

Designing aggregation criteria for end-users integration in energy communities: Energy and economic optimisation based on hybrid neural networks models

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HIGHLIGHTS

- Innovative methodologies tackle challenges in energy community real-case implementations.
- Prosumers share surplus energy with consumers, optimising energy interactions and pricing.
- New aggregation criteria maximize economic benefits and self-consumed renewable energy.
- A bi-level optimisation approach enhances self-sufficiency and community configurations.
- Case study in Italy shows 89% self-consumption, reducing power grid imbalances.

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ABSTRACT

This study presents innovative methodologies addressing critical challenges in energy community real-cases implementation. The investigation is conducted by exploring and enhancing the concept of Peer-to-Peer energy community, where prosumers interact with consumers by sharing surplus energy to meet their electricity demands. The end-users' connections are optimised by maximizing their energy interactions and the proposed pricing strategies are based on balancing the supply and demand curves for tailored unit costs.

This study aims to optimise the design of energy communities' configurations and the applicability in real case scenarios by suggesting novel aggregation criteria. These criteria are focused to select the type and the number of users in an energy community to maximize the economic benefit and the amount of self-consumed renewable energy. A bi-level optimisation approach is at the basis of these aggregation criteria. The first level maximizes self-sufficiency and economic benefits by aggregating prosumers and consumers into subgroups. The second level determines the optimal community configuration, prioritizing total energy self-consumption. This methodology requires the knowledge of users' electrical needs, therefore, to address the problem related to insufficient data, a Hybrid Neural Network model is proposed to simulate building electrical demands.

A case study in a residential area of Caserta, Italy, demonstrates the methodology's effectiveness. By identifying user types, predicting demands, and employing optimisation techniques, the study estimates economic benefits for consumers (1.6% to 19.5% savings) and prosumers (return on investment <3 years) compared to the reference scenario where the consumers and prosumers are connected only to the national electricity grid. Moreover, the optimised aggregation strategy achieves an 89% annual self-consumption compared to 64% of the reference scenario, significantly reducing network imbalances caused by prosumer surpluses.

1. Introduction

The need to mitigate greenhouse gas emissions has prompted a simultaneous increase in policies aimed at encouraging the development

and implementation of renewable energy technologies [1]. The Next-GenerationEU plan has set a key goal of reducing emissions at least 55% by 2030 compared to the level achieved in 1990 [2]. In light of this, urgent action is needed to transition sectors still dependent on fossil fuels towards a renewable and sustainable energy mix. Decreasing costs

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Nomenclature			
<i>Symbol</i>		<i>eq</i>	equipment
<i>A</i>	surface area [m ²]	<i>nom</i>	nominal
<i>c</i>	costs of energy [Euro/kWh]	<i>occ</i>	occupancy
<i>C</i>	energy market curves [Euro/kWh]	<i>prod</i>	production
<i>COP</i>	coefficient of performance [–]	<i>pros</i>	prosumer
<i>E</i>	energy [kWh]	<i>s</i>	supply
<i>f</i>	utilization factor [–]	<i>sur</i>	surplus
<i>G</i>	global irradiance [W/m ²]	<i>Nomenclature optimisation model</i>	
<i>NOCT</i>	nominal operating condition temperature [°C]	<i>X</i>	set of optimal cluster archetypes configurations
<i>P</i>	power [kW]	<i>Γ</i>	set of investigate energy community configurations
<i>Q</i>	thermal power [kW]	<i>Variables</i>	
<i>SC</i>	self-consumption [%]	<i>E_{load,j}</i>	j-th user energy demands
<i>T</i>	temperature [°C]	<i>E_{P2P,cons,j}</i>	j-th user energy demands satisfied by peer-to-peer mechanisms with prosumers
<i>Abbreviations</i>		<i>E_{PV,sc,pros,i}</i>	energy self-consumed by prosumers
<i>CA</i>	cluster archetype	<i>J_{pros,i}</i>	cash-flow for the i-th prosumer
<i>DER</i>	distributed energy resources	<i>P2P_{CA}</i>	optimal configuration of a specified cluster archetype
<i>DL</i>	dispatching layer	<i>pC_{pros,CA,m}</i>	percentage of prosumers in the m-th cluster archetype
<i>EC</i>	energy community	<i>pros_{type,CA,m}</i>	type of prosumers in the m-th cluster archetype
<i>HNN</i>	hybrid neural network	<i>SPB_{pros,i,thr}</i>	threshold of Simple Pay-Back time for the i-th prosumer
<i>MILP</i>	mixed integer linear programming	<i>SS_{CA,m}</i>	self-sufficiency of the m-th cluster archetype
<i>P2P</i>	peer-to-peer	<i>Parameters</i>	
<i>RES</i>	renewable energy sources	<i>n</i>	number of building archetypes of the community
<i>Greek letters</i>		<i>N</i>	number of user for a specified building archetype
<i>α</i>	absorbance [–]	<i>Indices</i>	
<i>η</i>	energy efficiency [–]	<i>CA_{pros,i}</i>	cluster archetype which include i-th prosumer
<i>Λ</i>	matrix of peers connections	<i>combCA</i>	combinations denoting cluster archetypes
<i>Subscripts</i>		<i>combCA_{pros}</i>	combinations denoting cluster archetypes including i-th prosumer
<i>av</i>	available	<i>i</i>	index for type of prosumer
<i>BOP</i>	balancing of plant	<i>j</i>	index for type of building users
<i>cons</i>	consumer	<i>m</i>	index for optimal cluster archetypes including i-th prosumer
<i>d</i>	demand		
<i>el</i>	electrical		

of renewable technologies, supportive government policies and incentives, rising awareness of environmental issues, and the desire for greater energy independence are driving the increase in installation of renewable distributed energy resources (DER) [3]. However, this is associated with issues related to the balance and stability of the conventional centralized electricity grid [4]. As a result, there has been a marked shift towards the development of methodologies that optimise the management of these energy systems. Among these, the concept of energy community (EC) represents a useful tool for achieving the set objectives [5], also considering that the installation of RES-based technologies, such as photovoltaic (PV) modules, has occurred significantly on buildings that have contributed to the decentralization of the RES system [6]. As a result, despite the positive benefits of the RES integration in buildings and in our communities, new challenges – such as intermittency, storage, and the need of policies and infrastructures, as well as novel energy management frameworks/paradigms – remain and call for advancements in technology and regulatory environment to maximize the benefits of decentralized RES installations [7]. From this point of view, the adoption of energy communities has become increasingly concrete as an effective measure to achieve multiple aims [8]: reduce the impact of RES on the traditional grid (e.g. reducing grid congestion and enhancing the overall grid efficiency), increase the self-consumption of RES production, support the integration of RES, and pursue just energy transitions [9]. Indeed, the European Renewable Energy Directive II (RED II) emerged with the aim of increasing the adoption of energy communities reflecting a growing awareness for

promoting collective self-consumption, thus maximizing the effectiveness of the use of renewable energy, and aligning with broader sustainability aims [10]. To this aim, energy communities foster community engagement, encouraging citizen to actively participate in the transition to sustainable energy towards common economic, social, and environmental goals [11].

