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Integrating Energy Generation and Demand in the Design and Operation Optimization of Energy Communities

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Abstract: The optimization of the energy system serving users' aggregations at urban level, such as Energy Communities, is commonly addressed by optimizing separately the set of energy conversion and storage systems from the scheduling of energy demand. Conversely, this paper proposes an integrated approach to include the demand side in the design and operation optimization of the energy system of an Energy Community. The goal is to evaluate the economic, energetic, and environmental benefits when users with different demands are aggregated, and different degrees of flexibility of their electricity demand are considered. The optimization is based on a Mixed-Integer Linear Programming approach and is solved multiple times by varying (i) the share of each type of user (residential, commercial, and office), (ii) the allowed variation of the hourly electricity demand, and (iii) the maximum permitted CO_2 emissions. Results show that an hourly flexibility of up to 50% in electricity demand reduces the overall system cost and the amount of energy withdrawn from the grid by up to 25% and 31%, respectively, compared to a non-flexible system. Moreover, the aggregation of users whose demands match well with electricity generation from renewable sources can reduce CO_2 emissions by up to 30%.

Keywords: energy community; decarbonization; MILP; multi-objective optimization; demand response; users aggregation

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1. Introduction

A sustainable energy transition is pivotal for limiting global warming to 1.5 °C by the end of the century and mitigating the increasingly evident consequences of climate change. One of the key drivers of this transition is the use of renewable energy sources. Although the competitiveness of renewables accelerates [1], large-scale deployment of these sources is hindered by (i) their low energy density compared to fossil fuels, i.e., the need for more space to generate the same amount of energy [2], and (ii) their intermittent and uncertain availability [3]. These challenges suggest moving from a central to a local generation of energy, called "distributed generation", in which renewable energy can be consumed as much as possible when and where it is generated. Moreover, renewable energy plants of smaller sizes can be exploited (lower energy to be provided to fewer users), thus simplifying the installation process. This scenario fosters the transformation of the current energy system, especially at the urban level [4], in which citizens are called upon to play an active role in the development of renewables by installing new RES-based plants at the local level and sharing the generated energy with others [5]. Government institutions, for their part, should establish a clear regulatory framework and reward those who help develop local communities based on clean energy generation [6]. The European Union (EU) addressed this task by introducing the Clean Energy for all Europeans package, which first framed the concept of the "Energy Community" (EC) [7]. The EC is a legal entity established on the initiative of a group of energy users located in a specific geographical area [8]. The community owns some energy conversion and storage plants and can self-consume, store, or sell the generated energy. If the generated energy comes exclusively

from renewable energy sources, the EC is called a "Renewable Energy Community" (REC), as defined in the recast of the Renewable Energy Directive (RED II) in 2018 [9].

The potential spread of ECs in the urban energy context makes it necessary to redesign the current energy system in order to accommodate, at best, the installation of new renewable energy plants [10]. First, ECs add generation capacity to the existing energy infrastructure, the resilience of which should be evaluated [11,12]. Dimovsky et al. [13] showed the importance of maximizing self-consumption in ECs to minimize their impact on the medium voltage distribution grid in terms of increased losses, over-voltages, and overloading of the lines. Second, the EC formation should be optimized by selecting, on one side, the optimal type and size of energy conversion and storage units to fulfill the energy demands (i.e., thermal energy and electricity demands) [14,15] and, on the other side, the optimal aggregation of different energy users (e.g., residential, commercial and office users) in a given geographical area [16]. Minuto et al. [17] addressed the conversion of an apartment block of passive residential consumers into an EC. They found out that installing only photovoltaic (PV) plants and heat pumps (HPs) allows for meeting both thermal and electrical energy demands while achieving the best tradeoff between economic convenience and environmental performance. Ceglia et al. [18] evaluated the economic and environmental benefits of adding new renewable energy plants to an existing energy system in an Italian municipality to build a Renewable Energy Community. They considered, on the generation side, different combinations of renewable energy plants of given sizes and, on the demand side, the aggregated thermal and electrical energy demands of the whole municipality without distinguishing the contribution of different types of users. Simoiu et al. [19] used a Mixed Integer Linear Programming approach to optimally design and operate a photovoltaic system coupled with electrical energy storage in an EC composed of households and a metro station. The optimization problem considers only electrical energy and, accordingly, aims at minimizing the net electrical energy exchanged between the EC and the main grid. The inclusion of the storage allows increasing the self-consumption and the self-sufficiency of the EC by up to 14% and 4%, respectively, compared to the scenario without electrical energy storage. Sousa et al. [20] calculated the optimal size of PV and wind power plants in a three-member energy community under different scenarios with different upper bounds on the capacity of each plant. The profitability of new renewable capacity is evaluated by comparing, for each technology, the marginal revenue and the marginal cost of investing in an additional unit of capacity. In particular, if PV and/or wind capacities do not have an upper bound, the optimal size of each technology is found when its marginal revenue equals its marginal cost. Only the electricity demand is considered among the energy demands and given as input to the design optimization problem, which does not include any sources of flexibility such as energy storage and demand response programs.

Most of the works dealing with the optimization of the EC energy generation units, as the ones mentioned above, focus on the energy generation side and take users' energy demands as input to the problem. Conversely, other works focus more on the demand side and evaluate the benefits that shifting the energy demand can provide in reducing the operational costs of ECs [21] and increasing energy sufficiency at the local level [22]. In a previous work [23], the authors applied both price-based and incentive-based demand response programs in the operation optimization of an EC, i.e., for a given type and size of the energy conversion units. The incentive-based demand response is more suitable for increasing the self-consumption of energy, while the price-based demand response leads to higher cost savings. Lu et al. [24] proposed a bilevel operation optimization of an energy community with energy conversion and storage units of given rated power. The upper level maximizes the profit of a service provider, while the lower level minimizes the cost of energy users considering user satisfaction and multi-energy demand response, i.e., demand response applied to different energy carriers. Despite considering the detailed composition of demands, the focus was only on residential users, namely retirees and office workers. The application of the multi-energy demand response allows for reducing operational

costs by up to 7.32% compared to the case without demand response. Mota et al. [25] addressed the application of electrical demand response both in single households and in a community of households, with the aim of minimizing energy expenditure in a certain period. The load shift is optimized while considering dynamic pricing, local generation and sharing of electricity from PV (with a given peak power of 7.5 kW for each household), DR participation, house priority in benefiting from energy cost reduction, and a time window for load management to comply with user comfort. Results show that DR succeeds in reducing energy costs and that this reduction is higher if households are aggregated in an energy community.

Most of the works focusing on the EC demand side analyze in detail the composition of the energy demand (mainly the electrical one) and carry out the optimization of the demand schedule by taking the set of energy generation and storage units as input to the problem. In other words, the energy demand change, or demand response, is currently applied mostly to the operation of ECs with a given design.

