/S2211467X23002389.

[28] P. Afzali, A. Rajaei, M. Rashidinejad, H. Farahmand, Peer-to-peer energy trading among prosumers in energy communities based on preferences considering holacracy structure, IEEE Trans. Eng. Manag. 71 (2024) 7756–7767, https://doi.org/10.1109/TEM.2024.3382881

[29] M. Di Somma, M. Dolatabadi, A. Burgio, P. Siano, D. Cimmino, N. Bianco, Optimizing virtual energy sharing in renewable energy communities of residential users for incentives maximization, Sustain. Energy Grids Netw. 39 (2024) 101492, https://doi.org/10.1016/j.segan.2024.101492, https://www.sciencedirect.com/science/article/pii/S2352467724002212.

[30] L. Gomes, Z. Vale, Costless renewable energy distribution model based on cooperative game theory for energy communities considering its members' active contributions, Sustain. Cities Soc. 101 (2024) 105060, https://doi.org/10.1016/j.scs.2023.105060, https://www.sciencedirect.com/science/article/pii/S2210670723006704.

[31] B. Mota, P. Faria, Z. Vale, Energy cost optimization through load shifting in a photovoltaic energy-sharing household community, Renew. Energy 221 (2024) 119812, https://doi.org/10.1016/j.renene.2023.119812, https://www.sciencedirect.com/science/article/pii/S0960148123017275.

[32] X.M. Fan, X.H. Li, Y.M. Ding, J. He, M. Zhao, Demand response scheduling algorithm for smart residential communities considering heterogeneous energy consumption, Energy Build. 279 (2023) 112691.

[33] P.A. Gbadega, Y. Sun, O.A. Balogun, Game-theoretic transactive control frameworks for scalable and privacy-preserving energy storage management in renewable-based energy communities, J. Energy Storage 138 (2025) 118611, https://doi.org/10.1016/j.est.2025.118611, https://www.sciencedirect.com/science/article/pii/S2352152X25033249.

[34] S. Ghashghaei, S. Favuzza, E.R. Sanseverino, G. Sciumè, A secure and distributed method for energy communities' optimal operation, in: 2024 IEEE International Humanitarian Technologies Conference (IHTC), 2024, pp. 1–7, https://doi.org/10.1109/IHTC61819.2024.10855015
[35] 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.
[36] Gestore Servizi Energitici, Servizio Di Scambio Sul Posto, 2019.
[37] 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 (2019) 131911–131928, https://doi.org/10.1109/ACCESS.2019.2940751
[38] H. Habibzadeh, C. Kaptan, T. Soyata, B. Kantarci, A. Boukerche, Smart city system design, ACM Comput. Surv. 52 (2) (2020) 1–38, https://doi.org/10.1145/3309545
[39] 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, p. 59.
[40] C. Bordin, H.O. Anuta, A. Crossland, I.L. Gutierrez, C.J. Dent, D. Vigo, A linear programming approach for battery degradation analysis and optimization in offgrid power systems with solar energy integration, Renew. Energy 101 (2017) 417–430.
[41] M.S. Javadi, A.E. Nezhad, P.H.J. Nardelli, M. Gough, M. Lotfi, S. Santos, J.P.S. Catalão, Self-scheduling model for home energy management systems considering the end-users discomfort index within price-based demand response programs, Sustain. Cities Soc. 68 (2021) 102792, https://doi.org/10.1016/j.scs.2021.102792, https://www.sciencedirect.com/science/article/pii/S2210670721000846.
[42] W. Tushar, T.K. Saha, C. Yuen, D. Smith, H.V. Poor, Peer-to-peer trading in electricity networks: an overview, IEEE Trans. Smart Grid 11 (4) (2020) 3185–3200, https://doi.org/10.1109/TSG.2020.2969657
[43] J. Kumar, A.K. Singh, A secure paillier cryptosystem based privacy-preserving data aggregation and query processing models for smart grid, Cluster Comput. 27 (6) (2024) 7389–7400.
[44] P. Paillier, Public-key cryptosystems based on composite degree residuosity classes, in: International Conference on the Theory and Applications of Cryptographic Techniques, Springer, 1999, pp. 223–238.
[45] Z. Michalewicz, Genetic Algorithms + Data Structures = Evolution Programs, Springer Science & Business Media, 1996.
[46] D. Fudenberg, Game Theory, MIT Press, 1991.
[47] R.C. Rao, Game theory, overview, In K. Kempf-Leonard (Ed.), Encyclopedia of Social Measurement, Elsevier, New York, 2005, pp. 85–97, https://doi.org/10.1016/B0-12-369398-5/00245-0, https://www.sciencedirect.com/science/article/pii/B0123693985002450.
[48] D.E. Golberg, Genetic algorithms in search, optimization, and machine learning, Addion wesley 1989 (102) (1989) 36.
[49] S.-I. Azuma, D. Sato, K. Kobayashi, N. Yamaguchi, Detection of defaulting participants of demand response based on sparse reconstruction, IEEE Trans. Smart Grid 11 (1) (2020) 368–378, https://doi.org/10.1109/TSG.2019.2922435
[50] W. Tushar, T.K. Saha, C. Yuen, D. Smith, P. Ashworth, H.V. Poor, S. Basnet, Challenges and prospects for negawatt trading in light of recent technological developments, Nat. Energy 5 (11) (2020) 834–841, https://doi.org/10.1038/s41560-020-0671-0
[51] A. Chiş, V. Koivunen, Coalitional game-based cost optimization of energy portfolio in smart grid communities, IEEE Trans. Smart Grid 10 (2) (2019) 1960–1970, https://doi.org/10.1109/TSG.2017.2784902
[52] J. Lemaire, R. Castro, F. Montemor, Empowering remote and off-grid renewable energy communities: case studies in congo, australia, and Canada, Energies 17 (19) (2024), https://doi.org/10.3390/en17194848, https://www.mdpi.com/1996-1073/17/19/4848.
[53] S. Kamali, T. Amraee, M. Fotuhi-Firuzabad, Controlled islanding for enhancing grid resilience against power system blackout, IEEE Trans. Power Deliv. 36 (4) (2021) 2386–2396, https://doi.org/10.1109/TPWRD.2020.3022967
[54] M. Fotuhi-Firuzabad, Guest editorial: reliability and resilience modelling, assessment, and enhancement of modern power systems with proliferation of grid-edge resources, IET Gener. Transm. Distrib. 18 (2023), https://doi.org/10.1049/gtd2.13072