With the aim to increase the knowledge and the awareness of energy communities towards their evolution and adoption, various innovative solutions mainly regarding the topology and market models of energy-sharing systems, have been extensively explored in literature [12]. These energy-sharing systems are broadly classified into off-grid and on-grid types, each serving distinct purposes and settings [13]. Off-grid energy communities typically exist in remote areas without access to the central electricity grid. These independent communities are designed to achieve complete self-sufficiency and energy autonomy by optimising the technologies mix of energy hub [14]. In these configurations, analysing the impact of different RES [15], integrating storage systems [16] to optimise the energy dispatch [17], and implementing energy flexibility actions [18] are pivotal to ensure the total coverage of energy demands from the electricity production mix [19]. On the other hand, on-grid energy communities consist of user aggregates categorized as consumers and prosumers [20]. They operate based on energy-sharing mechanisms while remaining interconnected with the central electricity grid. The primary aim of these systems is to maximize self-consumption investigating different Power-to-X strategies [21] while mitigating voltage and frequency imbalances that could impact the

overall grid stability [22].

With the aim to contribute to this research field, this work aims to introduce a method to optimise the design configuration of on-grid energy communities, implementing aggregation criteria where the users are grouped in building clusters able to optimally interact with central grid, by exploiting local renewable energy systems, and by adopting energy sharing management strategies [9,23].

To discover the research-gaps, the following paragraph will delve into a literature review, concentrating on methodologies, optimisation procedures and the electricity market strategies employed for the management of energy communities.

1.1. Literature review

Energy communities operate based on the fundamental principle of sharing energy among users. When electricity production systems are owned by users, they become primary contributors to the EC local energy market [24]. Conversely, when cooperatives manage these facilities, the energy market revolves around these entities coordinating the community's production systems and the users' requests within the same smart grid [25]. A centralized control strategy is envisaged for this configuration; conversely, for the first one where prosumers provide electricity to the local market, it is also possible to implement decentralized control strategies where each end-user has an independent energy and economic management.

Since the early implementation of energy communities or aggregators, how the exchange of energy is managed among all actors (prosumers and consumers, grid operators and users, etc.) and how the portfolio of energy production plants is coordinated have been highly investigated in literature [26]. In particular, efforts have been made for the creation of business and trading prices models [27] and for deriving control strategies and energy management schemes for the energy demand forecasting and flexibility [28], as discussed further.

Gao et al. [29] studied a cascade methodology for managing a community's energy resources. This methodology employs initial centralized control governing interactions between user requests and electricity production. Subsequently, an aggregator within the building cluster manages energy sharing among users. The proposed method was applied to a specific case study comprising four buildings with electrical requests simulated with assumptions made on the rated power of the equipment (e.g., HVAC, electrical vehicles, etc.). The aim was to achieve a net-zero energy cluster by minimizing reliance on the grid, leveraging both distributed resources and energy hubs owned by cooperatives. Similarly, Braeuer et al. [30], proposed a centralized control approach for an energy community characterized by four different single multi-family buildings classified based on the building age and number of occupants. The goal was to optimise the prosumer's energy system design through mixed integer linear programming (MILP) to minimize return on investment [31]. Centralized control strategies are also applicable to energy communities characterized by smart homes employing flexibility actions governed by demand-side management (DSM) strategies [32]. In this context, Lokeshgupta et al. [33] suggested a coordinated energy sharing mechanism, among 10 smart homes that include electric vehicles in their electrical appliances, adopting a centralized control. This strategy effectively manages user requests and prosumer storage functioning to minimize overall energy purchase costs. Implementing centralized control strategies becomes crucial, especially in scenarios lacking viable platforms and tools to connect users and facilitate information exchange regarding their requests and availability [34].

In energy communities characterized by decentralized control, the management focus shifts towards trading strategies [35]. Li et al. [36] conducted an economic analysis aimed to estimate the economic return for domestic users while exploring various methodologies determining the unit cost of exchanged electricity. These methods considered factors like peak and off-peak power hours, user electrical demands, and grid

Table 1

Taxonomy of literature review.

Study	Energy community research field	Case study characteristics	Aim of the work
[24]	Energy flexibility strategies to manage each electricity production and requests of the single user. Centralized control strategies governing energy sharing among users.	4 prosumers equipped with PV systems, wind turbine, batteries, and EVs	Net-zero energy cluster to maximize grid-independency
[25]	Optimising prosumer's energy system design.	4 different types of prosumers buildings equipped with PV systems, batteries, combined heat and power, and thermal storage.	Minimize return of investment
[26]	Centralized control strategies based on demand-side management of smart homes.	16 prosumers classified in 14 residential units, 1 office and 1 restaurant, equipped with PV systems, and batteries.	Minimize fossil fuel consumption.
[27]	Coordinated centralized home energy management (HEM) model with neighbourhood power sharing.	6 prosumers equipped with PV systems, wind turbines, and batteries. 4 consumers classified based on occupancy patterns.	Maximize the local renewable energy utilization, minimizing the electricity bills of all smart homes.
[30]	Economic feasibility of energy communities with two investment options: self-investment and third party investment.	10 prosumers of residential type equipped with PV systems and batteries.	Minimize pay-back time for investors.
[31]	Optimisation of the power to purchase in the day-ahead retailers market in EC.	17 prosumers with PV systems, 10 prosumers with wind turbines and 23 households consumers.	Assess the effect of self-sufficiency of EC consumers on the retailers' profit losses.
[32]	Energy sharing among communities (C2C).	9 prosumers equipped with PV systems and 24 households consumers.	Development of a platform to manage the energy sharing among peers of different ECs.
[36]	Regulation of demand/response events using a model predictive control strategy.	9 consumers (residential and offices) and 1 central energy hub with PV and batteries.	Optimisation to minimize CO ₂ emissions related to EC energy requests.
[34]	P2P energy trading among users adopting hybrid control models with market constraints dictated by a balance service provider	90 residential prosumers and 12 commercial prosumers equipped with PV and batteries.	Maximize economic revenues of energy balance service provider
[35]	Residential energy community load estimations with probabilistic and machine learning techniques	39 residential buildings classified based on floor area and number of occupants	Increase the accuracy of electrical load estimation of EC users.

electricity costs. Alonso Pedrero et al. [37] developed a market strategy for an EC of 50 neighbouring households based on determining the energy sales price from the previous day, relying on forecasting methodologies to evaluate influences on energy prices. Xia et al. [38] proposed a methodology to aggregate users of the EC into subgroups, demonstrating that employing trading mechanisms for electricity sharing among these subgroups could yield greater economic benefits.