In summary, the above literature review shows that on the one hand, most of the works carrying out the design optimization of the energy conversion and storage units do not include the quantities associated with the energy demand in the decision variables set, and on the other hand, all works optimizing the demand side are limited to the optimization of the operational costs of the EC and disregard the design optimization of the energy generation and storage units. However, the search for the global optimum in designing future energy systems should consider the generation and demand sides together [26–28]. Moreover, Leprince et al. [29] demonstrated that occupant behavior, which was measured as variations of set point temperature and electricity loads of buildings, is the uncertain parameter that most influences the optimal sizes of the energy systems in the EC. Thus, it is crucial to evaluate how changes in energy demand (i.e., demand response) can affect the design of an EC. An evaluation of this impact was proposed by the authors in [30], where demand response is applied upstream of the design optimization of the EC energy systems. In particular, the energy demand is first changed a priori by shifting it towards periods of higher availability of renewable energy sources and then given as input to the optimization problem. Results show the deployment of a larger area of photovoltaic plants, i.e., an increased renewable energy generation, which results in lower costs and CO_2 emissions. However, energy generation and demand were not integrated into a single optimization problem, thereby preventing the decision maker from evaluating different optimal EC designs under different shapes of the energy demand. A step forward in this integration has been made by Ji et al. [31], who found out that including demand response in the design optimization problem reduces the installed capacity of the energy conversion and storage units and, in turn, the total cost of the system (up to 15%). However, their work did not consider either the thermal energy demand and, in turn, the need for technologies (e.g., heat pumps or boilers) to fulfill it, nor the possibility of including types of users different from residential ones in the EC. Finally, some works (see, e.g., [32,33]) have considered demand side management along with planning for the future capacity of the generation system. However, the proposed analyses deal with long-term planning at the policy level, in which generation and demand side curves are considered as an aggregate, without going into the detail of hour-by-hour balancing between generation and consumption, i.e., the engineering constraints derived from characteristics of specific types of conversion units, and users are not taken into account.

It is clear from the above literature review that the problem of optimizing a CE as a whole has not yet been fully addressed. In fact, to the best of the authors' knowledge, there are no contributions that carry out the design and operation optimization of an EC while considering together all the following aspects:

(1) the inclusion of the demand side in the design phase by including in the decision variables sets the possibility of making energy demands flexible (i.e., demand response);
(2) the need to fulfill both thermal energy and electricity demands;

(3) the composition of the EC, i.e., the share of different types of users with different shapes of energy demands.

This paper fills this gap. Our goal consists of quantifying the benefits in terms of cost, energy consumption, and environmental impact deriving from the formation of ECs composed of different shares of different users with their heat and electricity demands, in the hypothesis that members are likely to modify to some extent their habits and, in turn, their electrical energy consumption.

To this end, a multi-objective optimization problem based on Mixed-Integer Linear Programming (MILP) is set up. The two objective functions to be minimized are (i) the total life cycle cost of the system, i.e., the sum of the investment (design) and operational (operation) costs, and (ii) the direct CO_2 emissions associated with electricity imported from the electricity grid and natural gas withdrawn from the gas network. The optimization problem is solved for an EC located in Padova, Italy, that is composed of three different types of users, i.e., residential, commercial, and offices, and is equipped with a photovoltaic plant connected to electrical energy storage, air-water heat pumps, gas boilers, and thermal energy storages.

2. The Renewable Energy Community

The considered EC is a "Renewable Energy Community" as implemented by the Italian legislation [34], which grants an incentive tariff to the electricity that is generated from renewables and contextually consumed within the community boundaries. The EC members are individually connected to the national distribution grid under the same primary substation.

Figure 1 shows the layout of the considered EC, located in Padova (northern Italy). It is connected to the main power grid by means of a high-to-medium voltage cabin and is composed of:

- residential users (Res), commercial users (Com), and offices (Off),
- a photovoltaic (PV) plant eventually connected to an electrical energy storage (EES),
- boiler (BOIL), heat pump (HP), and thermal energy storage (TES) that each user may install to satisfy their own thermal energy demand.

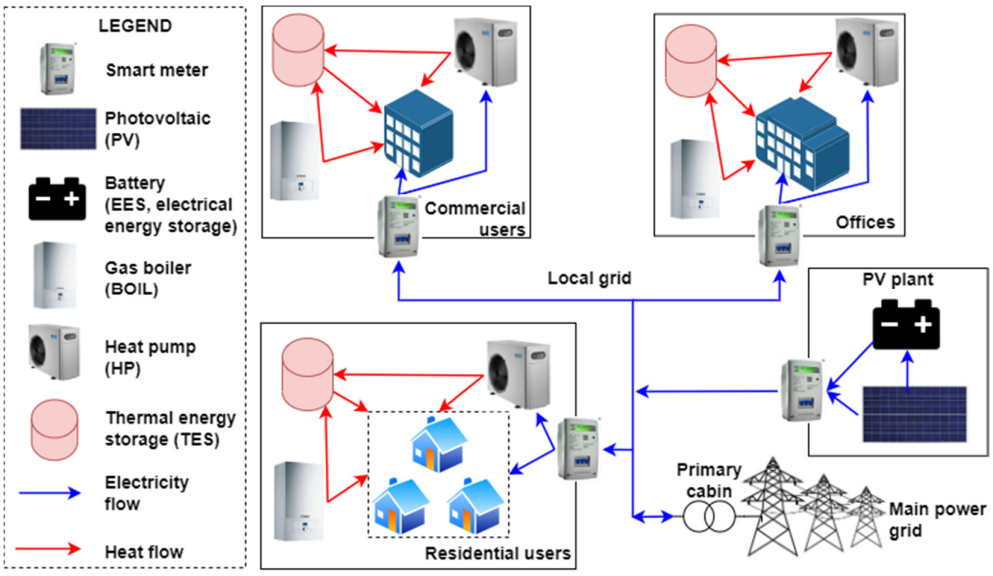


Figure 1. Layout of the Energy Community.

The three types of energy users differ in their energy demands. Figures 2 and 3 show the normalized electrical and thermal energy demands of the users on a typical summer and winter day, respectively. Four typical days, one day for each season, are assumed to be representative of the entire year. Each typical day embeds the seasonal

average ambient conditions taken as input in the optimization problem, i.e., solar irradiance and ambient temperature. The variation of the different quantities within the day has an hourly resolution.

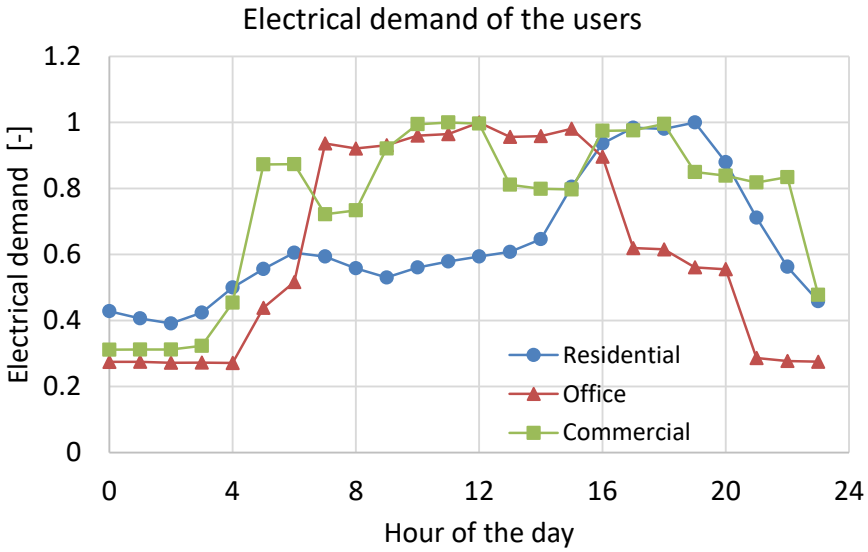


Figure 2. Normalized electrical energy demands of each user for a typical summer day.

