Economic and environmental perspectives of flexible demand in PV-based Italian energy communities with residential end-users

Energy & Buildings 342 (2025) 115853

Contents lists available at ScienceDirect

Energy & Buildings

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

Economic and environmental perspectives of flexible demand in PV-based Italian energy communities with residential end-users

Paolo Lazzeroni *, Gianmarco Lorenti, Aldo Canova, Maurizio Repetto

Politecnico di Torino - Dipartimento Energia "Galileo Ferraris", Corso Duca degli Abruzzi, 24, Torino, 10129, Italy

ARTICLE INFO

Keywords:
Energy communities
Flexible demand
MILP
Residential buildings
PV

ABSTRACT

Nowadays, the sharing of energy production within Energy Communities is promoting the diffusion of a decentralized energy system where renewable generation can be locally self-consumed by its members. The maximization of the matching between generation and demand is then crucial to ensure higher economic and environmental benefits for residential end-users joining Energy Communities. In this view, an optimization approach based on Mixed Integer Linear Programming is proposed to model end-users flexibility for investigating how the change in consumption habits can improve energy sharing by maximizing the match between renewable production and demand. The user's discomfort is also considered to figure out the impact on the existing behavior. An Italian multi-family residential building case study is considered to highlight energy, economic, environmental, and social impacts due to flexible demand. Results reveal that if end-users fully agreed to flexible demand, self-consumption increased up to 95.9 %, with a decrease in energy bills and carbon emissions of 4.6 % and 9 %, respectively. Otherwise, if a lower availability of end-users flexibility is also included in a multi-objective perspective, a possible trade-off between the energy and discomfort point of view can be found. In fact, suitable economic and environmental performances are still reached with self-consumption increased up to 93.7 % and cost and emission savings of 3.8 % and 7.5 %, respectively.

1. Introduction

Energy Communities (ECs) in Italy are a relatively new concept that has emerged as a response to the challenges posed by climate change and the need for a more sustainable energy future [1]. In fact, these communities aim to promote the use of clean and sustainable energy, reduce greenhouse gas emissions, and foster local economic development contrasting energy poverty [2]. For these reasons, in an EC, public and private entities as well as citizens and households jointly and collectively own and manage renewable energy resources (RES) to locally increase self-consumption [3]. Hence, ECs are based on the idea that energy production should be decentralized and democratized, with people taking an active role in shaping their energy future and in driving the energy transition towards a more sustainable energy system. Among all the possible EC configurations, Collective Self-Consumption (CSC) is the one where all participating users are situated in the same building. This configuration is ideal for residential users, as it has the potential to facilitate the installation of RES and to support the electrification of energy consumption within the building. Thus, EC could contribute in reducing the environmental impact of residential buildings as they are still ones of the largest energy consumers in European Union (EU) [4].

Since the main goal of an EC is to increase the match between the local RES-based production with the local electricity demand, battery energy storage systems (BESSs) are assuming a relevant role [5]. Storage systems are in fact assets for decoupling the timing of energy production from its consumption . Thus, the use of this system has the advantage of leaving the end-user free to keep its own consumption habits, while overproduction can be stored and released when needed. However, one of the possible critical aspects in adopting BESS is still its profitability without incentives [6–8].

A different and complementary approach can be instead considered by promoting the cooperation between community members (e.g. households) and the energy system (i.e. the EC). In particular, to increase self-consumption and self-sufficiency, changes in consumption habits may be either proposed or suggested to end-users to modify the timing at which these consumptions occur [9]. This led to the adoption of flexible demand strategies where the optimal usage of some electric appliances in the households can be identified and suggested to end-users for adapting their habits to more sustainable and profitable behavior. Consequently, also the BESS sizing could benefit from the adoption of flexible demand due to lower expected RES overproduction.

* Corresponding author.
E-mail address: paolo.lazzeroni@polito.it (P. Lazzeroni).

https://doi.org/10.1016/j.enbuild.2025.115853
Received 6 November 2024; Received in revised form 27 February 2025; Accepted 7 May 2025
Available online 12 May 2025

Nomenclature

EC	energy community
REC	renewable energy community
MILP	mixed integer linear programming
LP	linear programming
CSC	collective self-consumption
PV	Photovoltaic
MOT	minimum on time
MST	minimum shutdown time
P_s	power injected into the national grid (kW)
P_p	power withdrawn from the national grid (kW)
P_{PV}	power produced by the PV plant (kW)
$P_{st,c}$	power injected into the battery (kW)
$P_{st,d}$	power released by the battery (kW)
$U_{fix,j}$	demand of the fixed load for user j (kW)
$U_{flex,j,a}$	demand of the flexible load a for user j (kW)
P_s	contractually committed power for each user (kW)
U_{dm}	aggregated demand of the building due to flexible demand (kW)
U_e	aggregated demand of the building without flexible demand (kW)
N_a	number of appliances
N_u	number of users
N_i	number of time steps
BESS	battery energy storage system
α	weighting coefficient of the multi-objective problem
SC	self-consumption (%)
SS	self-sufficiency (%)
PCR	percentage cost reduction (%)
YC	yearly costs (€/y)
C_p	per unit electricity price purchased from the grid (€/MWh)
C_s	per unit electricity price sold to the grid (€/MWh)
C_{sh}	per unit incentive for the shared energy (€/MWh)
ΔCO_2	yearly carbon emission savings (%)
Dis	average daily time-shifting for the flexible loads (minutes)
E_s	yearly electricity injected into the National grid (MWh/y)
E_p	yearly electricity withdrawn from the National grid (MWh/y)
E_{sh}	yearly electricity shared within the community (MWh/y)
E_L	yearly electricity demand within the community (MWh/y)
EF_e	carbon emission factor for the consumed electricity (kgCO2/MWh)

In this view, the work presented by [10] gives a wider overview of the different approaches adopted to model flexible demand in the residential sector. In particular, a massive part of the literature faced the problem by linear programming (LP) and mixed integer linear programming (MILP) for deploying load-shifting and then minimizing the energy bills for end-users.

For instance, a MILP smart home energy management model has been presented in [11] to arrange the operation of household appliances to minimize costs by considering a time-varying pricing model to control the system. In particular, electrically controllable appliances are shifted to reduce electricity bought from the grid by harnessing RES production and storage usage. Load shifting is obtained by imposing a predefined time window where each programmable appliance can operate, while binary variables are used to select the best time instant where the corresponding consumption cycle must be switched on.

Similarly, a home energy management strategy to minimize the customer's billing is presented in [12], where different components and appliances are modeled by MILP. Each shiftable load is still modeled as a component with a fixed operational time window within which the scheduling can be arranged to reduce the electricity bought from the grid. Again binary variables are used to select the best starting time interval for each controllable load.

In [13] load-shifting is instead managed by considering different electricity prices, but the load is assumed as an aggregated consumption where the demand of a single appliance can not be specifically scheduled. Flexible demand by MILP approach is also evaluated in [14] where appliances can be controlled with different operating time priorities according to the consumers' preferences. In this way, appliances consumption can be eventually shifted to reduce energy bill. Although these studies, as the others presented in [10], formulated the flexible demand by means of MILP, in most of the cases the problem is faced for a single-family residential unit, so the energy community behavior is not considered at all.

More recently, other approaches have been proposed for integrating flexible demand in the energy community. For example, the study presented in [15] uses a MILP formulation for the optimal management and design of the energy assets, namely PV, CHP, and batteries, in an energy community. Flexible demand is simply modeled by potentially increasing the consumption during PV production, while the corresponding curtailment is just uniformly spread during nighttime. However, the demand of each member is considered as an aggregated load without the possibility of changing the consumption of each single programmable load. A different approach is proposed in [16] where MILP is used to identify, for each member of the EC, the best schedule to operate any single controllable appliance within end-users predefined time windows. Binary variables are used to identify which time windows have to be selected for the execution of a given task of the appliance. A similar study is presented in [17] where an optimal energy management framework for energy communities, integrating flexible demand, storage, and vehicle-to-grid is developed. Specifically the flexible demand is modeled through controllable appliances categorized as interruptible and non-interruptible with a MILP-based framework that ensures efficient scheduling, but again considering predefined time windows. Another study in [18] focuses on energy communities and the role of the willingness of members to modify their energy consumption behavior and habits to optimize consumption and production matching. The authors developed a multi-agent optimization model to provide personalized recommendations through a MILP approach minimizing the net energy exchanged with the grid. However, end-user flexibility is considered as a whole: the aggregated demand of the community can be modified to increase the match between production and consumption, but it is not specified which appliances should be act on.

Although the above-mentioned past and recent studies effectively contribute to promoting RES self-consumption even from an energy community perspective, in most of them the load shifting introduced by the flexible demand presents some unexplored points:

- since the demand is usually rearranged during the day to maximize self-consumption, the solution can suffer from possible overshooting leading to over-demand during RES production, while reducing demand during the rest of the day
- the use of predefined time windows where load-shifting operates can limit the flexibility
- only some of the above-mentioned research investigated the impact of household discomfort, but mainly related to electric air-conditioning systems, while discomfort in shifting consumption also for other programmable electric appliances has not been taken into account yet.

For this reason, although EC can involve various energy vectors, a MILP approach is proposed here to exploit the economic and environmental benefits due to load shifting (i.e., flexible demand) of some

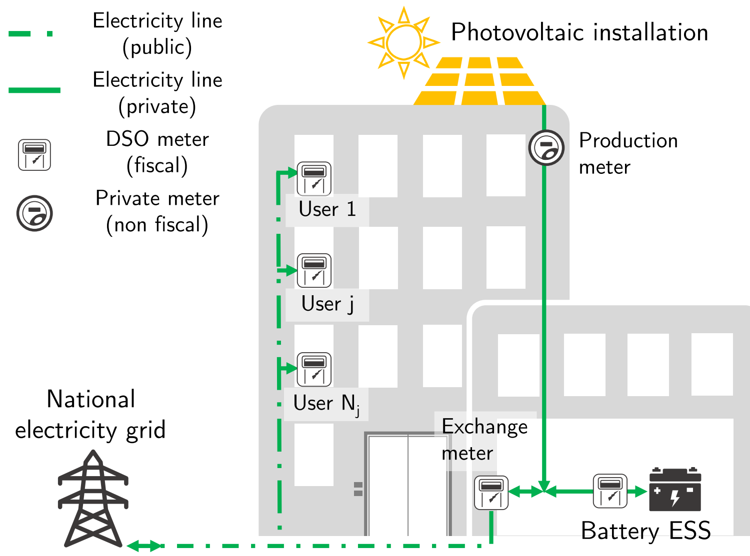


Fig. 1. Example of collective self-consumption in a residential building. [Adapted from [23]].

electrical appliances in the residential sector, but considering the perspective of an existing energy community. In this case, the self-consumption of RES-based production is maximized by suggesting different end-users' habits, so that the aggregated load demand can more efficiently match the RES production. Differently from the previous studies, the proposed solution in this study:

- increases the efficiency of energy sharing since the optimal scheduling of the electric appliances is modeled to limit or avoid possible over-demand during RES production
- is not limited by predefined time windows where each appliance can operate, so higher flexibility is expected.
- considers the discomfort for the end-users when it shifts the use of schedulable appliances following the suggestions from MILP

The MILP approach was then tested on a representative residential case study in Italy, where local energy communities (EC) are organized as a Collective Self-Consumption scheme. In addition, flexible demand is compared with the integration of an energy storage system to figure out also advantages and drawbacks. Eventually, end-users' discomfort is modeled to assess end-users' acceptance of changing habits. In fact, customers' perception of flexibility tools is still controversial [19].

Multi-objective optimization is also proposed to investigate how different disposition to take part in flexible demand can influence the benefits, as well as the solution of the optimization process.

The paper is organized as follows: a brief description of the current Italian regulatory framework for EC is described in Section 2; then the proposed methodology, the modeling of the EC and its management are presented in Sections 3 and 4; Key Performance Indicators for measuring the energy, economic, environmental and social impacts are introduced in Section 5; finally, the proposed case study and the results are presented and discussed in Sections 6 and 7.