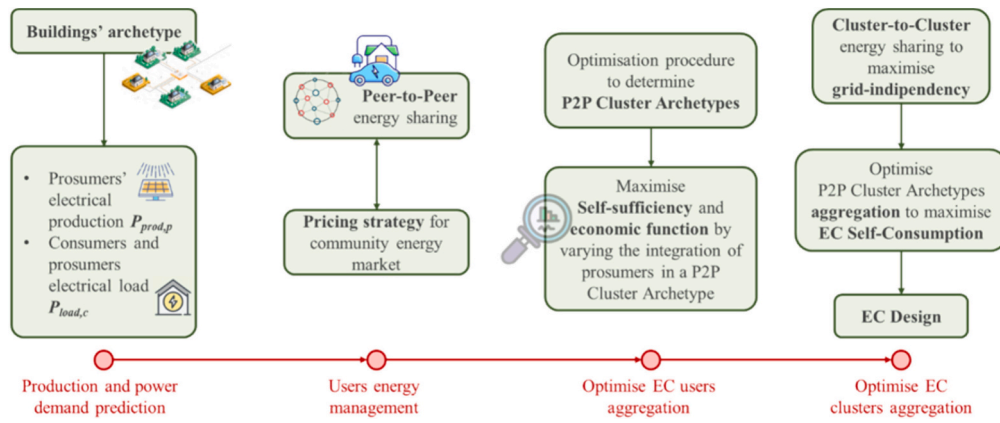


Fig. 1. Overview of the developed methodology for designing and optimising the management of energy communities.

Furthermore, game theory, notably Nash equilibrium and Stackelberg games, widely applied in literature, allows determining user interactions to maximize economic benefits for both user categories [39].

However, transitioning to a peer-managed market remains challenging due to economic-social conditions and the absence of specific management systems [24]. Consequently, centralized control solutions aimed at optimising the collective behaviour of energy communities are among the most prevalent. Further approaches involve hybrid control models, granting peers freedom to trade within the community but under the management of a balancing service provider, defining the trading rules [40].

Energy communities comprising individual electricity production plants, like micro-wind or photovoltaic systems, can be managed using rule-based control systems. However, when the system complexity increases, more efficient control mechanisms, such as model predictive control (MPC), become necessary in case studies. Both control types rely on forecasting models to accurately estimate electrical demands and energy production of these systems [41]. Houben et al. [42] studied a MPC control strategy to regulate demand/response events, optimising CO₂ emissions. This strategy leverages heating systems and electrical storage to enhance system flexibility, ensuring user requests are met. To bolster collective self-consumption and reduce dependence on the grid, electric vehicles were employed as storage sources, alongside heat pump thermal systems coupled with thermal storage [43] to enhance community flexibility [44].

Energy flexibility within these systems serves as a crucial property, maximizing self-consumption and self-sufficiency [27], especially in remote areas and in areas significantly impacted by extreme climate events. However, implementing these strategies may face challenges, particularly when users are reluctant to alter their energy behaviour [45].

The conducted review of the literature underscores the significance of energy communities in advancing sustainability goals through optimal utilization of renewable energy resources. Some of the investigated works in the literature review are categorized in the Table 1. It is evident that the outcomes and results of many studies are tailored to the specific choice of users that compose the case studies. Replicating and applying these case studies in real-world scenarios requires the presence of the same investigated boundary conditions, which are often challenging to attain. Therefore, this highlights a significant research gap: the absence of standardized criteria to effectively apply and fully leverage the benefits associated with energy community mechanisms. Addressing this gap necessitates taking a step back and prioritizing the design of energy community configurations by establishing aggregation criteria among users based on energy and economic objectives. While the literature has explored the role of aggregating users in an EC, the primary emphasis has often been on analysing the social impact on citizens [46], rather than considering the energy and economic

implications.

Moreover, providing inputs to fill this gap has a recognized twofold aim, encompassing the research and development of energy communities, and the formulation of policy and legal frameworks for enabling the effective implementation of energy community share models [47].

1.2. Work contributions

This study focuses on addressing the critical issues arising from the application of energy communities in real contexts by proposing innovative methodologies. The challenges identified with the literature review concern the influences that specificity of case studies have on the energy and economic performance of energy communities. Indeed, most of the conducted analyses are very case specific, preventing the adoption of the achieved results for different applications. These characteristics are very often linked to the energy demand of users and the typology of energy production technologies integrated into the community. Therefore, to overcome this limitation, the present work introduces a method to optimise the design configuration of energy communities, employing end-users' aggregation criteria for real implementation by stakeholders. This approach involves selecting the type and number of users – both consumers and prosumers – to be aggregated in an EC using a bilevel optimisation procedure. Initially, this procedure aggregates different types of end-users into subgroups to enhance self-sufficiency and ensure economic benefits for each member of the community. Subsequently, it prioritizes solutions that maximize self-consumption by aggregating these subgroups, thereby obtaining the optimal configuration for the EC. Furthermore, this aggregation approach is based on several key aspects:

- Development of a novel hybrid model to estimate demand curves of energy community users. This model integrates the strengths of both physical building models and neural networks, categorizing users based on building archetypes. This building classification considers not only their geometry and thermophysical properties but also the electrical usage habits of occupants conditioned by factors – working hours, age-related consumption preferences, etc. – which significantly influence the dynamism and amplitude of electrical demand. Furthermore, statistical analyses have been adopted to assess the impact of user types on the usage frequencies of equipment, lighting, and air conditioning systems.
- Implementation of a peer-to-peer energy sharing strategy between consumers and prosumers within the community. This approach relies on centralized control logic to optimise user connections, maximizing energy interactions while minimizing reliance on the central grid. Electricity market prices among peers are determined through the balancing of supply and demand curves.

In conclusion, these contributions collectively offer innovative

methodologies and strategies that advance the effective implementation and performance of energy communities in real-world contexts.

2. Methodology

The procedure implemented for the design and management of EC is focused on specific *end-user aggregation criteria*. The aim of this procedure is maximizing the economic return of each end-user and optimising the management of the EC's distributed energy resources.