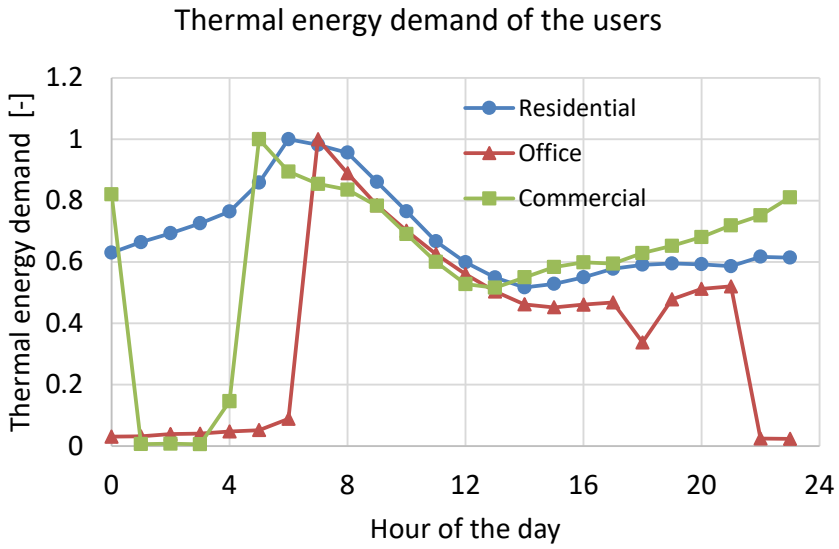


Figure 3. Normalized thermal energy demands of each user for a typical winter day.

3. The Optimization Problem

The optimization problem is based on a MILP approach, in which the life cycle cost of the system must be minimized, subject to equality and inequality constraints that represent the model of the EC. The problem is formulated in Equation (1) [35]:

$$\begin{aligned} &min_{x,y}\left\{LCC(\boldsymbol{x},\boldsymbol{y}) = \boldsymbol{c}^T\boldsymbol{x} + \boldsymbol{d}^T\boldsymbol{y}\right\} \\ &subject\ to\ \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{y} \leq \boldsymbol{b} \\ &with\ \boldsymbol{x} \geq 0 \in \Re^{N_x}, \boldsymbol{y} \in \{1,0\}^{N_y}. \end{aligned} \tag{1}$$

where LCC is the objective function, $\boldsymbol{c}$ and $\boldsymbol{d}$ are the cost vectors associated with the continuous variables $\boldsymbol{x}$ and binary variables $\boldsymbol{y}$, respectively; $\boldsymbol{A}$ and $\boldsymbol{B}$ are the constraint matrices and $\boldsymbol{b}$ is the array of the known terms; N_x and N_y indicate the dimension of $\boldsymbol{x}$ and $\boldsymbol{y}$, respectively.

For a given combination of user participation, the energy, economic, and environmental benefits provided by the EC are evaluated by solving the following cases:

(a) Design and operation optimization of the EC when each user keeps the original energy demand unchanged,
(b) Operation optimization of the EC while keeping the same optimal sizes of the energy conversion and storage units obtained from (a) but giving the possibility to users of shifting part of the demand at different times of the day,
(c) "New" design and operation optimization of the EC when users can shift their demand as in (b).

This Section explains the general design and operation optimization problem and specifies the differences among the cases (a), (b), and (c) above. In particular, Section 3.1 presents the objective function; Section 3.2 describes the equality and inequality constraints, i.e., the model of the EC, and Section 3.3 reports the input data.

3.1. Objective Function

The objective function of the optimization problem is the life cycle cost (LCC) of the EC actualized to one year operation (Equation (1)). It is calculated as the sum of the operational cost (OP) and the investment cost (INV) of the EC. The former is time dependent and results from summing the operating cost of a typical day k times the number of days w_k in the year represented by that typical day. The latter is time-independent and corresponds to the cost associated with the energy conversion and storage units to be installed in the EC. Equation (2) shows the contribution of these two terms in the calculation of the objective function LCC:

$$LCC_{EC} = OP_{EC} + INV_{EC} = \left(\sum_k w_k \cdot \sum_h OP'_{k,h}\right)_{EC} + INV_{EC} \quad (2)$$

where $k \in 1, 2, \ldots, K$ refers to the typical days representing the entire year, $h \in 1, 2, \ldots, H$ refers to time steps within a typical day, w_k represent the weight associated with the typical day k (i.e., the number of days of the year represented by the typical day k).

Equations (3) and (4) specify the terms included in the calculation of the operational cost and of the investment cost, respectively:

$$OP_{EC} = \sum_k w_k \sum_h \left[\sum_n \left(c_{gas} F_{BOIL,k,h,n} + c_{el,buy} P_{imp,k,h,n}\right) - inc_{sh} E_{sh,k,h} - c_{el,sell} P_{exp,k,h}\right] \Delta h, \quad (3)$$

$$INV_{EC} = \tau_{PV} c_{inv,PV} C_{PV} + \tau_{EES} c_{inv,EES} C_{EES} + \tau_{BOIL} c_{inv,BOIL} \sum_n C_{BOIL,n} + \tau_{HP} c_{inv,HP} \sum_n C_{HP,n} + \tau_{TES} c_{inv,TES} \sum_n C_{TES,n}. \quad (4)$$

The operational cost OP_{EC} in Equation (3) is the cost for purchasing the required energy carriers (electricity, natural gas) from outside the system minus the revenues for the shared energy within the EC and for the energy sold to the grid. c_{gas} in EUR/kWh is the purchasing cost of natural gas used as fuel for the boiler (F_{BOIL}); $c_{el,buy}$, in EUR/kWh, is the purchasing cost of electricity imported P_{imp} by user n; $c_{el,sell}$, in EUR/kWh, is the selling price of electricity exported (P_{exp}) to the national grid, inc_{sh} in EUR/kWh is the incentive awarded for the electrical energy shared within the EC (E_{sh}).

According to Italian legislation, the energy shared E_{sh} is defined as the hourly minimum between the energy imported from the grid to meet users' total electricity requirement (electric demand plus heat pump consumption) and the energy injected into the grid by the subsystem comprising the PV and battery (Figure 1).

The investment cost INV_{EC} in Equation (4) is the sum of the investment costs of the technologies included in the EC (Figure 1), which are both those shared by the EC, i.e., photovoltaic (PV) and electrical energy storage (EES), and those owned by each user n, i.e., boiler (BOIL), heat pump (HP), and thermal energy storage (TES). The investment cost of each technology is calculated as the product of the coefficient τ, which is the sum of

the actualization factor α and of the operation and maintenance cost (given as a percentage of the investment cost), the specific investment cost c_{inv} and the capacity C. α is calculated in Equation (5), where $r = 0.05$ is the interest rate and i is the lifetime of a technology.

$$\alpha = \frac{r(1+r)^i}{(1+r)^i - 1} \tag{5}$$

The optimization problem also gives the possibility of setting an upper limit on the annual CO_2 emissions (φ) directly associated with the energy carries (electricity and natural gas) crossing the boundaries of the EC. φ is calculated as reported in Equation (6):

$$\varphi = \sum_k w_k \sum_h \varphi'_{k,h} \tag{6}$$

where $\varphi'_{k,h}$ represents the CO_2 emissions at the time step h of the typical day k. The upper limit on the annual CO_2 emissions φ is made explicit in Equation (7):

$$\varphi \leq \varepsilon \varphi_0 \tag{7}$$

where ε is a non-negative real number between 0 and 1, and φ_0 represents the CO_2 emissions of a reference scenario, in which the entire yearly electricity demand is met by the national grid and the entire heating demand is fulfilled by gas boilers (see Section 4). By decreasing iteratively ε from 1 to 0, the CO_2 emissions are step-by-step reduced to desired targets and become the secondary objective of the optimization problem according to the epsilon-constrained multi-objective formulation [36].

The decision variables of the MILP problem are:

(i) continuous variables (constant in the whole period of analysis), including the capacities of the energy conversion and storage units
(ii) continuous variables describing the hourly value of the output power of the dispatchable units, the state of charge of the storage systems and their charging/discharging power, and the modified electricity demand if the possibility of changing the original demand is given to the EC members.
(iii) binary variables, including the hourly on/off status of the dispatchable energy conversion units.

3.2. Constraints

The constraints of the problem include the characteristic equations of the various components, the energy balances, and the flexibility limits of the electricity demand when demand response is considered.