2. Collective self-consumption in Italy

Nowadays, in the current Italian regulatory framework, the energy produced by RES can be shared within a group of jointly-acting renewable self-consumers, which is legally considered as a particular case of a Renewable Energy Community (REC) [20], since the members are located in the same building. Each member can collectively own and manage renewable generation assets (currently, smaller than 1 MW) and hence produce energy for their own consumption, while overproduction can be shared with the other members through a virtual scheme.

According to this scheme, all the members (i.e., consumers, producers, and prosumers) are connected to the same public distribution grid. The renewable energy overproduced within the REC (i.e., the one not self-consumed behind-the-meter by the prosumers and the whole generation of the producers) is injected into the grid and economically valued at the hourly zonal market price. While end users bought electricity from the grid at retail price (usually higher than the market price) and kept their electricity supply contract. When electricity is simultaneously injected and withdrawn into/from the grid by members of the REC, it is considered to be shared, through the public distribution grid. Consequently, the shared electricity is defined as the minimum, in each hourly time step, between the sum of the total injections and withdrawals into/from the grid of the end users present in the REC [21].

The current Italian regulation acknowledges an economic value to this energy sharing through both a fixed incentive and a variable economic compensation related to the grid tariffs for the electricity withdrawn from the grid and accounted as shared. Globally, the economic value of shared energy in RECs is roughly equal to 110 €/MWh or 120 €/MWh, depending if the REC is considered as a group of jointly-acting self-consumers or not. In the latter case, "Collective Self-Consumption" (CSC) is commonly used when referring to energy sharing in this context where consumption and production take place in the same building. Hence, "collective self-consumers" is used in the following to identify the members of this particular case of REC.

Fig. 1, shows a scheme for CSC in a multi-family residential building [22], used here as a reference. A collectively-owned photovoltaic system is installed on the building's rooftop. Electricity generation can be consumed on-site for shared services (e.g., elevator, lighting of common spaces) or injected into the public distribution grid. Potentially, even an electricity storage system (battery) can be coupled with the PV installation. The household users in the building can use the injected energy to fulfill their own electricity demand, thus sharing it. Injected energy that is not shared is then exchanged with the national electricity grid. Similarly, electricity demand (both on-site and virtual) that cannot be fulfilled using local RES generation is taken from the national grid.

In this context, an increase of the shared energy by fostering modification in end-users behavior is a valuable opportunity. In fact, a modified load profile gained by a different use of programmable household electric appliances may better match the RES production increasing local self-consumption and economic benefits while reducing environmental footprint.

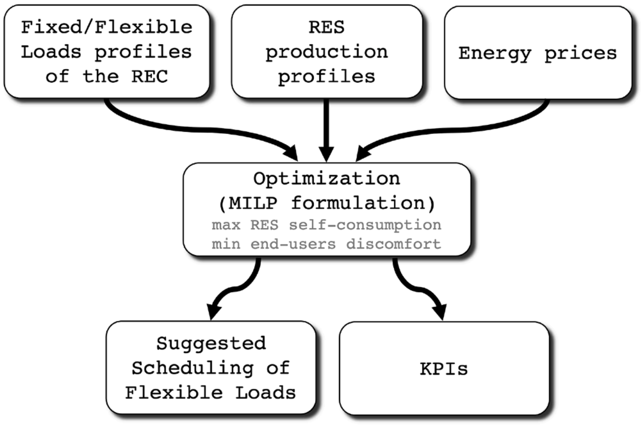


Fig. 2. Scheme of the proposed MILP approach.

3. Methodology

As mentioned, from the perspective of a REC with residential end users, flexibility on the demand of household electric appliances can represent an opportunity for improving energy, economic, and environmental benefits. The possibility to either modify customers' habits or suggest and promote different customers' behavior, might promote better RES-based energy sharing. In this view, suggestions to the end-users can be properly identified through an optimization process capable to model and simulate the energy exchange within the REC, maximizing the local self-consumption while reducing the mismatch between the RES production and the demand.

The proposed approach, as summarized in Fig. 2, assumes the RES production and the consumption profile of fixed and flexible (i.e. programmable) loads as inputs. Then, an optimization algorithm, formulated as a MILP problem, identifies how the consumption patterns for the programmable appliances should be changed or, in other words, shifted from the usual habits. The impact of the implementation of these suggestions is finally measured by energy, economic, environmental, and discomfort Key Performance Indicators (KPIs).

3.1. Problem formulation

A Mixed Integer Linear Programming (MILP) formulation is proposed here to model the flexible demand of electric appliances used by residential end-users joining a collective self-consumption configuration. Consequently, equations and constraints representing this energy system are linear or alternatively should be linearized. Similarly, the objective functions are represented by linear functions. In particular, two different sets of equations can be considered: energy balance equations and constitutive equations. The former is adopted for describing and simulating the energy exchange within the different assets of the energy community, while the latter is used for representing the energy behaviors of these assets (e.g., battery storage, electric appliances, local distribution grid, etc). If necessary, binary variables are also usually introduced to describe the on/off status of the assets and appliances and to consider their operational limits. A detailed description of this general approach can be found in [24].

Finally, the time horizon of the simulation is discretized by subdividing it into N_i intervals or time steps with length Δt equal to 5 minutes in this particular application for fully exploiting the potentiality of the flexible demand in residential end-users.

4. Modeling of REC with flexible demand

The modeling of a REC is fundamental to investigate, through simulation, how flexible demand can impact the performance of an energy community according to the formulation proposed in Section 3.1. Thus, a description of the models adopted for representing the assets behaviors as well as for describing the interaction between assets is presented in the following.

4.1. Flexible demand

Flexible demand aims to suggest modifications on end-users' habits in using electric appliances to meet specific goals of the energy community. As already pointed out, in this particular case, the objective is to increase the self-consumption of RES production to maximize energy sharing and improve the economic benefits.

Hence, end-users can actively participate by shifting the energy consumption for all those appliances that are programmable by definition as, for instance, washing machines and dishwashers [10]. These appliances, in fact, have a duty-cycle that can not be stopped once it has started, but the start-up can be anticipated or deferred with respect to the end-users' habits. As a consequence, assuming a daily time horizon discretized on N_i time intervals, the duty-cycle of an end-user's programmable appliance can potentially be started at any time intervals.

This condition, as suggested by [14], can be modeled by a squared matrix where each column represents the load pattern (or load profile) of the a-th programmable appliance by assuming a different starting time interval for the duty-cycle. Practically, the first column is the usual load pattern, while the other columns are obtained by cyclic permutation of the first one, as follows:

$$\mathbf{P}_{j,a} = \begin{bmatrix} p_{j,a,1} & p_{j,a,N_i} & p_{j,a,N_i-1} & \cdots & p_{j,a,2} \\ p_{j,a,2} & p_{j,a,1} & p_{j,a,N_i} & \cdots & p_{j,a,3} \\ p_{j,a,3} & p_{j,a,2} & p_{j,a,1} & \cdots & p_{j,a,4} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ p_{j,a,N_i} & p_{j,a,N_i-1} & p_{j,a,N_i-2} & \cdots & p_{j,a,1} \end{bmatrix} \tag{1}$$

where $\mathbf{P}_{j,a} \in \mathbb{R}^{N_i x N_i}$ is the matrix with different load patterns in each column and $p_{j,a,i}$ is the consumption of the a-th programmable appliances in a given i-th time interval for the j-th end-user. Clearly, an appliance can only adopt one load profile (i.e., one behaviour) from $\mathbf{P}_{j,a}$, while the other must be ignored. Thus, only one column of $\mathbf{P}_{j,a}$ must be considered for each a-th appliance. For this reason, N_i additional binary variables have to be introduced, one for each column, so that:

$$\sum_{i=1}^{N_i} \delta_{j,a,i} = 1 \tag{2}$$

where $\delta_{j,a,i}$ is the added binary variable equal to 0 if the i-th consumption pattern (i.e., the i-th column of $\mathbf{P}_{j,a}$) is not selected and equal to 1 if the corresponding i-th consumption pattern is chosen. Hence, Eq. (2) ensures that only a load profile can be selected, while the others are not considered. As a consequence, this representation introduces flexibility in the usage of programmable electric appliances.

Other electric appliances, for instance refrigerators, have no specific duty cycle and a specific load pattern that can be moved or rescheduled. These appliances are then non-programmable and their consumption pattern is assumed to be fixed. Thus, the energy demand of each end-users can be split into flexible and fixed ones so that the a minimum energy requirements that can not be adjusted is also taken into account, as better explained later in Section 4.5.

4.2. Public distribution grid

The public distribution grid is the asset through the PV plant and the end-users are connected. This public infrastructure is used to enable energy sharing in the REC, according to the virtual scheme presented in Section 2. The PV plant can thus inject RES production into the public distribution grid while households (members of the REC) can withdraw electricity from the grid. Eventually, energy sharing takes place when injection and consumption are simultaneous.

This shared energy is assumed to be produced/consumed within the REC boundaries, thus reducing the energy flows towards/from the outside of the REC. Nonetheless, energy exchange with the National Grid, outside the REC boundaries, still occur so the following constraints must be considered, as presented in [25]:

$$P_s(t_i) \leq \delta_s(t_i) P_{s,max} \tag{3}$$

$$P_p(t_i) \leq \delta_p(t_i) P_{p,max} \tag{4}$$

$$\delta_s(t_i) + \delta_p(t_i) \leq 1 \tag{5}$$

Specifically, two variables P_s and P_p are introduced to represent the interaction of the REC with the National grid. The former represents the injection to, while the latter is the electricity withdrawn from the grid. Additionally, two binary variables δ_s and δ_s and the following constraints have been included to prevent electricity from being injected and withdrawn at the same time. Parameters $P_{s,max}$ and $P_{s,max}$ are introduced to potentially limit both the electric power injected into and the electric power taken from the National grid.

4.3. PV

The energy produced by the PV plant in each time step is assumed as a function of the PV size and other factors (i.e. plant location, weather condition, etc.) by means of PVGIS data [26] and through the methodology presented in [27]. Following this approach, the PV production can be calculated in a simplified way, as follows [18,22,28]:

$$P_{PV}(t_i) = \frac{G(t_i)}{1000} \cdot P_n \cdot PR \tag{6}$$

where $G(t_i)$ is the solar irradiance from PVGIS database, P_n is the rated power of PV and PR is the performance ratio of the system [29] for taking into account DC/AC conversion losses, cable losses, and external air temperature effects on the yearly productivity of PV modules. In this case, since flexible demand is assumed to be applied within a limited time horizon (i.e., daily), the potential reduction of PV production, due to the aging of PV modules, is neglected.

4.4. Energy storage

A battery electric storage system (BESS) is also considered as an essential element to further introduce flexibility in the management of an energy community [30]. Even if its integration can be complementary to flexible demand, but leaving consumption habits unchanged, BESS operation needs to be modeled as well to exploit the interaction with flexible demand.

The BESS formulation adopted here is based on the one already introduced in [28], where the BESS is studied considering the passive sign convention. Under this assumption, the electric power input to the BESS has a positive sign (during charge), and vice versa the output one (during discharge) has a negative sign. As a consequence, the State Of Charge (SOC) of the battery (i.e., its energy content) in a given time interval is defined, as follows:

$$SOC(t_{i+1}) = \eta_{sd} SOC(t_i) + \left(\eta_c P_{b,c}(t_i) - \frac{P_{b,d}(t_i)}{\eta_d} \right) \Delta t \tag{7}$$

where η_{sd} is the self-discharge efficiency, η_c is the charge efficiency, η_d is the discharge efficiency and $P_{b,c}$ and $P_{b,d}$ are the battery power respectively during charge and discharge. However, electric power during charge and discharge are typically limited, so further constraints need to be introduced, as follows:

$$0 \leq P_{st,c} \leq \delta_c(t_i) \frac{SOC_{max}}{T_c} \tag{8}$$

$$0 \leq P_{st,d} \leq \delta_d(t_i) \frac{SOC_{max}}{T_d} \tag{9}$$

$$0 \leq \delta_c(t_i) + \delta_d(t_i) \leq 1 \tag{10}$$

where $SOC_{\max}$ is the storage capacity of the battery, T_c and T_d are the minimum charge and discharge time, while Eq. (10) is an operational constraint where δ_c and δ_d are binary variables that compel charge and discharge powers to be different from zero only one at a time.