The investigated EC is of the community prosumerism type [13] where end-users are differentiated into prosumers and consumers. The prosumers act as investors, while the consumers join the energy sharing mechanisms to enhance the efficiencies of the EC. This EC is connected to the central grid both to satisfy end-user requests that are not covered by distributed production systems and to sell the excess energy produced. The sharing mechanism is P2P type, EC users participate in a *local energy market* in which prosumers and consumers can directly trade electricity among themselves [35]. The analysed negotiation type relies on the national grid infrastructure for energy sharing purposes among the EC users. Furthermore, it has been demonstrated that this type of energy exchange may help the grid infrastructure in reducing losses associated with power transmission conversion and mitigating imbalances caused by undesired energy injection into high-voltage transmission lines [48]. A centralized control system governs this P2P model, applying logical rules to ensure the community's energy equilibrium.

Fig. 1 provides a schematization of the proposed methodology to optimise the design and configuration of an EC.

The proposed methodology is structured as follows:

- Development of predictive models to estimate the electrical loads and electricity production of EC users.
- Implementation of P2P energy sharing algorithms based on centralized control logics within ECs models.
- Definition of user aggregation criteria to investigate different EC configurations.
- Implementation of optimisation procedures aimed at determining the optimal design.

The first step of this methodology involves the identification of potential prosumers and consumers. Since it is not always possible to use real datasets relating to the dynamic measurement of end-users' energy demands, a predictive procedure has been developed. This procedure employs statistical analyses and a hybrid energy model of buildings to *forecast dynamic electricity demands*. To carry out this prediction, end-users are classified into building archetypes defined according to the socio-behavioural characteristics of the occupants and the geometric and thermo-physical characteristics of the building [49].

Once the typologies of potential EC users have been characterized, the next step involves defining *end-user aggregation criteria*. The first aggregation criterion consists of grouping the end-users into subgroups representing small energy communities. The second criterion is aimed to design the global EC by interacting the subgroups generated through the first aggregation criterion. Subsequently, these criteria have been adopted to study a bi-level optimisation problem.

The first level of the optimisation problem aims to maximize the annual self-sufficiency of each EC's subgroup, observing economic constraints, while accounting for variations in the number and types of prosumers. These EC's subgroups are characterized by a first dispatching layer (1st DL) of P2P type where the end-users of a single subgroup can share energy only among them. This optimisation problem is addressed using the MILP algorithm, and the optimised EC's subgroups are defined as *P2P cluster archetypes*.

Subsequently, the second level of optimisation involves aggregation between P2P cluster archetypes (*P2P_{CA}*) and is focused to determine the optimal design configuration of the whole EC. This optimisation seeks to maximize the entire EC's annual self-consumption. This stage involves

implementing a second P2P dispatching layer (2nd DL) among users of different *P2P_{CA}*, performed in series with the earlier established P2P mechanisms.

Finally, this holistic approach employed in the design and management of the EC, focused on *end-user aggregation criteria*, emphasizes the maximization of economic benefits and the efficient management of distributed energy resources, showing a structured methodology oriented towards optimising community-based energy systems.

2.1. Building archetypes for EC users' energy modelling

The estimation of the electricity demands and the production of the decentralized systems for each EC user, considered as all-electric – occur through an energy modelling of the building archetypes. As previously explained, end-users are categorized into these archetypes considering both the socio-behavioural attributes of occupants and the thermo-physical characteristics of the building, that contributing to its electric load.

2.1.1. Prosumers' energy production systems

EC prosumers are assumed as equipped with PV systems. Their sizing has been performed with the aim of determining the number of panels $N_{PV,i}$ that ensure an annual energy production equivalent to the annual energy demand of each *i*-th prosumer of the community. However, if the requested surface area is greater than the available one $A_{PV,av,i}$, the system sizing adheres to this constraint, as outlined in Eq. (1):

$$N_{PV,i} = f \left(\int_{\text{year}} P_{PV,prod,i} = \int_{\text{year}} P_{load,i} \right) \quad (1)$$

$$s.t. \rightarrow N_{PV,i} \leq A_{PV,av,i} / A_{PV}$$

Here, $P_{load,i}$ represents the electrical power demanded by the *i*-th prosumer, A_{PV} is the surface area of a single photovoltaic module, and $P_{PV,prod,i}$ [50] denotes the power produced by the PV systems, calculated using Eq. (2):

$$\begin{cases} P_{PV,prod,i} = (G \times A_{PV,tot}) \cdot \eta_{PV} \cdot \eta_{BOP} \cdot \eta_{shading} \\ \eta_{PV} = f \left(P_{MPP,STC}, C_{t,P}, T_{cell}, \frac{1}{G_{STC}} \right) \end{cases} \quad (2)$$

Eq. (2) introduce terms such as η_{PV} , η_{BOP} , $\eta_{shading}$ referring respectively to single module efficiency, global plant efficiency accounting for transmission losses, and efficiency considering shading losses. $P_{MPP,STC}$ and G_{STC} stand for the maximum power production and incident radiation in standard test conditions. $C_{t,P}$, and T_{cell} represent the coefficient for power variation under conditions different from *STC* and the cell temperature [51]. This term is a crucial parameter to estimate the PV module efficiency [52] and it is expressed in Eq. (3):

$$T_{cell} = T_{air} + G \times \frac{NOCT - 20}{800} \times \left(1 - \frac{\eta_{cell}}{\alpha \cdot \tau} \right) \quad (3)$$

Here, *NOCT* is the cell temperature in nominal operating condition, while α , and τ denote the absorbance and transmittance of the PV glass cover.

2.1.2. Electrical load estimation: Equipment and lights

As regard the evaluation of electrical load $P_{load,j}$ for each end-user type, it was assessed by considering the electric demands associated with equipment, lighting, and air conditioning, as represented in Eq. (4):

$$P_{load,j} = P_{lights,j} + \sum_{k=1}^{N_{eq}} P_{eq,j,k} + P_{HVAC,j} \quad (4)$$

Here, $P_{lights,j}$ denotes the lighting demand of the *j*-th end-user, $P_{eq,j,k}$ accounts for equipment (such as computers, TVs, ovens, washing machines, etc.), and $P_{HVAC,j}$ is associated with the building's space heating/