3.2.1. Photovoltaic Plant

The power generated by the photovoltaic plant P_{PV}, in kW, is given by Equation (8):

$$P_{PV,k,h} = C_{PV} \frac{I_{sun,k,h}}{I_{sun,ref}}, \tag{8}$$

where C_{PV} is the capacity of the PV plant in kW of peak (kW_p), I_{sun} is the global solar irradiation in W/m^2 given for each hour h of the typical day k, $I_{sun,ref} = 1000\ W/m^2$ is the global solar irradiation in the reference conditions associated with the kW of peak.

The lower bound of PV capacity is zero, while no upper limit is imposed, assuming that the space availability is such that the EC can be completely decarbonized (i.e., the annual CO_2 emissions φ can be brought to zero).

3.2.2. Gas Boiler

The fuel consumption F_{BOIL}, in kW, of the gas boiler ($BOIL$) owned by user n is given in Equation (9) as a function of the generated thermal power Q_{BOIL}:

$$F_{BOIL,n,k,h} = \frac{Q_{BOIL,n,k,h}}{\eta_{th,BOIL}}, \quad (9)$$

where $\eta_{th,BOIL} = 0.95$ is the boiler efficiency. Equation (10) limits Q_{BOIL} to be lower than the boiler capacity C_{BOIL}, in kW:

$$0 \leq Q_{BOIL,n,k,h} \leq C_{BOIL,n} \quad (10)$$

3.2.3. Air-Water Heat Pump

The power consumption P_{HP} of the heat pump (HP), in kW, owned by user n is given in Equation (11) as a function of the generated thermal power Q_{HP}, in kW:

$$P_{HP,n,k,h} = \frac{1}{COP_{ideal,k,h}}(Q_{HP,n,k,h}\, g + \delta_{HP,n,k,h}\, f) \quad (11)$$

where δ_{HP} is a binary decision variable indicating the on/off status of the HP, $g = 1.80$ and $f = 2.65$ are the coefficients of the linear function describing the HP performance, and COP_{ideal} is the coefficient of performance calculated in ideal conditions (Carnot) between the ambient temperature T_{amb}, in K, provided as a time series, and the supply temperature, T_{supply}, of the DHN, which is set to 343 K.

As for PV, the capacity C_{HP} of the HP, in kW, is not upper-bounded. On the other hand, the generated thermal power Q_{HP} is limited in between a minimum load and the nominal capacity of the HP. The minimum load is equal to 50% of the nominal HP capacity. Further details on HP modeling can be found in [37].

3.2.4. Energy Storage Systems

Energy storage systems are the only components that establish a temporal link between time steps, making the optimization problem dynamic. Both EES and TES are modeled with the same equations, the only difference being that TES equations also have the subscript n (because a TES belongs to each user and is not unique to the EC as the EES). For simplicity, only the set of equations for EES are shown below.

Equation (12) shows that the state of charge (SOC) of the storage at the time step $h+1$ is equal to the SOC at the previous time step h plus the charged power $P_{c,EES,\,k,h}$ minus the discharged power $P_{d,EES,\,k,\,h}$ net of losses occurring in each of the two processes (note that equal charging and discharging efficiencies are considered, which result in the square root of the round-trip efficiency η_{EES}).

$$SOC_{EES,k,h+1} = SOC_{EES,k,h} + P_{c,EES,\,k,h}\sqrt{\eta_{EES}}\Delta h - \frac{P_{d,EES,\,k,\,h}}{\sqrt{\eta_{EES}}}\,\Delta h, \quad (12)$$

The SOC at the beginning of each typical $(h = 0)$ day k must be equal to that at the end of the day $(h = H)$ to avoid that energy is added to or removed from the system for free, as shown in Equation (13).

$$SOC_{EES,k,0} = SOC_{EES,k,H} \quad (13)$$

Equations (14)–(16) show the other main constraints associated with the storage operation. Equation (14) states that the SOC cannot exceed the capacity of the storage (C_{EES}), while Equations (15) and (16) state that charge and discharge power must be

lower than or equal to the product between the specific input (cap_{in}) and output (cap_{out}) capacities (in kW/kWh) and the storage capacity, respectively:

$$SOC_{EES,k,h} \leq C_{EES}, \tag{14}$$

$$P_{cEES,k,h} \leq cap_{in} C_{EES}, \tag{15}$$

$$P_{dEES,k,h} \leq cap_{out} C_{EES}. \tag{16}$$

3.2.5. Flexibility of the Electricity Demand

When demand response is considered, the electricity demand of each EC user is flexible and can change the hourly value from the original demand $DemEl_{n,h}$ to the shifted one $DemEl_{n,h}^{shift}$, which becomes a decision variable of the optimization problem. The demand flexibility is governed by the two constraints expressed in Equations (17) and (18), respectively:

$$\sum_{h=1}^{24} DemEl_{n,h}^{shift} = \sum_{h=1}^{24} DemEl_{n,h}, \tag{17}$$

$$(1 - D^{var}) \cdot DemEl_{n,h} \leq DemEl_{n,h}^{shift} \leq (1 + D^{var}) \cdot DemEl_{n,h}. \tag{18}$$

Equation (17) states that the daily electricity demand remains the same for both the original and the shifted demands. Equation (18) constrains $DemEl_{n,h}^{shift}$ to vary in a range centered on the value of the original $DemEl_{n,h}$ and defined by the parameter D^{var} ranging from 0 to 1.

3.2.6. Energy Balances

The electrical balances define the exported and imported electricity and are formulated for the whole EC. Equation (19) shows that the exported power is the power generated by the PV net of the power charged into the battery and increased power discharged from the battery. Equation (20) shows that the imported electricity coincides with the sum of the electricity demand (which may be shifted in case demand response is considered) and the power consumed by the heat pumps. On the other hand, the thermal energy balance is defined for each user n and is stated in Equation (20), where $DemTh_{n,k,h}$ is the hourly heating demand of the user n in the typical day k, and Q_{dTES} and Q_{cTES} are the thermal power charged into and discharged from the TES, respectively.

$$P_{exp,\,k,h} = P_{PV,k,h} - P_{cEES,k,h} + P_{dEES,k,h} \tag{19}$$

$$P_{imp,\,k,h} = \sum\nolimits_n DemEl^{shift}{}_{n,k,h} + \sum\nolimits_n P_{HPn,k,h} \tag{20}$$

$$-DemTh_{n,k,h} + Q_{BOIL,n,k,h} + Q_{HP,n,k,h} + Q_{dTES,n,k,h} - Q_{cTES,n,k,h} = 0 \tag{21}$$

3.3. Input Data

Input data are the electrical and thermal energy demands of the users for each typical day k, weather data (ambient temperature, solar irradiation) for each typical day k and technoeconomic data of the technologies (e.g., investment costs, costs of energy carriers, efficiencies).

Given the EC layout in Figure 1, different kinds of ECs are modeled and compared by keeping the same yearly energy demand (809 MWh of electrical demand, 316 MWh of heating demand) but varying the share of residential, commercial, and office users among EC members. This results in different shapes of heat and electricity demand profiles that are given as input to the optimization problem. Moreover, different degrees of electrical demand flexibility ranging from 0 to 50% of the hourly demand are considered. The degree of flexibility is named "*DR*" in the following and corresponds to the parameter D^{var} in Equation (18).

Table 1 shows the technoeconomic data of the energy conversion and storage units, and Table 2 shows the costs and emission factors of the energy carriers.

Table 1. Specific investment cost of the energy conversion and storage plants [37–39].

Technology	Specific Investment Cost (c_{inv}) [EUR/kW or EUR/kWh]	Lifetime [years]
PV	1250	20
GB	100	20
HP	1500	20
TES	80	20
EES	800	10

Table 2. Specific costs and emission factors of the considered energy carriers [40].