Since the length of each time step Δt can be quite short (i.e., 5 minutes in this application as mentioned in Section 3.1), a further set of constraints is also introduced to prevent frequent switching from charge to discharge process and vice versa. The Minimum On Time (MOT) and the Minimum Shutdown Time (MST) are then included, as presented in [31]:

$$\begin{aligned} \sum_{k=i}^{i+MOT-1} \delta_c(t_k) &\geq MOT\left[\delta_c(t_i) - \delta_c(t_{i-1})\right] \\ \sum_{k=i}^{i+MOT-1} \delta_d(t_k) &\geq MOT\left[\delta_d(t_i) - \delta_d(t_{i-1})\right] \end{aligned} \tag{11}$$

$$\begin{aligned} \sum_{k=i}^{i+MST-1} \delta_c(t_k) &\leq MST\left[1 + \delta_c(t_i) - \delta_c(t_{i-1})\right] \\ \sum_{k=i}^{i+MST-1} \delta_d(t_k) &\leq MST\left[1 + \delta_d(t_i) - \delta_d(t_{i-1})\right] \end{aligned} \tag{12}$$

In other words, Eq. (11) ensures the charging/discharging process to be kept for at least MOT time intervals. Otherwise, Eq. (12) disable the use of the battery for at least MST time intervals.

4.5. Energy balance with flexible demand

As already depicted in Section 3, CSC is a scheme where local RES production, energy storage systems, and the end-users interact with each other to increase local self-consumption. In this context, where residential end-users jointly act as renewables self-consumers, if flexibility is also introduced for some of the appliances, the energy consumption for each end-user can be divided into two different main categories: fixed and flexible load. The corresponding energy balance for the community can be then defined in each time step, as follows:

$$\begin{aligned} &P_{PV}(t_i) + P_p(t_i) + P_{b,d}(t_i) \\ &= P_s(t_i) + P_{b,c}(t_i) + \sum_{j=1}^{N_u} U_{fix,j}(t_i) + \sum_{j=1}^{N_u} \sum_{a=1}^{N_a} U_{flex,j,a}(t_i) \end{aligned} \tag{13}$$

with:

$$\sum_{j=1}^{N_u} U_{fix,j}(t_i) + \sum_{j=1}^{N_u} \sum_{a=1}^{N_a} U_{flex,j,a}(t_i) = U_{dm}(t_i) \tag{14}$$

where U_{dm} is the aggregated demand of the building, P_{PV} is the RES production from PV, P_p is the electricity bought from the grid by the REC, $P_{b,d}$ is the electric power supplied by the battery, $P_{b,c}$ is the electric power consumed by the battery, $U_{fix,j}$ is the overall fixed load of the j-th end-user, while $U_{flex,j,a}$ is the flexible load of the a-th programmable appliance owned by the corresponding j-th end-user. Then, the left-hand side of Eq. (13) represents the *sources* for the energy community, while the right-hand side identifies the *loads*, where P_s has the role of representing power injected and sold to the National grid.

However, according to the modeling of flexible demand proposed in Section 4.1, each flexible load can be represented by N_i possible load patterns where only one of them is not actually zeroed. As a consequence, each flexible load introduced in Eq. (13) can be also represented as follows:

$$\mathbf{U}_{flex,j,a} = \sum_{i=1}^{N_i} \delta_{j,a,i} \mathbf{p}_{j,a}^{(i)} \tag{15}$$

where $\mathbf{p}_{j,a}^{(i)}$ is the i-th column of the matrix $\mathbf{P}_{a,j}$, $\delta_{j,a,i}$ is the binary variable introduced in Section 4.1 for selecting only one load profile for the given

a-th flexible load, while $\mathbf{U}_{flex,j,a}$ is the vector describing the load profile for the a-th programmable appliance of the j-th end-user. Of course, Eq. (2) ensures that only one load pattern will be selected during the search for the optimal solution.

Additionally, limitations due to the contractually committed power have to be considered for each end-user. In fact, shifting the flexible loads may cause power demand exceeding the available power for a residential end-user which is usually equal to 3 kW in most of the Italian domestic customers [32]. This can be avoided by introducing for each j-th end-user and in each i-th time step a further constraint, as follows:

$$U_{fix,j}(t_i) + \sum_{a=1}^{N_a} U_{flex,j,a}(t_i) \le P_c \tag{16}$$

where P_c is the contractually committed power for domestic customers, while $U_{fix,j}$ and $U_{flex,j,a}$ are still the overall fixed load of the j-th end-user and the flexible load of the a-th programmable appliance owned by the corresponding j-th end-user, respectively

4.6. Objective functions

In this paper, according to the recent Italian rules [33], a multi-family building is considered where a PV plant is used to supply the energy demand of the residential end-users jointly acting as renewables self-consumers. In this context, the demand of some electric appliances is supposed to be schedulable and flexible to increase and maximize the self-consumption of the RES production. This goal is equivalent to minimize both the electricity injected into the National grid P_s (i.e., the one not self-consumed/shared within the REC boundary) and the electricity withdrawn from the grid P_p (i.e. the one needed to supply the demand within the REC boundary) [28]. In this view, the objective function is evaluated, as follows:

$$OF_1 = \min\left(\sum_{i=1}^{N_i} P_s(t_i)\Delta t + \sum_{i=1}^{N_i} P_p(t_i)\Delta t\right) \tag{17}$$

Consequently, an increase in energy sharing is gained by improving the match between production and the aggregated demand of the building. Alternatively, an economic objective function as the one introduced in [25], could be potentially considered instead of Eq. (17). But, according to the National rules presented in Section 2, if flat tariff is assumed for the electricity bought from the grid, the optimization results will be coincident. Thus, since flat tariff is one of the most selected by Italian users [34], the objective function on energy-basis has been the one chosen in this analysis.

However, the shifting of the demand introduced in Eq. (17) can be obtained equivalently by involving any programmable appliances. This could lead to solutions where all the schedulable appliances are involved in the flexibility and the aggregated demand greatly overshoots the RES generation without essentially any further energy and economic benefits, as the shared energy will not increase anymore. These solutions can be limited by introducing additional constraints, as follows:

$$U_{dm}(t_i) \le P_{PV}(t_i) + \epsilon \quad \text{if} \quad P_{PV}(t_i) > U_e(t_i) \tag{18}$$

$$U_{dm}(t_i) \le U_e(t_i) \qquad \text{if} \quad P_{PV}(t_i) \le U_e(t_i) \tag{19}$$

where U_e is the aggregated demand of all building flats when flexibility in energy demand is not considered, P_{PV} is the production from the PV plant, while ϵ is the parameter introducing the maximum overshooting allowed, that is equal to the highest peak demand among all the programmable appliances, to avoid possible strong limitations in flexible demand. Specifically, Eqs. (18) and (19) stated that if PV production is lower than U_e (i.e., RES production is already fully shared with the community) the aggregated demand can be only reduced, but keeping the energy sharing goal. Conversely, if PV production is higher than U_e, aggregated demand can be increased by shifting the flexible loads but bounding it to avoid overshooting. Finally, both equations avoid all those solutions where flexible demand is not needed, for instance, when PV is absent, preventing the flexible loads from being shifted in the nighttime.

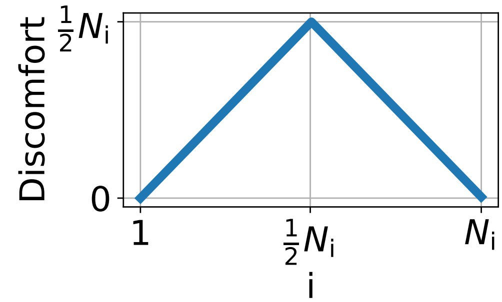


Fig. 3. Weights introduced in OF_2.

Nevertheless, minimizing Eq. (17) can be still complex according to the formulation presented in Section 4.1. In fact, the same increase in energy sharing can be performed by many combinations of load shifting of different electric appliances. For instance, if a full match between production and demand is supposed to be achievable by the load shifting of only one appliance in a given time interval, any other appliances can be equivalently considered for reaching this goal through load shifting. Thus, from the energy point of view, many equivalent solutions could be found for the same optimization problem.

However, some solutions could be potentially more in contrast with the users' habits. In simpler terms, the end user discomfort in adopting flexible demand is different even in equivalent solutions. For this reason, a measure of the end-users' discomfort needs to be introduced. This is represented by a sort of weighted distance between the scheduled path demand of the shiftable loads (e.g. the one suggested by solving Eq. (17)) and the end-user's usual consumption habits.

Consequently, a different objective function has been introduced to minimize user's discomfort, as follows:

$$OF_2 = min \sum_{j=1}^{N_u}\sum_{a=1}^{N_a}\left[\sum_{i=1}^{N_i/2} i\cdot\delta_{j,a,i} + \sum_{(N_i/2)+1}^{N_i}(N_i - i + 2)\cdot\delta_{j,a,i}\right] \tag{20}$$

where $\delta_{j,a,i}$ is the binary variable introduced in Eq. (2) for selecting only one load profile for each a-th programmable appliance.

In this objective function, the coefficients i and $(N_i - i + 2)$ are introduced to weight differently each consumption pattern represented by a column of the matrix **P**. In particular, the weights of OF2 are assigned in such a way that each consumption pattern, represented by a column of matrix **P**, is weighted differently based on discomfort levels. Specifically, it is assumed that consumption patterns that deviate further from usual habits are penalized more than those that are closer. However, the first column of matrix **P** reflects the typical usage habits of a particular appliance, while the other columns result from cyclic permutations of this first column. Consequently, the columns of **P** are symmetric in relation to the first column. In this view, for example, the second column and the last column of **P** are assigned the same weight because they correspond to two patterns that are symmetrically close to the user's usual habits. Similarly, the third column and the second-to-last column of **P** also share the same weight, but this weight is greater than that assigned to the second and last columns, as the third column's consumption pattern is farther from the user's established habits (i.e., the first column). Fig. 3 graphically summarize the weight given to each pattern (i.e. each column of **P**) with respect to the usual habits according to the proposed assumption.

Given these weights, the objective function in Eq. (20) naturally forces the solution to be close to the usual habits of the end-users. Thus, in this research, it is supposed that users stated the same willingness to participate in flexible demand (i.e., the worst condition). Clearly, a different approach for defining the weights can be considered. For example, if some users state a greater willingness to participate in flexible demand, some consumption profiles close to the usual one might be less equally penalized while others further away might be penalized more (e.g., linearly as done in Fig. 3).

4.6.1. Multi-Objective

Eq. (20) states that minimum discomfort has to be reached (i.e., end-users do not change their consumption habits), and practically this is in contrast to Eq. (17). For this reason, also a multi-objective approach has been explored. In particular, since the formulation proposed here is based on MILP, a weighted sum method [35] is adopted to combine the two objective functions, as follows:

$$MOF = min\left[\alpha OF_1^* + (1-\alpha)OF_2^*\right] \tag{21}$$

where $0 \leq \alpha \leq 1$, while OF_1^* and OF_2^* are the normalized objective functions. Specifically, a min-max normalization is assumed here by considering the Utopia and the Nadir points [36]. Different weights α in Eq. (21) give the possibility to explore solutions where the use of flexible demand is less compelling, consumption patterns are closer to end-users' habits, and discomfort is reduced.

5. Key performance indicators

KPIs are used here to investigate the performances of the flexible demand within an energy community on a yearly basis. Four groups of KPIs were considered: energy, economic, environmental, and social (discomfort).

5.1. Energy KPI

The energy impact of flexible demand in a multi-family residential building has been evaluated considering two different indicators: self-consumption (SC) and self-sufficiency (SS). The SC identifies the self-consumed PV production compared to the yearly PV production, while the SS identifies the self-consumed PV production compared to the yearly electricity demand of the building, as follows [37]:

$$SC = \frac{E_{sh}}{E_{PV}} = \frac{\sum_{year} P_{sh}(t_i)\cdot \Delta t}{\sum_{year} P_{PV}(t_i)\cdot \Delta t} \tag{22}$$

$$SS = \frac{E_{sh}}{E_{L}} = \frac{\sum_{year} P_{sh}(t_i)\cdot \Delta t}{\sum_{year} U_{e}(t_i)\cdot \Delta t} \tag{23}$$

where E_{PV} is the yearly energy production from PV, E_L is the aggregated yearly energy demand of the building, while E_{sh} is the yearly self-consumed PV production within the energy community also named shared energy and calculated considering the following energy sharing on hourly basis [20]:

$$P_{sh}(t_i) = min[(P_{PV}(t_i) + P_{b,d}(t_i)), (U_e(t_i) - P_{b,c}(t_i))] \tag{24}$$

5.2. Economic KPI

The economic impact of flexible demand in the CSC has been evaluated only in terms of cost savings for the end-users. In fact, as already pointed out, flexible demand is supposed to be adopted in existing scenarios of energy communities. Hence, the economic feasibility and profitability of investing in the active assets of the community [38] are not considered here, so economic indicators evaluating the return on investment are not included in this work.