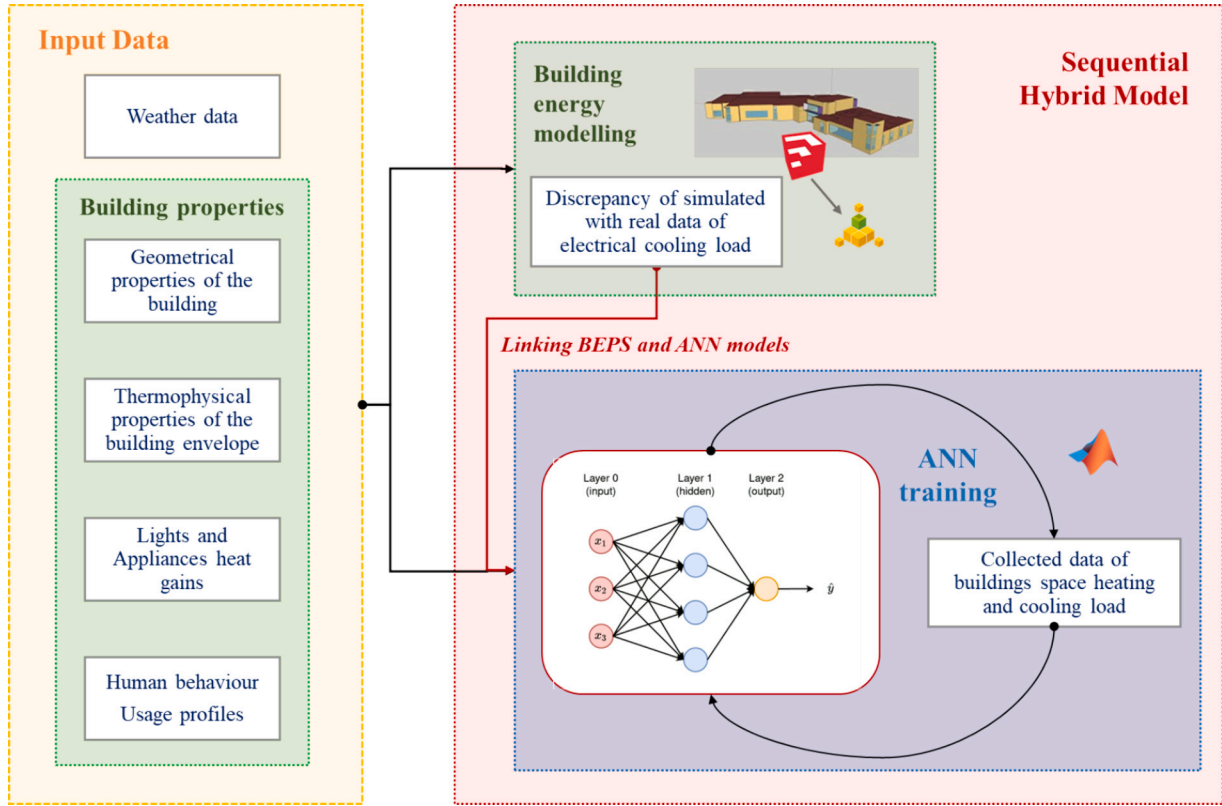


Fig. 2. Schematization of sequential Hybrid Neural Network model.

cooling thermal needs.

A predictive method, employing statistical analyses, was utilized to model dynamic electricity usage profiles for lights and equipment. These profiles can be obtained by knowing the nominal electrical power and determining the hourly frequency of use [53].

The electrical load related to the operation of k -th electrical equipment for the j -th user is estimated as described in Eq. (5):

$$P_{eq,j,k} = f_{occ,j} \cdot f_{use,eq,k} \cdot P_{nom,eq,k} \quad (5)$$

Where $P_{nom,eq,k}$ represents the nominal electrical power of equipment, and $f_{use,eq,k}$ the utilization factor that is derived by the work of Paatero et al. [53]. While $f_{occ,j}$ is the occupancy factor that represents the building occupancy rate multiplied by an enhancement coefficient expressing the number of occupants. Its role is fundamental in assessing how the number of occupants influences the electrical consumption of equipment during specific time periods.

For lighting, the electrical load $P_{lights,j}$ is calculated as reported in Eq. (6):

$$P_{lights,j} = f_{occ,j} \cdot f_{use,lights,j} \cdot P_{lights,density,j} \cdot A_{floor,j} \quad (6)$$

The nominal power of the lights is derived from the product of the power density $P_{lights,density,j}$ and the floor area $A_{floor,j}$ of the j -th building archetype. While the dynamism of the usage profile is estimated based on $f_{occ,j}$ and the lighting utilization factor $f_{use,lights,j}$ which is influenced by the contributions from natural sunlight during the years.

Lastly, the prediction of the electrical load associated with the air conditioning demands of buildings is estimated through a hybrid model, further detailed in the subsequent paragraph.

2.1.3. Sequential HNN model for heating / cooling demands

The sequential hybrid neural network (HNN) model combines a building energy performance simulation tool with a feed-forward artificial neural network (FFANN) to assess the HVAC electrical load profile of EC users building archetypes. This sequential approach exploits a

feedforward connection between the physical building model and the FFANN, represented by the error signal generated from comparing the simulated energy demand of the physical model with the actual demand. By incorporating this additional input/information from the physical model, the accuracy of the FFANN model is improved while avoiding the complexities associated with integrating physical laws directly into the FFANN architecture.

A schematization of developed hybrid model is reported in Fig. 2. The input data for both building energy simulation models are represented by the climatic conditions, geometric properties of the archetypal building, thermophysical properties of the building envelope, heat inputs from equipment and lighting, as well as the occupancy profile of the occupants [54].

The physical modelling of the building consists of geometric and energy modelling. The geometric modelling was developed using Google Sketchup version 8 software. This geometric model was then imported into TRNSYS version 17 software and, by using its building energy modelling libraries, it was possible to simulate the thermal energy requests for each type of building in the EC. Once the thermal demands $Q_{th,load,j}$ were estimated, the following correlation was employed to determine the electrical consumption linked to the operation of the HVAC, denoted as $P_{HVAC,j}$:

$$\begin{cases} P_{HVAC,j} = Q_{th,load,j} \cdot COP_{hp,j} \\ COP_{hp,j} = f\left(hp_{type}, \frac{Q_{th,load,j}}{Q_{th,load,j,max}}, T_{hp,source}, T_{hp,sink}\right) \end{cases} \quad (7)$$

Where the efficiency of the heat pump $COP_{hp,j}$ was estimated based on factors such as the type of heat pump (e.g., air-to-air, air-to-water, water-to-water, etc.), the fraction of the required heat load on the maximum one, as well as the temperatures on the source and sink sides of the heat pump [55].