Carrier	Cost [EUR/MWh]	Emission Factor [kg_{CO2}/MWh]
Natural gas	98	197
Electricity from the grid	234	356
Electricity to the grid	−50	0
Shared energy (incentive tariff)	−110	−356

4. Results

Our results allow an understanding of whether ECs are suitable tools to accommodate the benefits of changes in energy consumption and quantify to what extent these changes lead to economic, energetic, and environmental benefits. The MILP model is developed in Python (version 3.9.13) and uses the Gurobi solver (version 9.5.2) as optimizer.

A reference scenario in which the entire yearly electricity demand is met by the national grid, the entire heating demand is fulfilled by gas boilers, and demand response is not considered is assumed as a term of comparison. In this case, the life cycle cost of the system, actualized to one year, results to be $f_{ref} = 221.2$ kEUR, while the yearly emissions of CO_2 are $\varphi_{ref} = 352.1$ ton.

An EC composed of 33.3% residential users, 33.3% commercial users, and 33.3% office users is considered as baseline. Initially, neither constraints on CO_2 emissions nor demand response are considered. The design and operation optimization problem results in a life cycle cost of the system equal to 197.7 kEUR/year and CO_2 emissions equal to 206.2 tons, which are 11% and 41% lower than the reference scenario, respectively. The reduction of emissions is due to the installation of 375.5 kW_{peak} of PV, which results in a renewable electricity generation of 547.7 MWh/year. Almost 70% of this electricity is shared and virtually self-consumed among the EC members, whereas the remaining 30% is a generation surplus that is exported to the main power grid due to the mismatch with the electrical demand during the hours of peak production. From the demand side perspective, the PV generation allows to cover 46% of the overall electrical demand (which includes 23 MWh consumed by heat pumps), whereas the remaining 54% of demand is withdrawn from the main power grid, which currently mostly relies on fossil fuels.

Once the sizes of the energy conversion and storage units of the EC are optimally decided, if the demand response is considered and, for instance, EC's members have the possibility of changing their hourly electrical demand of ±30% while keeping the daily integral unchanged, the resulting benefits improve. The life cycle cost decreases by 3% to 191.1 kEUR/year, while carbon emissions further decrease by almost 11%. In fact, demand flexibility allows for an increase of 16% of the shared energy, which reaches 442 MWh/year (55% of the demand). This decreases by 12% the demand share that is not covered by PV generation.

A further improvement can be achieved by considering the demand flexibility already in the design phase. In this case, the best size of the energy conversion and storage systems

is chosen together with the best modification of the demand curve. Even though the life cycle cost does not vary sensibly, the installed PV power grows by 18% to 442 kW_{peak}. This results in further reducing CO_2 emissions by 5%, increasing the shared energy by 6% and decreasing by 7% the electricity demand that is not covered by PV.

But what happens when caps are imposed on CO_2 emissions? To answer this question, the optimization runs have been repeated by including the constraint stated in Equation (7) and iteratively decreasing the allowed share of emissions from 100% to 0% compared to the reference scenario. This corresponds to the so-called ε-constrained multi-objective optimization (the life cycle cost and carbon emissions are the two objectives), the outcomes of which are the Pareto fronts shown in Figure 4.

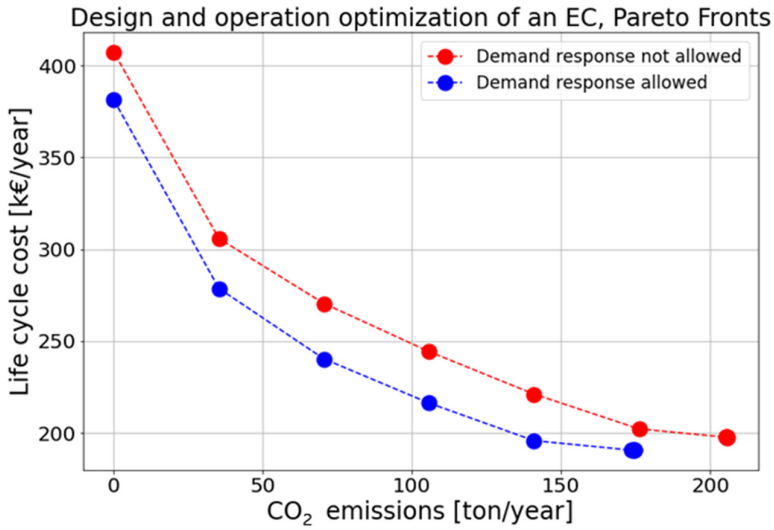
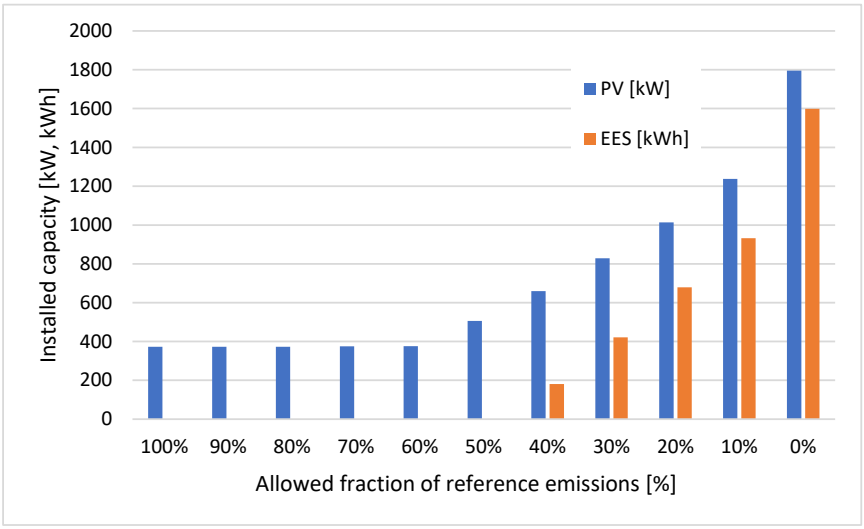


Figure 4. Life cycle cost vs. CO_2 emissions for different applications of demand response. Demand-response programs allow a degree of demand flexibility to hourly changes of ±30%. The EC is composed of an equal share (33%) of residential, commercial, and office users.

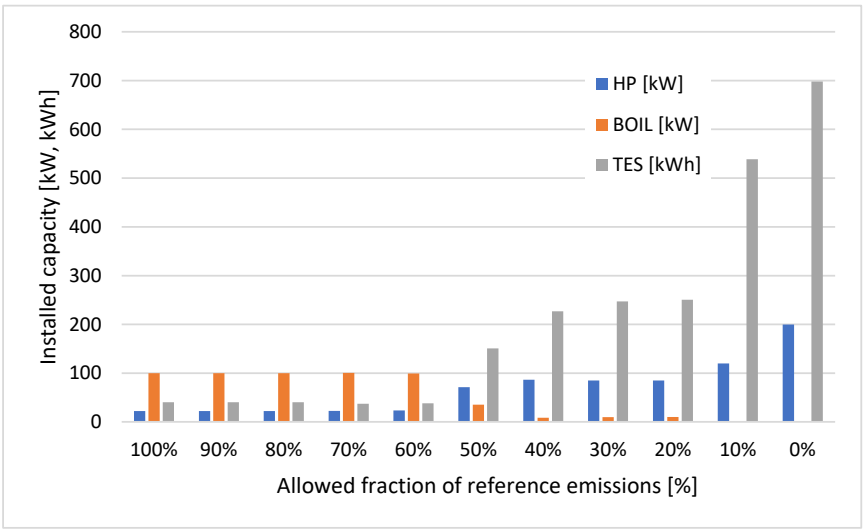
Further reducing the CO_2 emissions requires increasing the life cycle cost. Initially, when allowed emissions are higher, a relevant decrease can be obtained at a low cost. For instance, in the case without demand response (red dotted line in Figure 4), reducing emissions by 14% (29 tons/year) from 206 tons/year to about 176 tons/year requires a cost increase of 2% (4.6 kEUR/year), from 197.7 kEUR/year to 202.3 kEUR/year. On the contrary, when the allowed emissions are already low, a further reduction is much more expensive. In fact, the last step of emission reduction, occurring from 35 tons/year to 0 tons/year, costs 102 kEUR. The reason behind the cost increase is that an increasing share of energy demand must be covered by PV, which is the only system among those considered to be completely fed by renewables. This increasing PV share is obtained, on the one hand, by increasing the installed PV power and, on the other hand, by installing batteries, which are required to consume the energy generated by PV during the hours without available solar irradiation (i.e., during night and cloudy days).