In this light, the indicator named Percentage Cost Reduction (PCR) [22] is used to compare the yearly costs of the electricity bills YC_{dm} obtained by the energy community adopting flexible demand with the ones YC_{ref} where it is not adopted. Practically, PCR is calculated as follows:

$$PCR = \left[1 - \frac{YC_{dm}}{YC_{ref}}\right]100. \tag{25}$$

Both yearly costs are calculated considering the per unit cost C_p for the electricity bought from the grid E_L and the economic benefits and incentives offered to energy communities by the current Italian regulatory framework, as follows:

$$YC = E_L C_p - E_{PV} C_s - E_{sh} C_{sh}. \tag{26}$$

Specifically, the PV production injected into the grid E_{PV} is economically valued at the wholesale market price C_s, while the shared energy E_{sh} benefits of the mentioned incentive C_{sh}. The former, considering 2019 as the reference year, is assumed fixed at approximatively 50e/MWh [39], while the latter is equal to around 110e/MWh.

Instead, the tariff C_p for the electricity bought by each household from the grid is assumed flat, as commonly adopted by Italian residential end users, and equal to the retail price of 200e/MWh on average [22].

5.3. Environmental KPI

Environmental KPI measures instead how the flexibility in the demand influences the reduction in the primary energy consumption or, alternatively, in CO_2 emissions in an energy community adopting a CSC scheme. The carbon saving is in fact calculated by comparing the carbon emissions with and without flexible demand, as follows [22]:

$$\Delta CO_2 = \left[1 - \frac{CO_{2,dm}}{CO_{2,ref}}\cdot 100\right] = \left[1 - \frac{E_{p,dm}\cdot EF_e}{E_{p,ref}\cdot EF_e}\right]\cdot 100 \tag{27}$$

where EF_e represents the National CO_2 emission factor equal to 255 kgCO_2/MWh for the electricity withdraws from the National grid, as reported in [40]. Instead, $E_{p,dm}$ and $E_{p,ref}$ are the net yearly electricity demand of the building when flexible demand is implemented and not, respectively.

5.4. Social KPI

Finally, a further KPI is introduced to measure how flexible demand changes the usual habits of end-users and contemporarily creates discomfort. This can be basically measured by comparing the suggested optimal path demand (gained by solving Eq. (17)) with the end-user's habits. Since each of the flexible loads considered in this study has a specific duty-cycle, this comparison is equivalent to measuring the distance between two duty-cycles with different starting times or, in other words, this distance is the difference between two starting times. An overall discomfort KPI can be then introduced by averaging these time differences obtained for all the programmable appliances, as follows:

$$Dis = \sum_{k=1}^{d} \frac{N_k}{N_y}\left[\frac{1}{N_u N_a}\sum_{j=1}^{N_u}\sum_{a=1}^{N_a} \mid t_{j,a}^{us} - t_{j,a}^{op} \mid\right] \tag{28}$$

where ${}^{us}_{j,a}$ and $t_{j,a}^{op}$ are the usual and optimal starting time of the duty-cycle for the j-th user and its programmable appliance a, d is the number of reference days adopted to represent a whole year, N_k is the number of k-th reference days in a year, while N_y is the number of days in a year. Clearly, $t_{j,a}^{op}$ is get from the solution obtained by solving Eq. (17), (20) or (21).

6. Case study description

The building being studied here is a multifamily residential building of 40 apartments, already presented by the authors in [22]. This building typology is the most representative according to the current Italian building stock [41]. The electricity demand of each apartment was estimated by an open-source simulator developed by the CADEMA research group of the Politecnico di Torino [42]. The open-source simulator creates daily load profiles of the electric appliances for each household in the residential building. In particular, for the sake of simplicity but without loss of generality, the whole yearly demand is represented by 8 reference daily load profiles generated for each apartment. These reference days, with a time resolution of 5 minutes, differ from each other according to the season and the day of the week (i.e. weekdays and weekend days).

The simulated load profile of each appliance is based on statistical data obtained from past load measurement campaigns in National research projects, so the generated patterns can be assumed as related to end-users' habits. The appliances considered in the simulator are reported in Table 1.

Audio-videos as well as other electronic devices (laptop, personal computers) and lighting are considered to be on demand and thus not shiftable in time. Instead, only dishwashers and washing machines are assumed here as the ones suitable for the application of flexible demand due to their ability to be programmed [10].

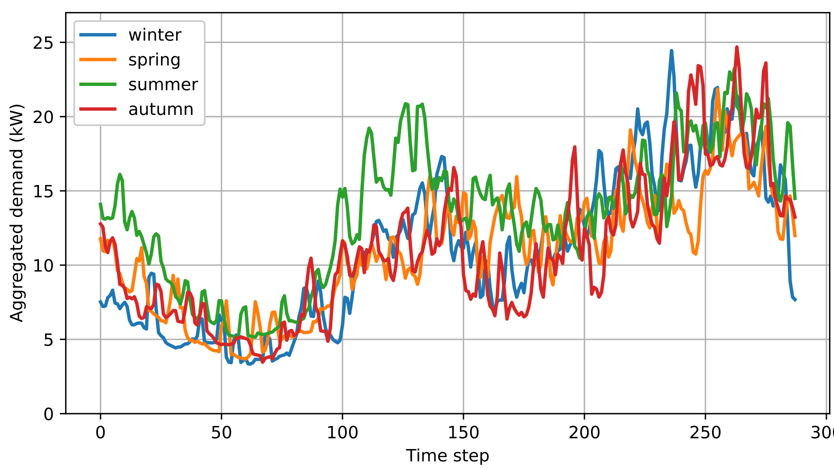
Fig. 4 shows the resulting aggregated electricity demand estimated for the residential building, including both fixed and flexible loads of each end-user. Approximately, this aggregated yearly demand counts for around 101.52 MWh, corresponding to about 2.54 MWh/year for each household, close to the average yearly consumption of Italian households as depicted by the Italian Regulatory Authority for Energy, Networks, and Environment [43].

Table 1
List of considered home appliances (derived from[10]).

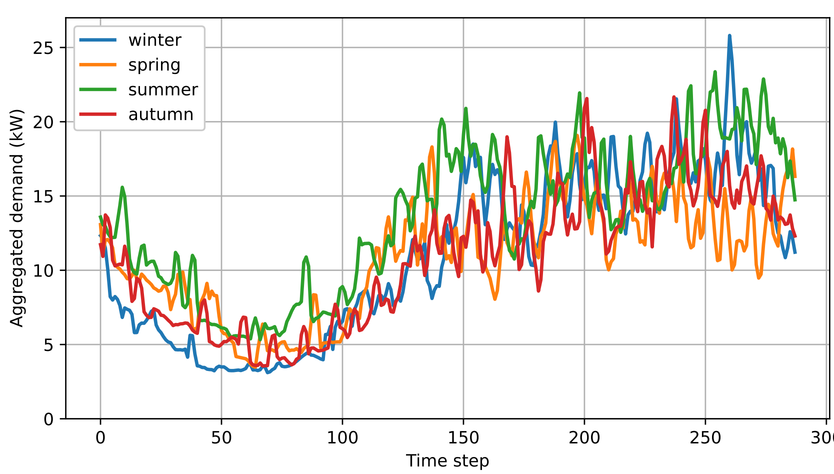
Appliance	Programmable
Vacuum cleaner	No
Dishwasher	Yes
Washing machine	Yes
Tumble drier	No
Audio-video devices	No
Other devices	No
Lighting	No

A focus on a given end-user is presented in Fig. 5, where fixed demand (blue line) and the consumption of programmable appliances (orange and green lines) are highlighted. It can be noticed how flexible loads usually have a duty cycle that can be anticipated or delayed with respect to the habits.

On the other hand, as mentioned in Section 4.3, PV production is assumed as a function of the PV size and the solar irradiance to take into account the effect of the solar beam at the location of the case study. Specifically, PV size was estimated a priori by using the criteria presented in [28], but assuming no flexible demand. In this light, the PV size is calculated on an energy basis according to the simultaneous maximization of the self-consumption (SS) and self-sufficiency (SC) for the energy community, so that the chosen PV size ensures the lowest dis-



(a) Week days.



(b) Weekend days.

Fig. 4. Aggregated demand for the residential building by season and daytype.

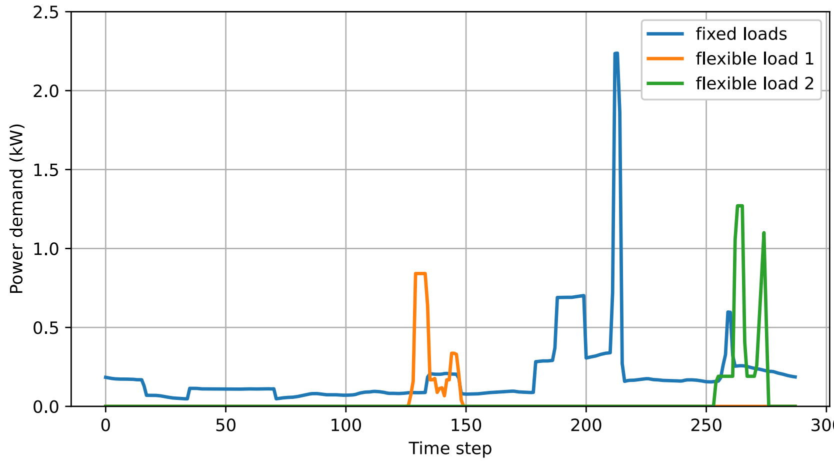


Fig. 5. Example of fixed and flexible loads of an end-user in the case study.

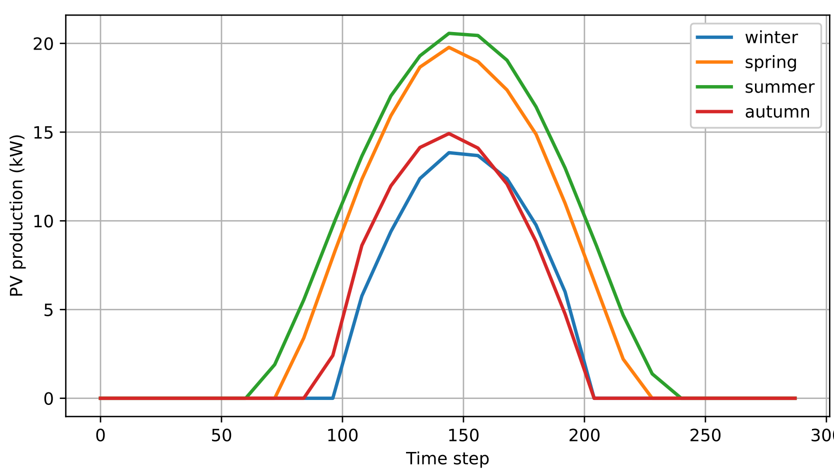


Fig. 6. PV production of the plant designed for the case study.

tance with respect to the Utopia point in the $SC - SS$ plane. The maximum PV size is also limited to 70kW$_p$ due to the available roof surface of the residential building being studied [22]. The aim of this energy-based sizing approach is to identify a plausible RES asset already available within the energy community, so this study does not explore the economic feasibility of the PV as a new installation that should be eventually considered in an investment perspective. Of course, since fixed and flexible loads are on a daily basis, PV production was estimated on the same time-frame considering different reference days, to limit the computational effort in simulating the proposed model.

Since the use-case considered is a residential multi-family building located in the North-West of Italy, the installed PV capacity for maximizing both SS and SC of monocrystalline modules is equal to 40 kW$_p$, according to the sizing approach in [22], where an azimuth and tilt angle of zero and 30 ° are considered, respectively. Fig. 6 shows the resulting production profiles in the different seasons and assumed as references for the analysis. As a result, the PV production is approximately close to 45.3 MWh/year for a South-oriented plant with an optimal tilt angle.