The FFANN employed within the hybrid model was developed by using MatLab functions. It consists of an input layer corresponding to

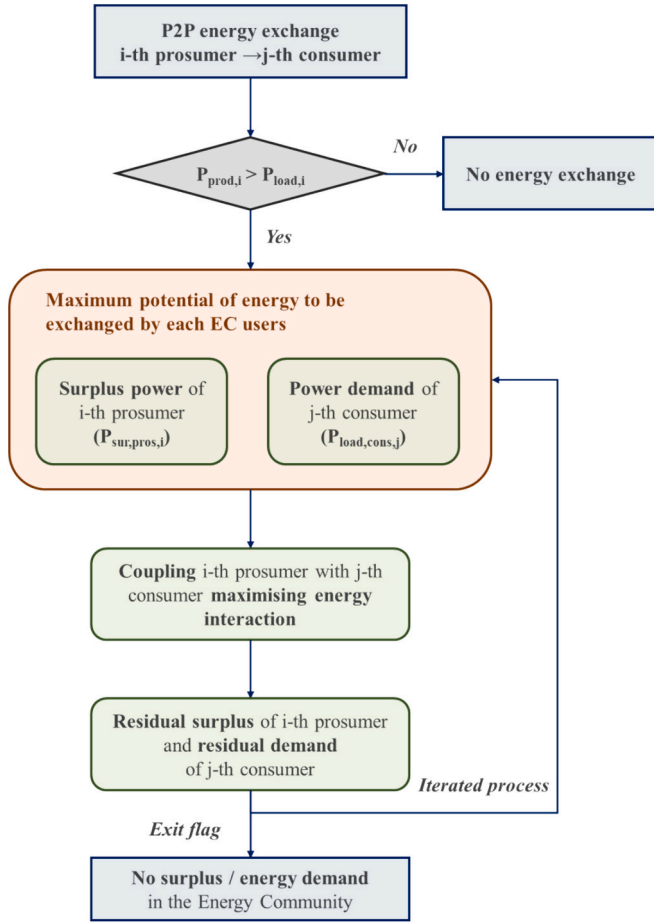


Fig. 3. Algorithm used to model the P2P energy exchange mechanism.

various input variables (e.g., weather conditions, building characteristics, occupancy patterns, etc) and an output layer representing the electrical loads requiring prediction. The number of neurons in the hidden layer is determined by averaging the number of neurons in the input and output layers, and it utilizes the Rectified Linear Unit (ReLU) activation function, typically used in artificial neural networks [56]. During the network's training phase, the Adaptive Gradient Algorithm (Adagrad) serves as the optimiser. This algorithm adjusts the learning rates for each weight (i.e., parameter) based on the square root of the sum of squared gradients [57].

The structure of the HNN model used to predict the electrical load associated with end-user air conditioning demands is described below. First, the difference between the real data and that obtained from the physical model of the building is estimated. This discrepancy is then incorporated as an input to the FFANN model to fine-tunes its training process, thus defining the hybrid HNN model. The HNN model training was performed with real data sets normalized to their respective maximum values on the time string to enhance the accuracy of the HVAC electrical load prediction. Subsequently, multiple HNN models are developed for each archetypal building, utilizing data sets that mirror its thermophysical and socio-behavioural characteristics of the occupants.

Finally, this sequential hybrid model capitalizes on the strengths of both approaches – the accuracy of physics-based models and the adaptability of ANN models – to enhance prediction accuracy while capturing intricate relationships and learning from available data.

2.2. Peer-to-Peer model for users' energy sharing

The P2P energy sharing mechanism, implemented in the proposed and developed EC model, adopts a centralized control strategy. This

strategy aims to regulate the connections between prosumers and consumers, maximizing energy interaction for each end-users coupling, while reducing dependence on the central grid. The procedure adopted to determine the price of shared energy is based on the equilibrium point criteria between *consumers demand curve* and *prosumers supply curve*.

Fig. 3 depicts a flowchart illustrating the algorithm used to model the P2P energy exchange within the community.

The initial step of this mechanism involves evaluating the surplus of energy generated by each prosumer's PV systems. Once the availability of electricity from a single prosumer for sharing purposes has been identified, the methodology is engaged in establishing the rules governing the *local energy market*. These rules aim to evaluate the connections among end-users that maximize their energy match. The function adopted to assess these connections is expressed in the following Eq. (8):

$$\Lambda_{opt[i \times 1]} = \underset{j \in \text{cons}_{type}}{\operatorname{argmin}} (P_{sur,pros,i} - P_{load,cons,j}) \quad (8)$$

In this equation, Λ_{opt} represents a matrix with rows equal to the number of prosumer types within the investigated EC. The matrix elements are obtained through the arguments of the minimum of the function represented by the difference between the prosumer's surplus $P_{sur,pros,i}$ and the consumer's request $P_{load,cons,j}$. Consequently, each element of the matrix Λ_{opt} establishes the best coupling between the i -th prosumer and the j -th consumer.

The power exchanged by prosumers with consumers is determined by Eq. (9):

$$P_{exch,P2P[i \times 1]} = \min \{ P_{sur,pros,i}, P_{load,cons,\Lambda_{opt}(i)} \} \quad (9)$$

This equation calculates the exchanged power $P_{exch,P2P,i}$ by each prosumer as the minimum value between the available surplus and the consumer request. Where $P_{load,cons,\Lambda_{opt}(i)}$ represents the electrical load of the consumer that maximizes the energy interaction with the i -th prosumer surpluses $P_{sur,pros,i}$, as determined in Eq. (8). Following this, it is possible to determine the residual surplus of each prosumer and the unmet demand of consumers.

Finally, this process is iterated to couple the community's end-users until either the surplus of prosumers or the requests from consumers have been entirely shared or satisfied.

2.2.1. Pricing strategy

The pricing strategy for the P2P energy community relies on balancing supply and demand curves to determine the market price for exchanged energy.

The demand curve, relating to consumers, expresses their willingness to pay for electricity as the quantity of energy requested varies. This curve is obtained from the utility curve, reflecting consumers' satisfaction or utility from consuming energy [58]. It is expressed with this equation:

$$\begin{cases} C_d = \frac{dU(E_d, c_{el,max})}{dE_d} = c_{el,max} - a_j \cdot E_d \\ U(E_d, c_{el,max}) = c_{el,max} \cdot E_d - \frac{a_j}{2} E_d^2 \end{cases} \quad (10)$$

Where the demand curve C_d is evaluated as the derivative of the utility curve U . C_d is a function of the quantity of requested energy, denoted as E_d , and considers the maximum cost of electricity $c_{el,max}$ that the consumer is willing to pay. In this strategy, the maximum cost aligns with the purchase cost from the central grid. Additionally, the demand curve is influenced by a calibration constant a_j which depends on the j -th consumer type, which, in this case, is impacted by factors such as the number of occupants [58].