Figure 5 shows the installed capacities of the different energy conversion and storage units when the allowed share of emissions decreases from 100% to 0% compared to the reference scenario. These results refer to the red Pareto front in Figure 4, where demand flexibility is not allowed. Figure 5a shows the capacities of the units associated with power generation, i.e., PV and EES (which are in common for the EC), while Figure 5b shows, for each type of unit associated with thermal energy, the sum of the capacities installed by all users. As the cap on CO_2 emissions becomes more stringent, the installed capacities of PV and EES exponentially increase in order to make the EC completely grid-independent, thereby avoiding indirect emissions coming from the presence of fossil fuels in the energy mix of the national power grid. The increase in renewable power generation fosters the shift

from gas boilers to heat pumps that have the advantage of consuming renewable electricity to push the decarbonization of thermal energy production. In this case, zero emissions can be achieved only by increasing the capacity of the thermal storage that allows thermal energy to be stored when HPs produce it (i.e., when the sun is available) and used outside of the central hours of the day. It is worth noting that the constraint on CO_2 emissions becomes "active" when the allowed fraction of reference emissions is reduced to 50%. In fact, as mentioned above, the solution of the design and operation optimization problem without imposing emission constraints results in a system that already emits 41% less than the reference scenario.



(**a**)



(**b**)

Figure 5. Installed capacities of the electrical (**a**) and thermal (**b**) energy conversion and storage units within the EC as the allowed CO_2 emissions decrease. The EC is composed of an equal share (33%) of residential, commercial, and office users.

The inclusion of the demand response in the design optimization of the EC allows for shifting the electrical demand towards the hours of the day with higher PV generation availability, thereby reducing generation surplus. Moreover, this avoids investing in batteries and, in turn, reduces the life cycle cost of the system. Figure 4 shows that considering a demand flexibility of 30% in the design of the EC (blue line) shifts the entire Pareto front to the left, i.e., towards lower costs.

For instance, in case of a reduction target in CO_2 emissions of 60% compared to the reference scenario, which corresponds to a cap of 141 tons/year, demand flexibility of 30% avoids the installation of 181 kWh of batteries, and results in a lower life cycle cost of the system by more than 11%, from 221 kEUR/year to 196 kEUR/year. Figures 6 and 7 show the energy balances of the EC in the winter typical day when demand response is not considered and when demand flexibility of 30% is assumed, respectively. The shared energy is highlighted by the light blue area and is almost the same in the two cases. However, in the first case, it is enhanced by using batteries, whereas in the second case, it is enhanced "for free" by increasing the electrical demand during the middle hours of the day and decreasing it when PV generation is not available.

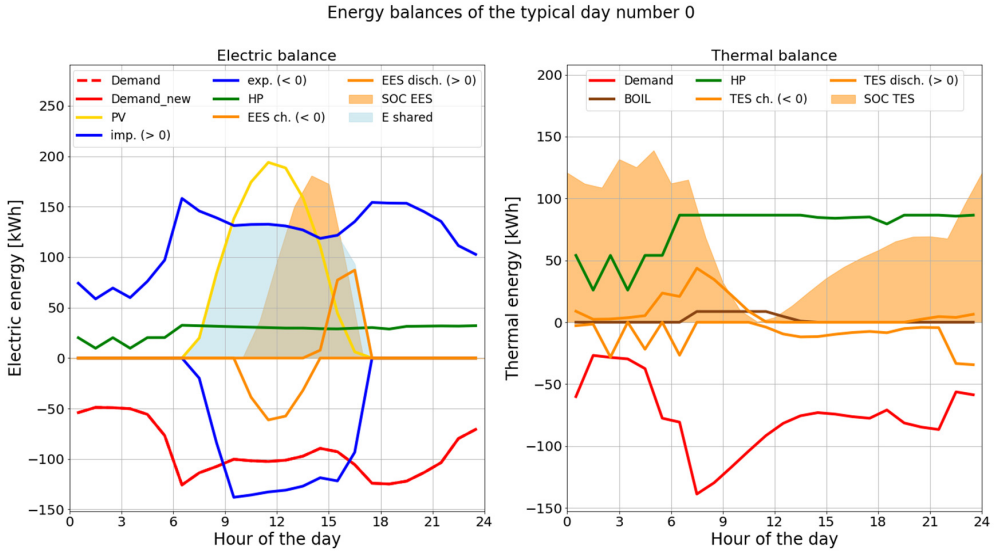


Figure 6. Electrical (**left**) and thermal (**right**) energy balances of the EC for the typical winter day (day number 0). Demand response is not considered, i.e., the curves "demand" and "demand_new" are superimposed. The EC is composed of an equal share of residential, commercial, and office users.

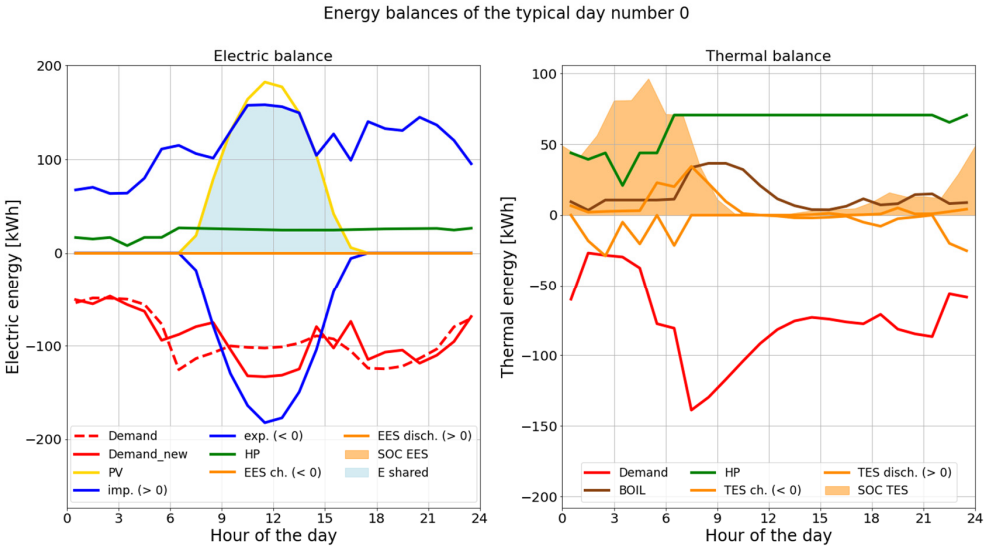


Figure 7. Electrical (**left**) and thermal (**right**) energy balances of the EC for the typical winter day (day number 0). The degree of demand flexibility is 30%. The EC is composed of an equal share of residential, commercial, and office users.