The resulting PV size was then considered to identify the reference configuration for the case study where the energy community exploits the RES production for increasing local self-consumption but without flexible demand or BESS.

Starting from this reference configuration, namely Scenario 0, without a battery energy storage system (BESS), the other scenarios being studied are summarized in Table 2. These scenarios are introduced to bring out the comparison of the flexible demand with the alternative solution offered by the integration of a BESS and its management. Both are in fact capable of increasing the energy sharing in REC adopting the CSC scheme, although the former can be potentially implemented without additional investment in a new energy asset (i.e. the BESS).

Table 2
PV and BESS size in different Scenarios.

Scenario	0	1	2	3	4
PV	✓	✓	✓	✓	✓
BESS (kWh)	-	-	15	30	30
DM	-	✓	-	-	✓

Specifically:

- Scenario 1 is introduced to highlight the impact of flexible demand in a CSC scheme. In this Scenario, dishwashers and washing machines are the household's appliances whose consumption patterns are considered to be potentially modified by end-users following the suggestion figured out from the optimization;
- Scenarios 2 and 3 focus on the impact of BESS management with increased storage capacities of 15 kWh and 30 kWh, without flexible demand.
- Scenario 4 is further included to exploit also potential interaction between the two different flexibility approaches within the energy community.

Regarding Scenario 2, the sizes of 15 kWh and 30 kWh were chosen based on two different simplified energy-design approaches derived from [30]. The first approach focuses on the need to fully store daily PV overproduction during the worst-case condition, which typically occurs on summer reference days when higher energy injection into the grid is around 29 kWh. In this condition, the entire surplus from the PV system is expected to be stored in the BESS, even on non-summer days, to enhance energy sharing. However, this approach anticipates a reduced BESS utilization factor, defined as the ratio between the average daily PV overproduction and the size of the BESS, at around 60 %. Conversely, the second design approach aims to store an average PV surplus, calculated as the mean between the reference winter and summer days, which have lower and higher PV overproduction, respectively. In this condition, the PV surplus is expected to be fully stored in the BESS during winter, but only partially stored during summer days and on other reference days. This results in a decrease in energy sharing but increases the BESS utilization factor to approximately 85 %. As a result, the lower BESS capacity of 15 kWh is assumed to increase the average daily usage rate of the battery and consequently its economic sustainability. While the higher capacity of 30 kWh aims to minimize the energy injected into the national grid while maximizing energy sharing and economic incentives.

The main BESS characteristics considered in the simulations are finally reported in Table 3. In this case, a charging/discharging efficiency of 90 % is assumed for lithium based technology, the rated fully charging and discharging time are equal to 3 hours, while the self-discharge effect is substantially neglected.

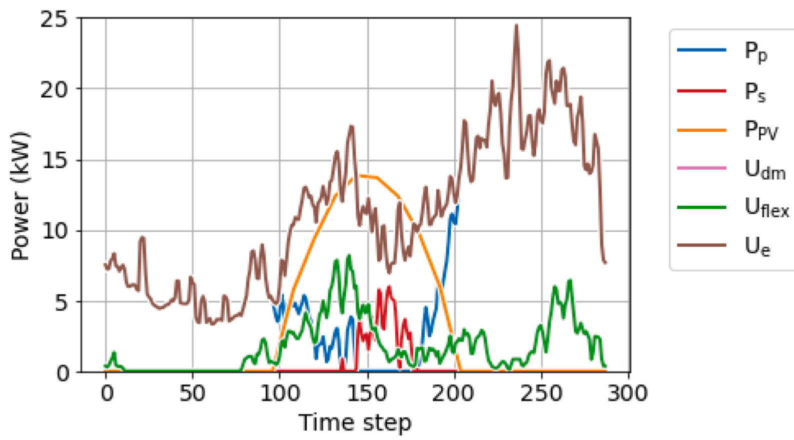
Table 3
BESS characteristics assumed in the simulations (data from Italian TSO [44]).

η_c	η_d	η_{sd}	T_c (h)	T_d (h)
0.9	0.9	1	3	3

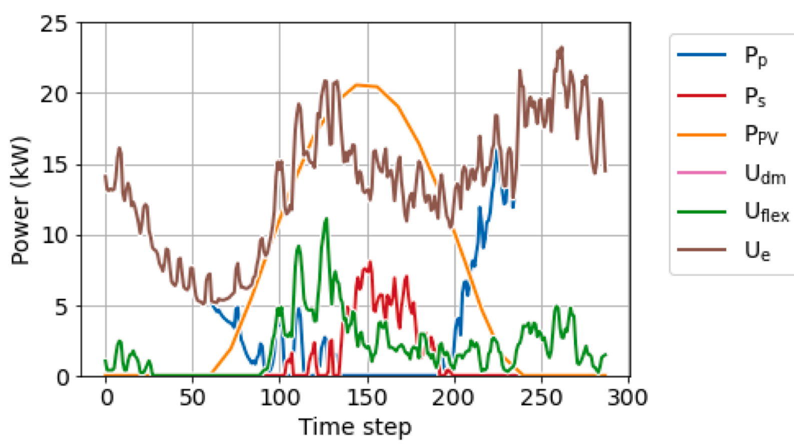
7. Results

The assessment of flexible demand in an energy community with a collective self-consumption configuration is presented in this section. Results without flexible demand and BESS are briefly reported in Fig. 7 as reference. It can be noticed how the mismatch between RES overproduction and demand creates power injection P_s into the National grid especially during summer days, with smaller economic benefits for the community. These injections are valued at zonal market prices, but they can not benefit from the incentives for the energy sharing of RES production. Flexible demand, as well as BESS, can instead reduce the mismatch increasing economic gains, as well as the environmental ones.

Table 4 shows the energy, economic, environmental, and social KPIs obtained by the different Scenarios. From the energy point of view, the SC and SS indexes refer to the same yearly energy production from PV and the same yearly energy demand from the residential building



(a)



(b)

Fig. 7. Results for Scenario 0 in a) winter and b) summer.

Table 4
KPIs obtained for different Scenarios maximizing energy sharing.

	Scenario				
KPI	0	1	2	3	4
SC (%)	83.2	95.9	90.6	94.5	99.2
SS (%)	37.2	42.8	40.5	42.2	44.3
PCR (%)	–	4.6	2.7	4.1	5.7
ΔCO_2 (%)	–	9.0	5.7	8.5	11.4
Dis (min)	0	206	0	0	214

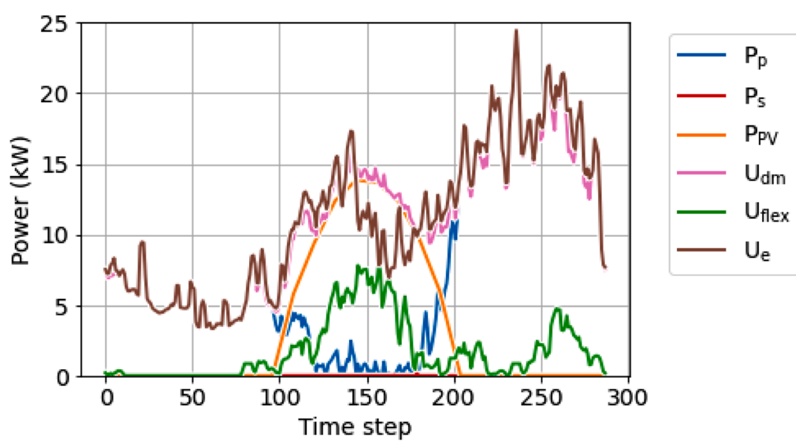
(i.e., respectively 45.3 MWh/year and 101.52 MWh/year, as depicted in Section 6). Relative cost and emission savings (namely PCR and ΔCO_2) refer instead to the yearly cost and the yearly CO_2 emission of about 13,885 e and 25.88 tCO_2 obtained for Scenario 0, as discussed in Section 5.

Table 5 summarizes instead the main energy flows exchanged by the CSC both internally and with the National grid, where E_p, E_s and E_{sh} are the yearly electricity injected into the grid, the electricity taken from the grid and the shared one, respectively. It can be noticed that flexible demand in Scenario 1 has a positive impact from the economic, energy, and environmental point of view. In fact, the shift of energy consumption for programmable appliances can improve the match of the demand with PV production. In other words, the aggregated demand of the flexible loads U_{flex} should preferably occur during PV production, leading end-users to more virtuous behaviors from the energy community perspective.

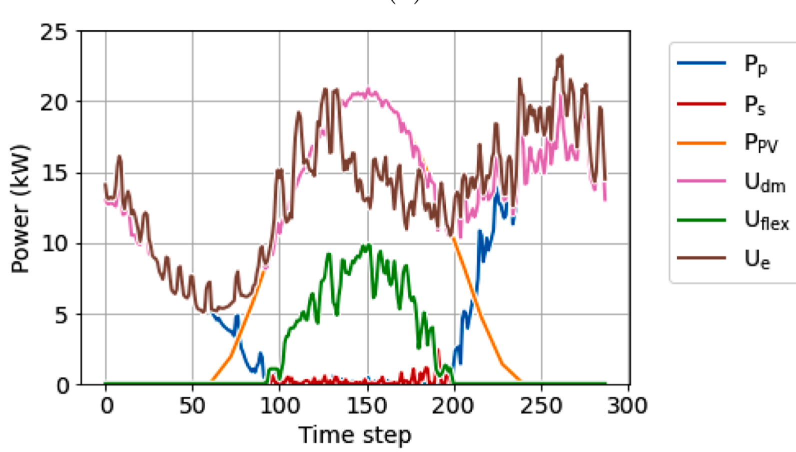
Table 5
Energy results obtained for different Scenarios expressed as MWh/y.

Scenario	0	1	2	3	4
E_{sh}	37.7	43.5	41.1	42.9	44.9
E_s	7.6	1.9	2.9	0.8	0.0
E_p	63.8	58.0	60.2	58.3	56.5

In fact, as depicted in Fig. 8 for winter and summer days, the optimization suggests modifications in the usual users' habits, so the aggregated demand increases during daylight, while progressively decreasing during nighttime. In particular, the whole flexible demand U_{flex} is shifted during daylight in summer (see Fig. 8b). Consequently, self-consumption and self-sufficiency can be enhanced up to 12.7 % and 5.6 %, respectively. The resulting net load is then significantly reduced during the daytime so that RES production is mainly self-consumed within the community and not injected into the grid. Contemporarily, shared energy E_{sh} improves by about 15 %, while electricity injected and withdrawn to/from the grid decreases by 75 % and 9 % if compared to Scenario 0, respectively. The energy costs (i.e. the energy bills) as well as the CO_2 emission can instead be reduced by 4.6 % and 9 %, making the more sustainable and environment-friendly the CSC scheme from the member's point of view. Thus, the environment can also exploit lower externalities up to around 245e/year assuming a CO_2 external cost of 109e/tCO_2 [45]. Clearly, the positive economic impact due to bill cost savings can also contribute to increase cash flows, making more sustainable the PV investment for the community. On the other hand, as



(a)



(b)

Fig. 8. Results for Scenario 1 in a) winter and b) summer.