The supply curve C_s demonstrates the price at which prosumers are willing to sell energy as the exchanged quantity varies.

$$C_s = f(a_j, E_s, r_{sp_{el,max}}) \quad (11)$$

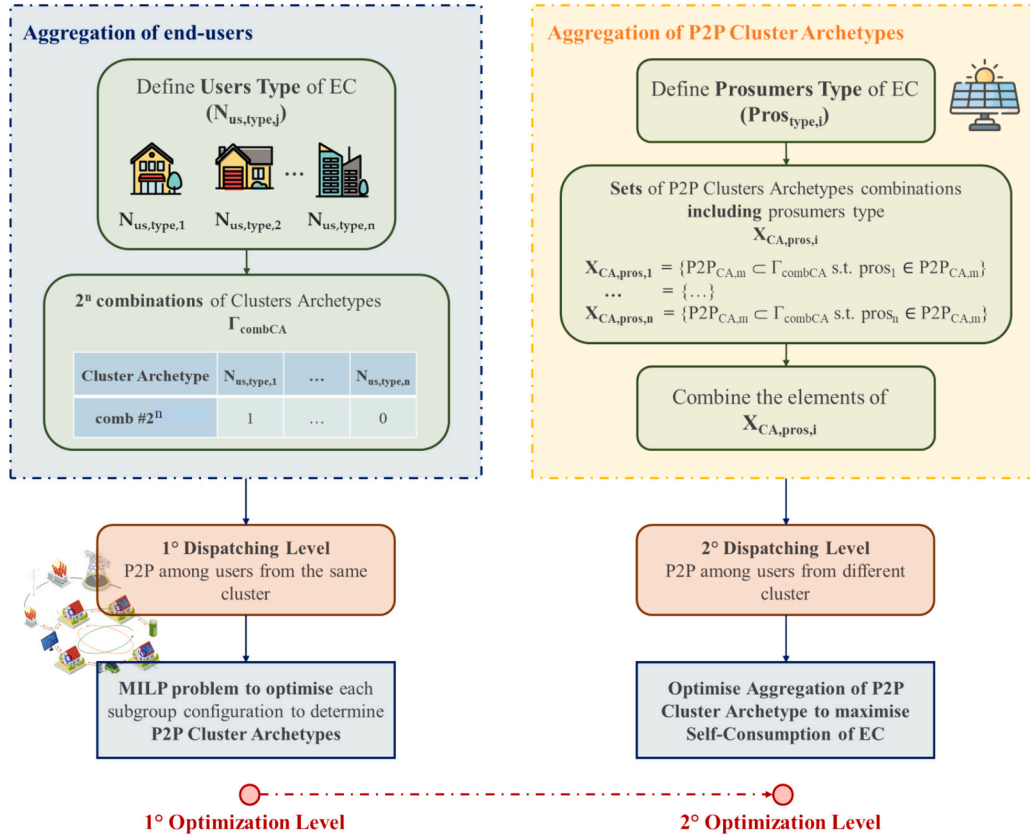


Fig. 4. Synoptic diagram related to the aggregation criteria for EC design.

As expressed in Eq. (11) the supply curve is determined as a function involving the calibration constant a_j , the offered supplied energy E_s , and the maximum retail selling price, $rsp_{el,max}$, from the grid.

The intersection between the demand and supply curves enables the determination of the market's equilibrium point, thus establishing the unit cost of electricity, $c_{el,P2P,j}$, for the j -th consumer participating in the local energy market.

This strategy for determining the unit price of energy was aimed to establish a fair criterion that guarantees the right trade-off between consumer savings and prosumers revenues compared to the reference scenario of purchasing and selling from/to the central grid.

2.3. EC design methodology

This paragraph offers an overview of the aggregation criteria that have been suggested to identify different EC configurations. These configurations will be the focus of a bi-level optimisation analysis to assess the best possible P2P energy community design.

The intermittency of PV production can be noted as a critical consideration in the optimisation routine. It acts as a key variable influencing the optimal aggregation among users, selecting consumers whose energy demand profiles can minimize or mitigate the effects of this intermittency and fluctuating production on the national grid infrastructure.

As illustrated in the synoptic diagram of Fig. 4, the aggregation criteria are categorized into two classes, respecting the bi-level structure of the optimisation procedure. The two levels of the optimisation problem are executed sequentially, making the second aggregation criterion dependent on the results obtained from the first optimisation level.

The primary objective of the first optimisation level is to identify subgroups among community end-users, optimised in accordance with economic and energy indices. Furthermore, within each EC's subgroup,

the implementation of the first dispatching layer (1st DL) of the P2P model is executed. This dispatching layer involves energy sharing mechanisms among peers of the same cluster.

The second level focuses on the aggregation of these optimised subgroups to obtain the best EC configuration that optimises the management of the EC's energy resources. Within this optimisation process, for each investigated EC configuration, the second level of P2P dispatching (2nd DL) is implemented. This level operates in sequence with the 1st DL, enabling energy sharing among users associated with different optimised subgroups.

Further details regarding the aggregation criteria, optimisation procedures and objective functions employed for the development of the two-level problem will be described below.

2.3.1. Aggregation criteria

Establishing precise end-user aggregation criteria stands as a pivotal procedure in determining the design of energy communities. This study introduces and elaborates two aggregation levels to perform this process.

The primary step of the first aggregation criterion involves identifying and categorizing all types of end-users within the EC (see Fig. 4). Therefore, an analysis is conducted to assess all potential combinations for grouping them into subgroups. These combinations are referred to as *cluster archetypes* within this manuscript. For each *cluster archetype*, the assumption is that at most one end-user belonging to each type will be considered. Subsequently, the combinations were evaluated as follows:

$$\Gamma_{combCA}[N_{comb,CA} \sim N_{us,type}] = combinations(N_{us,type,1}, \dots, N_{us,type,n}) \quad (12)$$

This equation defines Γ_{combCA} as the set that includes all combinations of elements derived from the input arrays denoted as $N_{us,type,j}$. This array corresponds to the j -th set of end users, where its elements indicate the presence or absence of the same user type within the *cluster archetype*

(refer to Eq. (13)).

$$N_{us,type,j} = \{0, 1\} \quad (13)$$

The number of rows of Γ_{combCA} , hence the number of combinations, is determined by the product of the elements within each set $N_{us,type,j}$, as indicated in Eq. (14):

$$N_{comb,CA} = \prod_{j=1}^n size(N_{us,type,j}) \quad (14)$$

Meanwhile, the number of columns in Γ_{combCA} corresponds to the total number (denoted as n) of end-user types within the EC. The elements of Γ_{combCA} matrix were obtained through the Cartesian product of the elements of the n sets $N_{us,type,j}$. It is worth noting that combinations resulting in a total number of users fewer than two were not investigated, as it is impossible to create a subgroup of ECs under such circumstances.

Subsequently, the configurations of *cluster archetypes*, previously defined, are optimised through a MILP-type procedure, taking into account the variation of prosumers based on their types and numbers. The resulting optimised configurations of EC subgroups are referred to as $P2P$ cluster archetypes ($P2P_{CA}$).