The inclusion of demand flexibility in the design and operation optimization problem also leads to different optimal PV capacities compared to the case without flexibility. As

mentioned above, if no cap on CO_2 emissions is set, the possibility of shifting the demand to periods of sun availability enhances the PV installation. This holds for all combinations of users' shares and all DR values. For example, in the case of an equal share of users, the higher installed PV capacity reduces the CO_2 emissions from 206 tons when $DR = 0$ (-41.4% of the emissions of the reference scenario) to 174 tons when $DR = 30\%$ (-50.5% of the emissions of the reference scenario). However, when caps on emissions become more stringent (e.g., below -50.5% of the reference emissions in the case of equal users' share), the installed PV capacity decreases when $DR > 0$. The reason for this opposite trend is that the same emission target can be achieved with lower renewable energy capacity, i.e., lower installed PV if a higher amount of demand can be fulfilled in the hours of sun availability (due to $DR > 0$).

The flexibility of the electricity demand also affects the way the thermal energy demand is fulfilled. Compared to the thermal balance in Figure 6 ($DR = 0$), the one in Figure 7 ($DR > 0$) shows a higher share of thermal energy demand covered by BOIL at the expense of HP and TES. In fact, the shift of the electrical demand when $DR > 0$ results in (i) a lower excess of renewable electricity and, in turn, a greater cost-effectiveness in installing BOIL rather than the more expensive HP and TES [41] and (ii) lower electricity demand met by nonrenewable energy, which allows reaching the same emission target with a higher share of thermal energy demand covered by fossil fuels (i.e., the natural gas feeding boilers).

Finally, it has been analyzed how variations in the share of the various EC members affect optimization results. Table 3 shows as a heatmap the CO_2 emissions resulting from the design and operation optimization problem applied to ECs formed by different shares of residential (Res), commercial (Com), and office (Off) users with different degrees of demand flexibility (*DR*). In the same way, Table 4 reports the electrical demand that cannot be met by PV generation and, therefore, is withdrawn from the main power grid; Table 5 reports the total costs of the ECs. These results refer to the case in which no cap on CO_2 emissions is imposed. In all cases, an EC composed of 100% office users shows the best performance thanks to the good match between the electrical demand profile of office users and the shape of the solar irradiation profile (red line in Figure 2), whereas the EC with 100% residential users has the lowest benefits due to the demand pick in the evening (blue line in Figure 2). Clearly, for a given EC composition, increasing demand flexibility reduces both carbon emissions and the need for grid electricity. However, for a fixed degree of demand flexibility, the 100% residential community emits 30% more CO_2 than that composed of 100% offices. Contextually, the electrical demand is not covered by PV, and, in turn, the associated consumption of fossil fuels is 45% higher. This shows that for some types of users, greater flexibility in demand (and thus habits) is required than for others to achieve the same emission reduction benefits. The cost of the system is affected by the type of user aggregation and degree of demand flexibility in the same way as emissions and electricity taken from the grid, albeit with smaller percentage changes. The adoption of the maximum degree of flexibility (DR = 50%) allows reducing the cost of all aggregations by 6% on average compared to the case without flexibility (DR = 0%). More or less, the same reduction is obtained with a 100% office community with respect to the 100% residential one.

Table 3. Heatmap of CO_2 emissions for different shares of EC's members (Res = residential, Off = offices, Com = Commercial) and different degrees of demand flexibility (DR 0 to 50%). Green color indicates lower emission values, while red color indicates higher emission values.

CO_2 Emissions [ton/year]	**DR = 0%**	**DR = 10%**	**DR = 20%**	**DR = 30%**	**DR = 40%**	**DR = 50%**
Res = 0%; Off = 100%; Com = 0%	177.75	170.73	165.59	153.73	146.72	141.52
Res = 0%; Off = 50%; Com = 50%	194.86	184.15	175.70	166.49	154.43	145.14
Res = 33%; Off = 33%; Com = 33%	206.23	193.79	183.97	174.01	164.38	154.64
Res = 50%; Off = 50%; Com = 0%	206.25	194.58	183.26	172.93	161.46	151.74
Res = 0%; Off = 0%; Com = 100%	215.73	203.35	191.39	179.29	168.09	155.59
Res = 50%; Off = 0%; Com = 50%	221.08	209.76	198.71	187.34	175.78	164.87
Res = 100%; Off = 0%; Com = 0%	235.20	225.00	215.47	203.72	195.60	185.54

Table 4. Heatmap of the electricity demand met by electricity withdrawn from the national grid for different shares of EC's members (Res = residential, Off = offices, Com = Commercial) and different degrees of demand flexibility (DR 0 to 50%). Green color indicates lower amounts of electricity withdrawn from the grid, while red color indicates higher amounts.

Electrical Demand Met by the National Grid [MWh/year]	DR = 0%	DR = 10%	DR = 20%	DR = 30%	DR = 40%	DR = 50%
Res = 0%; Off = 100%; Com = 0%	394.72	370.53	358.22	324.58	303.69	291.78
Res = 0%; Off = 50%; Com = 50%	442.27	414.06	390.14	365.25	333.49	304.95
Res = 33%; Off = 33%; Com = 33%	479.87	452.25	421.35	392.12	363.92	341.33
Res = 50%; Off = 50%; Com = 0%	483.04	454.30	421.81	389.02	357.92	331.07
Res = 0%; Off = 0%; Com = 100%	498.61	466.19	432.79	399.02	365.43	332.30
Res = 50%; Off = 0%; Com = 50%	527.44	494.48	463.63	432.61	401.95	370.34
Res = 100%; Off = 0%; Com = 0%	574.90	547.23	519.80	487.85	464.85	436.73

Table 5. Heatmap of the system cost for different shares of EC's members (Res = residential, Off = offices, Com = Commercial) and different degrees of demand flexibility (DR 0 to 50%). Green color indicates lower system costs, while red color indicates higher costs.

System Cost [kEUR/year]	DR = 0%	DR = 10%	DR = 20%	DR = 30%	DR = 40%	DR = 50%
Res = 0%; Off = 100%; Com = 0%	191.84	189.36	187.04	184.71	182.82	180.96
Res = 0%; Off = 50%; Com = 50%	194.65	191.99	189.50	187.12	184.76	182.72
Res = 0%; Off = 0%; Com = 100%	197.13	194.53	192.09	189.57	187.29	184.70
Res = 50%; Off = 50%; Com = 0%	197.36	195.06	192.70	190.60	188.32	186.05
Res = 33%; Off = 33%; Com = 33%	197.68	195.34	193.02	190.70	188.37	186.11
Res = 50%; Off = 0%; Com = 50%	200.02	197.75	195.63	193.45	191.18	189.04
Res = 100%; Off = 0%; Com = 0%	202.35	200.43	198.56	196.69	194.80	192.81

5. Discussion

This Section highlights critical aspects that emerged from the results and addresses the potential limitations of the developed model.

The innovative feature of the proposed approach is the consideration of flexibility in electricity demand in the design phase of a multi-energy system. The latter operates within the framework of an EC, which is a promising tool to enhance sustainability in urban areas. The EC includes typical urban energy users and is considered the only renewable energy technology suitable for deployment in urban areas, i.e., PV. These characteristics allow the results of the optimization problem to be immediately exploitable for urban energy system planning.

The first aspect to be considered about our results is the integration, potential conflicts, and synergies between DR strategies and electrical energy storage systems. Demand response works as a virtual storage system that adjusts the demand curve to the available electric generation from RES. This way, DR shifts peak loads to match peak generation while improving local RES utilization. This reduces the need to install storage systems and the associated costs (DR infrastructure has negligible investment costs compared to electric storage systems such as batteries). For instance, considering a 60% reduction target in CO_2 emissions, a 30% demand flexibility avoids the installation of more than 180 kWh of batteries, thus reducing the total system cost by more than 25 kEUR/year (approximately 11% of the total). This trend is the same for every cap on CO_2 emissions, as the Pareto frontiers in Figure 4 demonstrate (the curve associated with DR is entirely shifted towards lower costs). Thus, to provide demand flexibility, the optimization model will always choose the DR option, if available, compared to the installation of batteries. However, the adoption of DR strategies depends on the end users' attitude. The more end users are willing to change their energy use habits (i.e., change their demand curve), the less storage capacity will have to be installed to achieve the desired benefits in terms of peak shaving and enhanced RES utilization, and the less expensive the system will be. In the practical implementation of energy community projects, a tradeoff should always be sought between DR strategies and the installation of storage systems compatible with users' preferences.