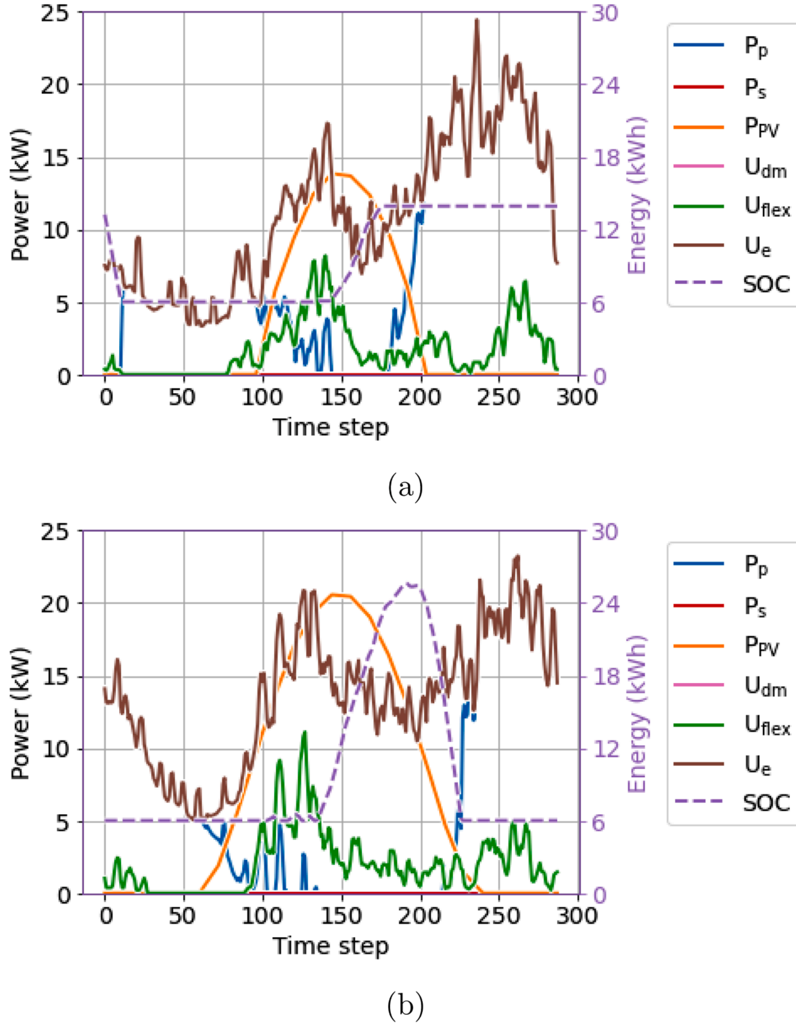


Fig. 9. Results for Scenario 3 in a) winter and b) summer.

expected, social KPI worsen since users should either postpone or move up their consumption by about 206 minutes on average.

Similar benefits can be gained in Scenarios 2 and 3 by optimally managing BESS to increase self-consumption, as noticed in Table 4 and 5. Of course, the greater the battery size the better the KPIs improvement from all perspectives. In fact, although flexible demand is not considered in these scenarios, the integration of a BESS with a rated capacity of 15 and 30 kWh can contribute to reaching high levels of SC and SS up to 95 % and 42 % respectively, while cost and emission savings can be increased up to 4.1 % and 8.5 %. As a result, the energy sharing increases as well up to 42.9 MWh/y, while energy injected to and withdrawn from the National grid decreases down to 89 % and 9 % with respect to Scenario 0. Nevertheless, this approach needs of the installation of a costly asset (i.e. a stationary battery) while the end-users' behavior is not involved at all (i.e., social KPI is zeroed in Table 4). Additionally, BESS needs to be replaced once its technical life cycle is reached, making not yet totally profitable its usage in residential applications without the adoption of incentives [6,46]. In fact, considering the yearly aggregated energy demand, the electricity tariff, the BESS cost [28] and the cost savings for these scenarios, the resulting simple pay-back time for BESS installation ranges from 9.7 to 12.6 years close to the technical lifetime of a stationary battery [47].

Fig. 9 presents an example on how optimal management of BESS contributes in increasing energy sharing: PV overproduction is stored by increasing battery SoC, and then BESS is discharged later to cover the demand of the building, so that the net demand decreases.

Additionally, when the interaction of the two different flexibility approaches is considered (i.e., Scenario 4), all the KPIs benefit from the flexible demand. In fact, despite in Scenario 1, 2, and 3 the flexible demand and BESS prevent PV overproduction from being injected into the national grid and thus sustain the energy sharing, a residual PV surplus is still not locally exploited within the CSC scheme (see E_s for Scenario 2 and 3 on Table 5). In fact, some reference days, such as the spring one, have low electricity demand from the building compared to the PV production (see Fig. 10a and b). The increase in energy sharing, which corresponds to lower power injection P_s into the national grid, can be then performed by combining BESS and flexible demand (see Fig. 10c). In this case, a full self-consumption of PV production is almost reached, while cost and emissions savings can be close to 5.7 % and 11.4 %, respectively. Nevertheless, BESS costs still make not profitable this option.

Thus, from the economical point of view, changing in users' habits has to be preferred instead of BESS usage. In contrast, discomfort rate increases as highlighted by a higher social KPI in Table 4. But, if a BESS is already installed in the REC configuration lower utilization factor is performed thanks to flexible demand, ensuring a longer BESS technical lifetime, and postponing the need to invest in its replacement [30].

7.1. Multi-objective

Despite the promising results offered by the flexible demand, even in combination with BESS usage, load shifting inevitably suffers of high

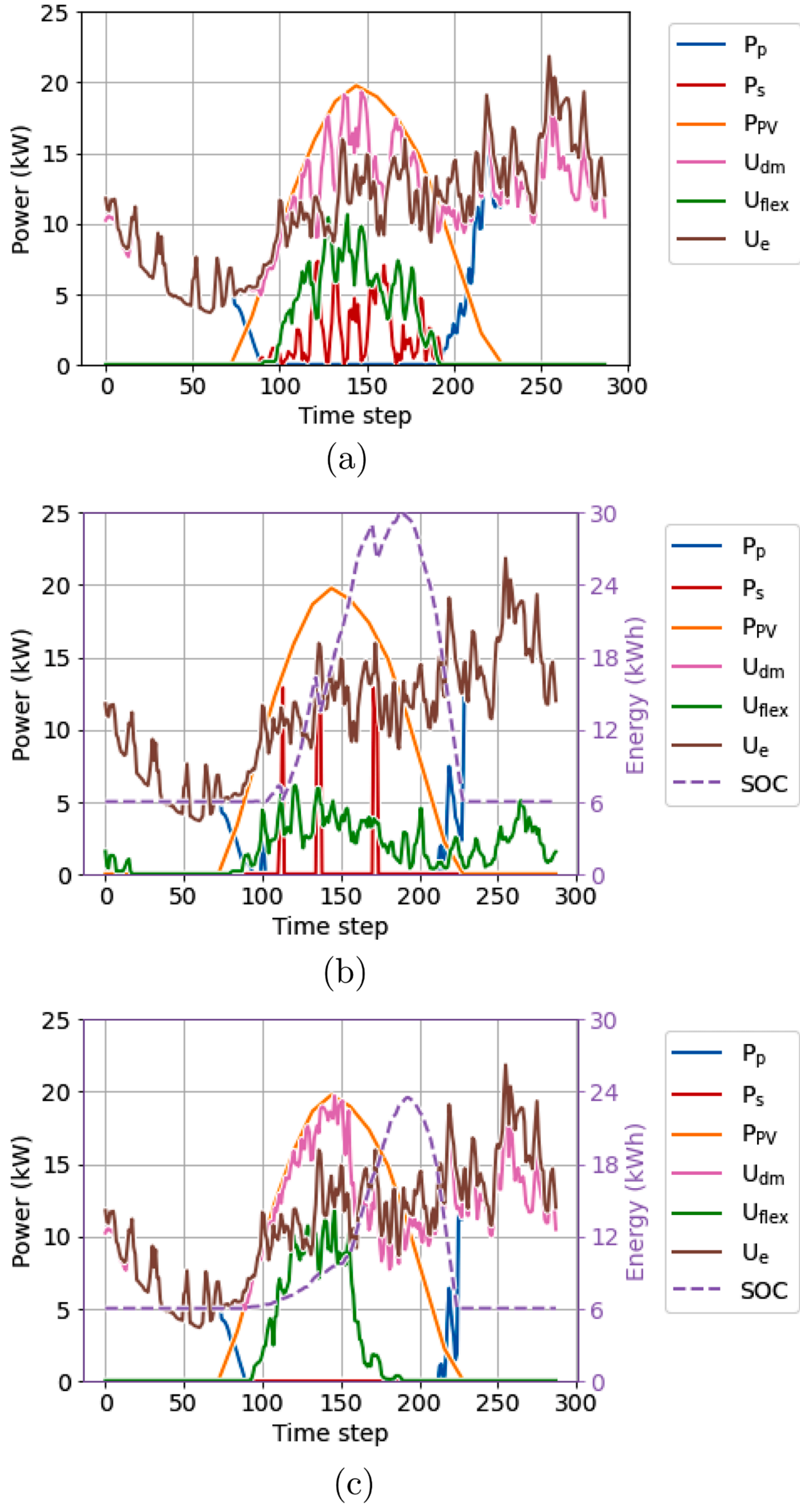


Fig. 10. Results for Scenario 1, 3 and 4 during spring.

social KPI, because end-users should somehow change their habits, even significantly. The simulation of the multi-objective problem presented in Section 4.6.1 is then necessary to explore the impact of different end-users' availability in changing their habits for following or adopting flexible demand. Practically, different end-users' adaptability can be explored by considering different weights α in Eq. (21): the smaller the α value, the lower willingness to participate in flexible demand, and vice versa. In fact, when α is zeroed OF_1 does not influence the problem, hence end-users' discomfort leads to solutions where essentially flexible demand is not accepted. In contrast, when α is equal to one, end-users' discomfort OF_2 is neglected.

Fig. 11 shows the corresponding Pareto front achieved considering different α values for Scenario 1 according to the weighted sum method of Eq. (21). It can be noticed that combining end-user discomfort (i.e. OF_2) with the energy objective function (i.e. OF_1) has a significant impact in reducing average time-shifting for programmable appliances, even with higher α values (i.e., when discomfort is less influencing the solution).

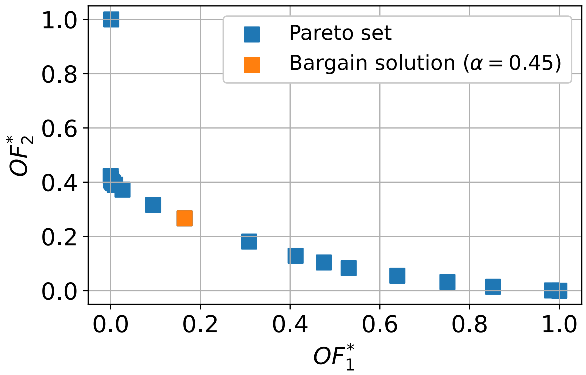


Fig. 11. Pareto front obtained for Scenario 1 highlighting a selected bargain solution.

As summarized in Table 6 and Fig. 11, the average time-shifting for the household appliances is promptly reduced from 206 to 88 minutes when α is just equal to 0.95, while energy, economic and environmental KPIs are very slightly worse if compared to the solution where the energy sharing (i.e. OF_1) is the only target (see Table 4).

This reveals that higher energy, economic, and environmental performances can be still gained through flexible demand, while considering the end-users preferences. This result confirms the coexistence of multiple equivalent solutions that can maximize self-consumption, as mentioned in Section 4.6.

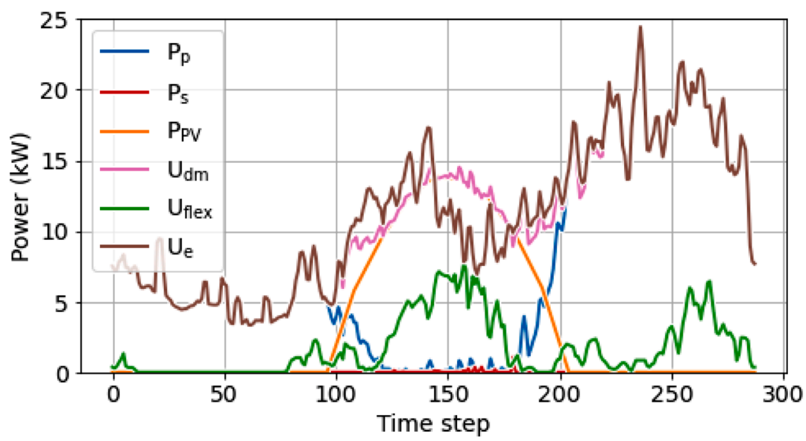
Table 6 shows also the results of the multi-objective simulation for Scenario 1 considering other weights. The greater is α the better the economic, environmental, and energy KPIs, while worsening the social KPI with higher discomfort. Correspondingly, the net load (measured by the energy exchanged with the National grid E_p and E_s), and the energy self-consumed within the CSC (measured by E_{sh}) increase when OF_2 (i.e., end-user discomfort) is weighting more than the OF_1 (i.e., self-sufficiency) (see Table 7).

Table 6
KPIs obtained for Scenario 1 considering different weights in multi-objective simulation.

	α				
KPI	0.95	0.7	0.5	0.3	0.05
SC (%)	95.8	95.8	94.7	89.9	83.4
SS (%)	42.7	42.7	42.3	40.2	37.3
PCR (%)	4.5	4.5	4.1	2.4	0.1
ΔCO_2 (%)	8.9	8.9	8.2	4.7	0.1
Dis (min)	88	83	66	22	0.2

Table 7
Energy results obtained for different α in Scenario 1 expressed as MWh/y.

	α				
	0.95	0.7	0.5	0.3	0.05
E_{sh}	43.4	43.4	42.9	40.8	37.8
E_s	1.8	1.8	2.4	4.9	7.5
E_p	58.0	58.0	58.6	60.0	0.1



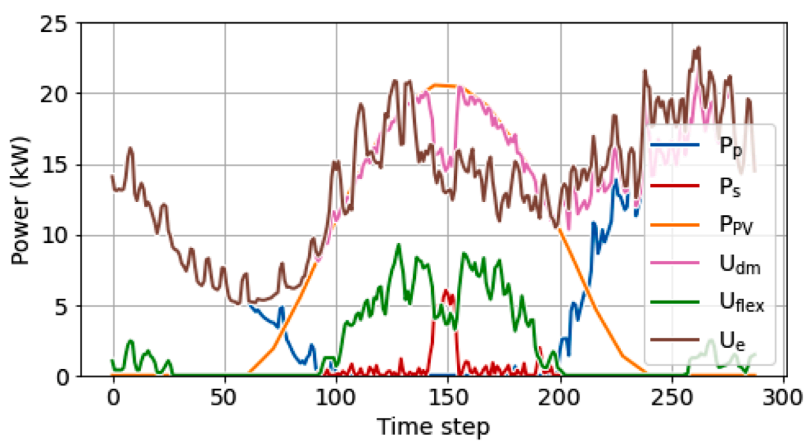


Fig. 12. Results for the bargain solution of Scenario 1 in a) winter and b) summer.

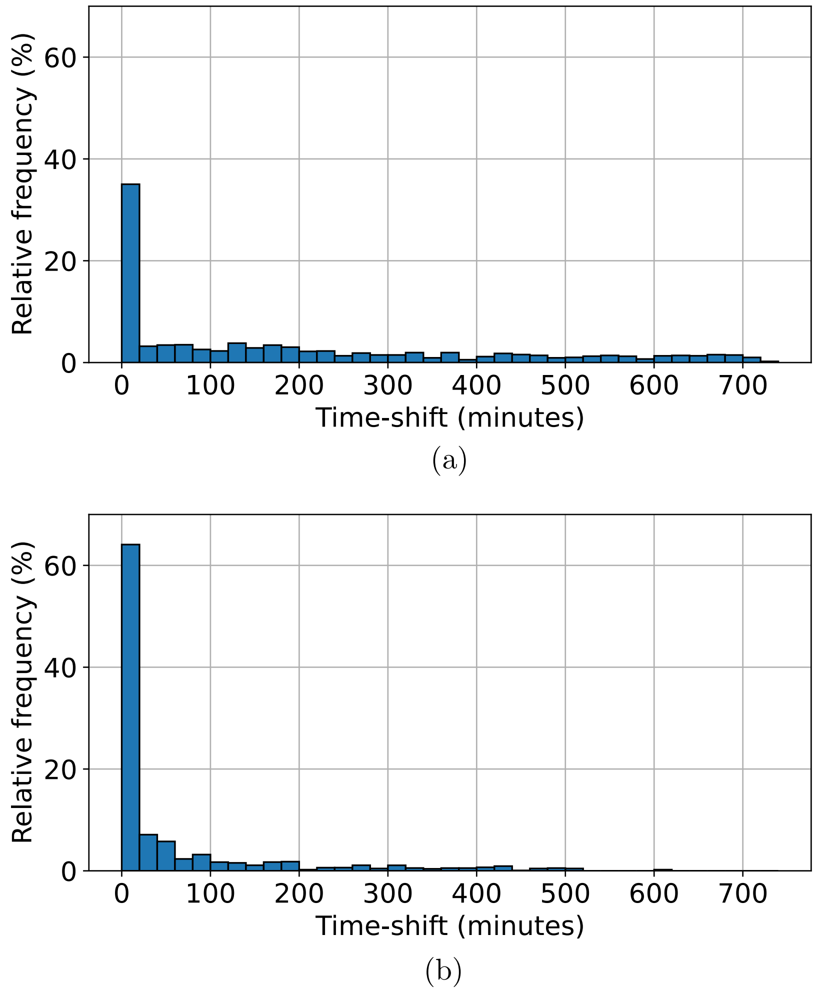


Fig. 13. Relative frequency of the time-shifting for the programmable appliances occurring in Scenario 1 with a) $\alpha = 1$ and b) $\alpha = 0.45$.

Indeed, these results suggest that some trade-off solutions are achievable where end-users acceptance or availability in adopting flexible demand is only partially agreed. Starting from the approach proposed in Section 6 for the PV sizing [28], a similar methodology can be considered here for finding a bargain solution. This compromise solution mediates the need to maximize the energy sharing of RES production (i.e., to reduce bill costs and CO_2 emissions) and the social need to minimize discomfort (i.e., maintain users' current habits in managing programmable loads).

In this way, the non-dominated solution of the Pareto front closest to the Nadir point with $\alpha = 0.45$ can be a reasonable candidate. It can be noticed from Fig. 12 that flexible demand for this bargain solution basically does not shift the consumption of all programmable appliances from the evening to the daylight. This is even more evident during the summer reference day (see Fig. 12b), where PV overproduction is injected into the National grid in the middle of the day. As a consequence, considering that the number of programmable appliances is 59 for the case study, the average number of appliances potentially being involved in flexible demand changes from 54, when $\alpha = 1$, to 33 when $\alpha = 0.45$. This suggests that, in the proposed bargain solution, only the appliances usually used during daylight (i.e., during PV production) are expected to be involved in rescheduling their demand. Otherwise, appliances used at nighttime are less or not considered. The comparison, for instance, of the aggregated flexible demand U_{flex} (green line) in Figs. 12a and 8a confirms this suggestion for the barging solution.

Fig. 13 gives a similar outlook but with higher granularity. It is noticeable, in fact, that the relative frequency distribution of time-shifting changes in the bargain solution for the programmable appliances (see Fig. 13a) compared to the solution where all end-users agreed to follow flexible demand suggestions (see Fig. 13b). An increase of about 35 % of small time-shifting (usually lower than 20 minutes) can be observed, with a corresponding reduction of all those higher than 100 minutes.

Table 8
KPIs obtained for Scenario 1 by the bargain solution ($\alpha = 0.45$) and the full flexible demand ($\alpha = 1$).

	α	
KPI	1	0.45
SC (%)	95.9	93.7
SS (%)	42.8	41.9
PCR (%)	4.6	3.8
ΔCO_2 (%)	9.0	7.5
Dis (min)	206	55

Nevertheless, as depicted in Table 8 positive results can be still obtained. In fact, all the economic, energy, and environmental KPIs are still close to the one achievable if discomfort is neglected (i.e. $\alpha = 1$, while the average time-shift of the programmable appliances is reduced by almost four times. For instance, self-consumption is just reduced by around 2.2 % in the bargain solution, but the average time-shifting passes from 206 to 55 minutes. This, once again, reveals that end-users' acceptability can be thus promoted to increase the willingness to participate in flexibility [9].

7.2. Limits of the study

The findings presented in this paper aim to illustrate the necessity of improving the match between renewable energy generation and demand within energy communities established in residential buildings. These findings emphasize that such improvements can be achieved by altering consumption habits rather than by investing in currently expensive storage systems.

However, it is important to note that these results concern to a specific context (Italy), reflect average user habits, and assume that all users have the same willingness to engage in flexible demand. Additionally, the model used to describe the behavior of photovoltaic (PV) systems, while valid, is simplified. It consolidates the impact of temperature variations on the modules and inverter efficiency into a single metric the performance ratio (PR). However, since the yearly electricity consumption of the building is supposed here to be represented by 8 reference days, this simplistic approach is still valuable. In reality, PV production as well as inverter efficiency can vary significantly across different regions of the country due to temperature variation. Thus, if simulation of energy consumption involved a wider time frame (i.e., weekly or monthly) temperature effect should be taken into account.

Given these limitations, a more comprehensive study could be conducted in the future. Such a study would consider the uncertainties related to consumption habits and users' willingness to participate in flexible demand [18], as well as the application of these approaches on a larger scale, taking regional temperature effects into account [48].

8. Conclusion

Energy communities represent a great opportunity to promote self-consumption of RES-based production with lower operational costs, as they foster sustainability, economic competitiveness, and reduction of energy poverty. In this context, energy flexibility plays an important role because it can increase the match between energy consumption and production. Classically, storage systems are considered for decoupling the time of energy production from the demand, so that overproduction can be stored and released when needed, leaving the customers' habits unchanged.

As stationary energy storage is still costly, a complementary approach based on the flexible demand was considered in this study, by promoting changes in consumption habits that may be proposed to end-users of an energy community. In particular, a Mixed Integer Linear Programming formulation is proposed here to model the flexible demand of the programmable electric appliances used by residential end-users joining an energy community under the Italian regulatory framework. Eventually, the cooperation of both flexibility solutions is also explored to better understand the potential integration of these systems.

An Italian residential multi-family building, with 40 flats and a $40kW_p$ PV plant in its premises, is assumed to exploit the energy, economic, and environmental benefits of flexibility due to flexible demand. On the other hand, the social aspect, measured by end-users discomfort, was also evaluated to highlight how the load-shifting suggested by the optimization for some appliances impacts the households' consumption habits.

The simulations found that flexible demand can effectively encourage energy sharing within a community, resulting in a significant increase in local self-consumption from 83 % to 96 % and leading to a reduction in energy costs and CO_2 emissions by 4.6 % and 9.1 %, respectively. It is important to highlight how these results could be obtained without investing in additional energy assets, but just adopting different energy habits. However, the social aspect is negatively affected, as achieving these results requires a significant change in end-users behavior. In fact, members of the community need to postpone or anticipate the usage of programmable appliances by an average of more than 3 hours.

Differently, the use and management of a 30 kWh battery storage system, without flexible demand, can result in similar benefits in terms of energy, economics, and environmental KPIs, while maintaining the user's energy usage habits. In this case, the cost and emission savings reach almost 4.1 % and 8.5 %. However, the costs of investing in and operating battery systems are currently higher, making it less profitable for implementation within the energy community, since payback period can be estimated in around 12 years close to the BESS technical lifetime. This reveals also how the adoption of flexible demand without BESS could be a solution in all those contexts suffering energy poverty (i.e., investment in storage solution is not sustainable), but better economic benefits can be exploited for all the members of the community. Furthermore, interoperability between battery and flexible demand can be supported, as storage units can be potentially undersized while improving energy, environmental, and economic performance indicators.

Therefore, while flexible demand may be more economically attractive, the main challenge in adopting this solution is related to household discomfort as end-users have to adjust their consumption according to a more community-based goal. To evaluate the impact of different levels of willingness to participate in flexible demand a multi-objective simulation was conducted. The simulation used the weighted sum method to balance the maximization of economic benefit and the minimization of end-users' discomfort. The results revealed that a Pareto set of non-dominated solutions could be found, which would lead to a potential trade-off solution. This bargain solution would require programmable appliances to shift the usage by less than one hour on average, but would still offer performances from the energy, economic, and environmental point of view close to the ones gained when all the members of the community fully participate in flexible demand. Specifically, the bargain solution would achieve self-consumption, cost, and emission savings close to 94 %, 4 %, and 7.5 %, respectively.

In conclusion, flexible demand is an effective way to encourage the efficacy of new renewable energy communities. This flexible approach motivates consumers to participate more actively and gain a better understanding of the ongoing energy transition by adopting positive energy habits. Of course, digitalization has to be integrated in the energy community to measure energy consumption and production, simulate the system and then to provide suggestions to end users. The results obtained for the Italian reference residential building can be applied to other contexts using the methodology proposed here. However, it is important to note that these results are heavily influenced by the existing regulatory framework that supports and incentivizes shared energy. Additionally, the willingness of users to adjust their consumption habits in line with production from renewable sources plays a significant role in the outcomes. In situations where shared energy is not incentivized or where users are resistant to changing their habits, the effectiveness of flexible demand may be limited, making solutions that include storage more attractive.