A second aspect concerns the reduction in fossil fuel consumption resulting from the increase in the share of demand covered locally by renewable sources. In particular, the proposed approach acts in two directions to reduce fossil fuel usage and related emissions:

1. Reduction of electricity withdrawn from the national grid. In fact, in 2023 in Italy, electricity was generated (on average) more than 63% from fossil fuels, and the related average CO_2 emission factor stands at 356 kg_{CO2}/MWh. This reduction results from the economic convenience of maximizing self-consumption within the EC, even without considering any cap on CO_2 emissions. Compared to the reference scenario, the optimization of an EC composed of an equal share of users with DR = 0 and without a cap on CO_2 emissions reduces both costs and emissions by about 11% and 41%, respectively. Further reductions can be achieved by aggregating different types of users (offices allow greater reductions due to demand already concentrated in the hours of high PV production), increasing the flexibility of electric demand, and imposing caps on emissions.
2. Progressive replacement of gas boilers with heat pumps (HP) to meet more stringent caps on CO_2 emissions (Figure 5b). In this case, the approach pushes toward a self-consumption of locally produced renewable electricity also to meet part of the thermal demand by HPs, up to a complete replacement of boilers, which corresponds to the zero-CO_2 emission solutions in Figures 4 and 5. The total cost of this latter solution is roughly twice that of the cases discussed in point 1 above, up to over 400 kEUR/year when DR is not allowed.

Finally, it is worth noting that both directions of action of the proposed approach have the additional benefit of reducing the flows in long-distance electric distribution networks (given that local self-production -consumption is encouraged), with an associated reduction in transmission and transformation losses.

The potential limitations and simplifications of the model are listed and motivated below:

- *Non-consideration of the uncertain nature of renewable energy sources (RES)*. The deterministic optimization approach used in the developed model does not directly consider the uncertain nature and unpredictable short-term variability of RES availability (solar irradiance in this work). However, the need to optimize the system design requires considering a multiyear time horizon compatible with the expected lifetime of the components to be installed. Thus, if no significant variations in the trend of solar irradiance time series are expected over the years, four representative (deterministic) typical days are sufficient to capture both seasonal and daily variabilities, which determine the size of the PV systems to be installed. The use of stochastic optimization techniques to more accurately capture uncertainty in RES availability would have an almost negligible effect on the choice of PV sizes and, in turn, on system costs (differently, the use of such techniques would be crucial in a problem of optimizing operation over a short time horizon, where uncertainty in RES availability inherently determines the hour-by-hour scheduling of the system). In fact, short-term fluctuations are dampened in a long-term scenario, thereby not significantly affecting the results of the design problem. It has been, therefore, preferred to avoid using stochastic optimization techniques so as not to increase the computational demand of the model unnecessarily;
- *Disregard conventional energy sources for power production*. In this paper, only RES-based systems (namely PV) are considered for power production, whereas traditional and combined heat and power plants based on fossil fuels or biomass are not. The reason for this choice is the difficulty of integrating traditional plants at the urban level. It has been, therefore, preferred to consider a typical case study for the urban level, where PV is the dominant technology for electricity production. In addition, the inclusion of fossil fuel plants would certainly worsen the environmental impact of the system in terms of both CO_2 and pollutant emissions, thus counteracting the objective of this work. Despite this choice, the developed model has a general perspective and a flexible structure that can consider any type of plant (RES-based or traditional). A higher level of integration with other energy plants could be achieved by including, for

example, biogas engines for combined heat and power generation [30] and/or electric vehicles to increase the flexibility of the system further [42]. The addition of these plants into the model can be easily implemented, provided that their characteristic curves are described by linear equations and their energy inflows and outflows are properly accounted for in energy balances.

- *Consideration of DR only from the technical point of view and not from the behavioral one*. In this paper, it is assumed that end users act according to the optimal DR scheduling proposed for their loads. This is not always the case in practical applications, where the adoption and fulfillment of DR strategies depend on the habits and behaviors of those users. An effective implementation of DR requires further studies that involve sociological and behavioral aspects and go beyond the scope of this research, which is aimed at the technical and energy aspects of energy communities. The objective of this paper is, in fact, the quantification of the energy, economic, and environmental benefits that DR can produce under different levels of deployment, which simulate varying degrees of end users' engagement.

6. Conclusions

This paper evaluates the economic, energetic, and environmental benefits of Energy Communities when considering the possibilities of applying demand response and aggregating different types of users. A design and operation optimization problem of the energy conversion and storage units is set up based on Mixed Integer Linear Programming and solved under different combinations of user types (being the choice among residential, commercial, and office users) by imposing a cap on CO_2 emissions and by considering different degrees of flexibility of the hourly electricity demand.

The application of the concept of Energy Community at the urban level demonstrated a key role in pushing the installation of renewable energy plants and decreasing the environmental impact of the energy system by reducing direct CO_2 emissions. However, the formation of Energy Communities does not affect the energy demand unless users are willing to adapt their energy consumption, for example, by adhering to demand response programs.

The flexibility of energy demand applied to the case of Energy Communities shows great potential in reducing the investment and operational costs required for decreasing carbon emissions. The trend is shifting energy consumption towards periods of high availability of energy from renewables in order to increase energy sharing and local self-consumption and, in turn, decrease the share of energy demand covered by fossil fuels.

Including demand flexibility in the design and operation optimization of the energy system of an Energy Community leads to the following key findings:

- The flexibility given by the costly installation of electrical energy storage can be achieved "for free" by making electricity demand flexible. For example, in an Energy Community composed of an equal share of residential, commercial, and office users, the possibility of changing the hourly electricity demand by up to 30% allows for avoiding the installation of electrical storage to achieve the same target of 60% emission reduction.
- Although emission reductions imply an increase in installed photovoltaic capacity, demand flexibility allows less PV to be installed for the same emission cap. From the perspective of more stringent constraints on CO_2 emissions imposed by energy directives, this means less economic effort to achieve the same emission reduction target.
- The shift of electrical demand towards periods of sun availability implies less excess of renewable electricity production and more convenience in using boilers to fulfill thermal energy demand while maintaining the same CO_2 emissions. This outcome is of utmost importance when considering the first stages of energy transition because it enhances flexibility as a no-cost alternative to replacing boilers with heat pumps.
- Compared to the case without flexibility, the increase of demand flexibility from 0% to 50% decreases the amount of electricity withdrawn from the national grid in a range

from 23% to 31%, depending on the share of users. Thus, the higher the flexibility, the higher the energy and self-sufficiency of the community.

Finally, users with a demand profile having a good match with that of renewable sources are facilitated in the decarbonization process and can achieve the same benefits as users having a worse match by modifying their habits and, therefore, their electricity demand in a minor way. For a given degree of demand flexibility, the community composed entirely of residential users, who have the worst match with the PV generation profile, emits 30% more CO_2 than the community having the best match, i.e., that composed entirely of office users.

This paper has shown the benefits that demand flexibility can provide to speed up the decarbonization process and reduce the consumption of fossil fuels. However, further investigations, both in technical, economic, and social fields, are required to understand how users can be pushed towards a change in their energy consumption behavior that complies with the desired level of comfort.

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