A future development of this work will regard how to share the benefits of the energy community among consumers, granting to those available to change their habits a larger portion of the REC revenues. Moreover, better economic results could be potentially gathered by including other programmable loads, such as the charging sessions of electric vehicles. An increasing future diffusion of e-mobility will facilitate the introduction of a smart-charging process improving flexibility and reducing costs.

CRediT authorship contribution statement

Paolo Lazzeroni: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization; **Gianmarco Lorenti:** Writing – original draft, Visualization, Methodology, Data curation; **Aldo Canova:** Writing – review & editing, Validation, Supervision, Formal analysis; **Maurizio Repetto:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization.

Data availability

Data will be made available on request.

Declaration of interests

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.

References

[1] European Commission, Energy communities. https://energy.ec.europa.eu/topics/markets-and-consumers/energy-communities_en.

[2] European Parliament, 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. https://eur-lex.europa.eu/eli/dir/2018/2001/oj.

[3] M.H. Bashi, L.D. Tommasi, A.L. Cam, L.S.R. no, P. Lyons, J. Mundó, I. Pandelieva-Dimova, H. Schapp, K. Loth-Babut, C. Egger, M. Camps, B. Cassidy, G. Angelov, C.E. Stancioff, A review and mapping exercise of energy community regulatory challenges in european member states based on a survey of collective energy actors, Renew. Sustain. Energy Rev. 172 (2023) 113055.

[4] M. Abdunnabi, N. Etiab, Y.F. Nassar, H.J. El-Khozondar, R. Khargotra, Energy savings strategy for the residential sector in libya and its impacts on the global environment and the nation economy, Adv. Build. Energy Res. 17 (4) (2023) 379–411.

[5] A. Abdulgader, A. Emad, A.A. Ali, K. Mohamed, Y.F. N, H.J. E.-K, Optimal sizing of hybrid renewable system for residential appliances, in: 2024 IEEE 4th International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering, MI-STA, 2024, pp. 290–295.

[6] B. Zakeri, S. Cross, P. Dodds, G.C. Gissey, Policy options for enhancing economic profitability of residential solar photovoltaic with battery energy storage, Appl. Energy 290 (2021) 116697.

[7] P. Lazzeroni, I. Mariuzzo, M. Quercio, M. Repetto, Economic, energy, and environmental analysis of pv with battery storage for italian households, Electronics 10 (2021) 146.

[8] A. Manso-Burgos, D. Ribó-Pérez, T. Gómez-Navarro, M. Alcázar-Ortega, Local energy communities modelling and optimisation considering storage, demand configuration and sharing strategies: a case study in Valencia (Spain), Energy Rep. 8 (2022) 10395–10408.

[9] J. Barnes, P. Hansen, T. Kamin, U. Golob, M. Musolino, A. Nicita, Energy communities as demand-side innovators? assessing the potential of European cases to reduce demand and foster flexibility, Energy Res. Soc. Sci. 93 (2022) 102848.

[10] S. Panda, S. Mohanty, P.K. Rout, B.K. Sahu, M. Bajaj, H.M. Zawbaa, S. Kamel, Residential demand side management model, optimization and future perspective: a review, Energy Rep. 8 (2022) 3727–3766.

[11] E. Shirazi, S. Jadid, Cost reduction and peak shaving through domestic load shifting and ders, Energy 124 (2017) 146–159.

[12] S. Golshannavaz, Cooperation of electric vehicle and energy storage in reactive power t compensation: an optimal home energy management system considering pv presence, Sustain. Cities Soc. 39 (2018) 317–325.

[13] M. Parvania, M. Fotuhi-Firuzabad, M. Shahidehpour, Optimal demand response aggregation in wholesale electricity markets, IEEE Trans. Smart Grid 4 (2013) 1957–1965.

[14] B. Lokeshgupta, S. Sivasubramani, Multi-objective home energy management with battery energy storage systems, Sustain. Cities Soc. 47 (2019) 101458.

[15] E.D. Cin, G. Carraro, G. Volpato, A. Lazzaretto, P. Danieli, A multi-criteria approach to optimize the design-operation of energy communities considering economic-environmental objectives and demand side management, Energy Convers. Manage. 263 (2022) 115677.

[16] M. Sangaré, E. Bourreau, B. Fortz, A. Pachurka, M. Poss, Loads scheduling for demand response in energy communities, Comput. Oper. Res. 160 (2023) 106358.

[17] M. Tostado-Véliz, S. Kamel, H.M. Hasanien, R.A. Turky, F. Jurado, Optimal energy management of cooperative energy communities considering flexible demand, storage and vehicle-to-grid under uncertainties, Sustain. Cities Soc. 84 (2022) 104019. https://doi.org/10.1016/j.scs.2022.104019.

[18] M.S. Simoiu, I. Fagarasan, S. Ploix, V. Calofir, Modeling the energy community members' willingness to change their behaviour with multi-agent systems: a stochastic approach, Renew. Energy 194 (2022) 1233–1246. https://doi.org/10.1016/j.renene.2022.06.004.

[19] S. Hagejärd, G. Dokter, U. Rahe, P.F. ás, It's never telling me that i'm good!" household experiences of testing a smart home energy management system with a personal threshold on energy use in Sweden, Energy Res. Soc. Sci. 8 (2023) 103004.

[20] G. Italiano, D. Legislativo, 2021. In Italian, https://www.gazzettaufficiale.it/eli/id/2021/11/30/21G00214/sg.

[21] G. Italiano, 2020. In Italian, https://www.gazzettaufficiale.it/eli/id/2020/02/29/20G00021/sg.

[22] A. Canova, P. Lazzeroni, G. Lorenti, F. Moraglio, A. Porcelli, M. Repetto, Decarbonizing residential energy consumption under the italian collective self-consumption regulation, Sustain. Cities Soc. 87 (2022) 104196.

[23] U. Rse, O. Book, Le Comunità Energetiche in Italia, 2021. In Italian, https://www.rse-web.it/wp-content/uploads/2022/02/OrangeBook-22-Le-Comunita-Energetiche-in-Italia-DEF.pdf.

[24] P. Lazzeroni, M. Repetto, H. Gabbar, 21 - introduction to energy management in smart grids, In: Vacca, J.R. (Ed.), Solving Urban Infrastructure Problems Using Smart City Technologies, Elsevier, 2021, pp. 447–473. https://doi.org/10.1016/B978-0-12-816816-5.00021-8.

[25] F. Gullì, P. Lazzeroni, G. Lorenti, I. Mariuzzo, F. Moraglio, M. Repetto, Recoupled: a simulation tool for renewable energy communities coupling electric and thermal energies, Econ. Policy Energy Environ. 2 (2022) 49–60.

[26] Joint Research Center, Photovoltaic geographical information system, https://re.jrc.ec.europa.eu/pvg_tools/en/#PVP.

[27] P. Lazzeroni, I. Mariuzzo, M. Quercio, M. Repetto, Economic, energy, and environmental analysis of pv with battery storage for italian households, Electronics 10 (2020) 146.

[28] A. Cielo, P. Margiaria, P. Lazzeroni, I. Mariuzzo, M. Repetto, Renewable energy communities business models under the 2020 italian regulation, J. Clean. Prod. 316 (2021) 128217.

[29] A.M. Khalid, I. Mitra, W. Warmuth, V. Schacht, Performance ratio - crucial parameter for grid connected pv plants, Renew. Sustain. Energy Rev. 65 (2016) 1139–1158. https://doi.org/10.1016/j.rser.2016.07.066.

[30] F. Minuto, P. Lazzeroni, R. Borchiellini, S. Olivero, L. Bottaccioli, A. Lanzini, Modeling technology retrofit scenarios for the conversion of condominium into an energy community: an Italian case study, J. Clean. Prod. 130 (2021).

[31] F. Freschi, L. Giaccone, P. Lazzeroni, M. Repetto, Economic and environmental analysis of a trigeneration system for food-industry: a case study, Appl. Energy 107 (2013) 157–172.

[32] Italian Regulatory Authority for Energy, Networks and Environment, Composizione percentuale del prezzo dell'energia elettrica per un consumatore domestico tipo, https://www.arera.it/it/dati/ees5.htm.

[33] Italian Regulatory Authority for Energy, Networks and Environment, Definizione, Ai Sensi Del Decreto Legislativo 199/21 E Del Decreto Legislativo 210/21, Della Regolazione Dell'autoconsumo Diffuso, in: Approvazione del Testo Integrato Autoconsumo Diffuso, 2023. https://www.arera.it/it/docs/22/727-22.htm.

[34] M. Lage, R. Castro, G. Manzolini, V. Casalicchio, T. Sousa, Techno-economic analysis of self-consumption schemes and energy communities in italy and portugal, Sol. Energy 270 (2024) 112407.

[35] C.A. Floudas, Nonlinear and Mixed-Integer Optimization: Fundamentals and Applications, Oxford University Press, 1995.

[36] K.K. Annamdas, S.S. Rao, Multi-objective optimization of engineering systems using game theory and particle swarm optimization, Eng. Optim. 41 (2009) 737–752.

[37] Iea, Photovoltaic Power Systems Programme - A Methodology for the Analysis of PV Self-Consumption policies, 2016. https://iea-pvps.org/wp-content/uploads/2020/01/IEA-PVPS_-_A_methodology_for_the_Analysis_of_PV_Self-Consumption_Policies.pdf.

[38] A.A. Hafez, Y.F. Nassar, M.I. Hammdan, S.Y. Alsadi, Technical and economic feasibility of utility-scale solar energy conversion systems in Saudi Arabia, Iran J. Sci. Technol. Trans. Electr. Eng. 44 (2020) 213–225.

[39] G.G. Dei, M. Energetici, http://www.mercatoelettrico.org/It/Download/DownloadDati.aspx?Val=MGP_Prezzi.

[40] Istituto Superiore per la Protezione e la Ricerca Ambientale, Indicatori di efficienza e decarbonizzazione del sistema energetico nazionale e del settore elettrico, 2022. https://www.isprambiente.gov.it/files2022/pubblicazioni/rapporti/r363-2022.pdf.

[41] I. Ballarini, V. Corrado, F. Madonna, S. Paduos, F. Ravasio, Energy refurbishment of the Italian residential building stock: energy and cost analysis through the application of the building typology, Energy Policy 105 (2017) 148–160.

[42] Cadema, Household load profiler, https://github.com/cadema-PoliTO/household_load_profile.

[43] Italian Regulatory Authority for Energy, Networks and Environment Analisi dei consumi dei clienti domestici, https://www.arera.it/rapporti-e-relazioni/monitoraggio-retail/monitoraggio-retail-conclusioni-rapporto-2022/analisi-dei-consumi-dei-clienti-domestici.

[44] Terna, Study on Reference Techonologies for Electricity Storage, 2023. https://download.terna.it/terna/Study_on_electricity_storage_reference_technologies_8db99b53d98c32b.pdf.

[45] Estimating the external costs of industrial air pollution: trends, European Environment Agency, 2012.

[46] O. Alavi, J. Despeghel, W.D. Ceuninck, M. Meuris, J. Driesen, M. Daenen, Economic study of battery profitability in residential solar panel systems: a case study of Belgium, 2020 IEEE 14th International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG) 1 (2020) 358–363.

[47] C. Boennec, L. Albuquerque, B. Sareni, F. Lacressonnière, S.U. Ngueveu, Comparison of battery models integrating energy efficiency and aging for the design of microgrids, Smart Grids Sustain. Energy 9 (2024).

[48] K.A.A. Amer, M.A. Irhouma, M.I. Hamdan, A.A. Aqila, A. Ahmed, M.A. Fakher, A.R. Alkhazmi, Economic-Environmental-Energetic (3E) analysis of photovoltaic solar energy systems: case study of mechanical & renewable energy engineering departments at wadi alshatti university, Wadi AlShatti Univ. J. Pure Appl. Sci. 3 (2025) 50–58.