Regarding the second aggregation criterion, the focus lies on determining all the possible configurations of the entire EC obtained by combining the $P2P_{CA}$ (see Fig. 4). Initially, after identifying the quantity and types of prosumers within the investigated EC, the $P2P_{CA}$ obtained from the first level of optimisation are chosen. Specifically, this selection considers $P2P_{CA}$ that include at least one type of prosumer from the investigated EC. These selected $P2P_{CA}$ are grouped into sets according to the following definition:

$$X_{CA,pros,i} = P2P_{CA,m} \subset \Gamma_{combCA} \rightarrow s.t. \ pros_i \in P2P_{CA,m} \quad (15)$$

$$\begin{cases} i \in pros_{type} \\ m \in [1, 2^n] \end{cases}$$

Where $X_{CA,pros,i}$ denotes the sets formed by the m -th $P2P_{CA,m}$ elements contained in Γ_{combCA} , which encompass the i -th type of prosumer. At this stage, the elements within the sets $X_{CA,pros,i}$ are combined using the same procedure outlined in equations Eq. (12) and Eq. (14). The resultant set of combined elements from $X_{CA,pros,i}$ is defined as $\Gamma_{combCA,pros}$.

Once the sets of potential end-user subgroups $X_{CA,pros,i}$ are defined and combined to assess all possible aggregation scenarios $\Gamma_{combCA,pros}$, an iterative optimisation procedure is executed. This procedure aims to identify the optimal EC configuration which maximizes the annual self-consumption.

In conclusion, these criteria have been employed to delineate sets of subgroups within the EC and configurations for the entire EC. The subsequent description details the procedures utilized to determine the optimal scenarios within these defined sets.

2.3.2. Optimisation of $P2P$ cluster archetypes

The first optimisation level aims to determine the best configuration of each m -th *cluster archetype*, defined in the matrix Γ_{combCA} using Eq. (12).

This optimisation procedure, as previously reported, was solved with a MILP-type algorithm. The decision variables investigated for the optimisation of each *cluster archetype* are the number and type of prosumers, and were defined as follows:

$$\begin{cases} pc_{pros,CA,m} = n_{pros}/n_{CA,m} \\ pros_{type,CA,m} = combinations \left(\begin{pmatrix} n_{CA,m} \\ n_{pros} \end{pmatrix} \right) \end{cases} \quad (16)$$

The variable $pc_{pros,CA,m}$ denotes the percentage of prosumers within the *cluster archetype* (CA) under investigation. This percentage ranges from a minimum value which ensure the presence of at least one

prosumer, to a maximum value equal to half the number of users (i.e., $n_{CA,m}$) in the CA. Meanwhile, the second variable, $pros_{type,CA,m}$, is determined by computing all the binomial coefficient's combinations of the $n_{CA,m}$ user types taken n_{pros} at a time. This variable's role is to determine all the potential configurations of the m -th CA, that can be obtained by varying the type of prosumer for a fixed $pc_{pros,CA,m}$ percentage.

The objective function adopted to discover the best involvement of prosumers within the m -th CA, considering both their quantity and type, is the annual self-sufficiency $SS_{CA,m}$. By modifying the variables $pc_{pros,CA,m}$ and $pros_{type,CA,m}$, the parameter space determines all feasible configurations for the CA. These potential solutions are subject to constraints related to an economic function that incorporates prosumers' revenues.

Formally, the optimisation problem is defined as follows:

$$\begin{cases} \max \left(SS_{CA,m} = \left(\sum_i E_{PV,sc,pros,i} + \sum_j E_{P2P,cons,j} \right) / \sum_j E_{load,j} \right) \\ s.t. \rightarrow J_{pros,i} = C_{el,P2P,j} \cdot E_{P2P,cons,j} + C_{el,g} \cdot E_{PV,sc,pros,i} \\ \geq J_{pros,i,thr} = f(SPB_{pros,i,thr}) \end{cases} \quad (17)$$

Hence, as depicted in this equation, the goal is to identify the optimal solution that maximizes the annual $SS_{CA,m}$, calculated as the ratio between the sum of photovoltaic-produced energy self-consumed ($E_{PV,sc,pros,i}$) and shared by each i -th prosumer ($E_{P2P,cons,j}$), and the total energy demanded by the users ($E_{load,j}$). While, the solution set is constrained by the condition that the cash-flow $J_{pros,i}$ for each prosumer must exceed or be equal to its threshold value $J_{pros,i,thr}$, determined as a function of the minimum required pay-back time $SPB_{pros,i,thr}$.

Finally, this optimisation procedure is performed for each m -th CA with the aim of determining all the optimal $P2P_{CA}$ configurations, which can be exploited for the next step related to the EC design.

2.3.3. $P2P$ cluster archetypes aggregation

The second optimisation level is performed in series with the previous one, and as described in the previous paragraphs, is aimed at determining the optimal design of the EC.

The first step consists in determining the quantity of each type of prosumers of the investigated EC. The next step involves the implementation of an iterative procedure to obtain the EC configuration for each combination of the set $\Gamma_{combCA,pros}$.

As seen previously, the elements of each combination will be represented by $P2P_{CA,m}$ which contain at least one of the types of prosumers of the investigated EC. Through this iterative process, the goal is to determine the count of each $P2P_{CA,m}$ contributing to the EC configuration. The method (expressed in Eq. (18)) is constrained by the objective of including all the prosumers $N_{pros,i,EC}$ within the configuration EC_{conf} while simultaneously considering the maximum availability of each consumers type $N_{us,j,conf}$ present within the EC under investigation.

$$\begin{aligned} EC_{conf} &= N_{P2P_{CA,m}} \rightarrow \forall \text{element of } \Gamma_{combCA,pros} \\ s.t. &\rightarrow \exists N_{us,j,conf} \wedge N_{pros,i,EC} \subset EC_{conf} \end{aligned} \quad (18)$$

The configurations generated through this iterative process for each $\Gamma_{combCA,pros}$ combination are evaluated and compared. The most favourable configuration is determined based on its ability to maximize self-consumption, defined as follows:

$$SC_{EC} = \left(\sum E_{PV,sc,pros,EC} + \sum E_{P2P,cons,EC} \right) / \sum E_{PV,production} \quad (19)$$

Here, the self-consumption of the overall EC configuration (SC_{EC}) is determined by calculating the ratio between the total energy self-consumed by all EC prosumers and the energy shared among all consumers within the investigated EC configuration, divided by the total PV production of the EC prosumers.

Table 2
Users building archetypes properties.

Properties		Building archetype					
Class	Subclass	#1	#2	#3	#4	#5	#6
Type of occupants	Age range [years]	18–64	>64	18–64	>64	18–64	18–64
	Number of employee	1	0	2	0	2	2
	Number of no employees	0	1	0	2	0	0
	Number of children	0	0	0	0	2	3
	Floor area [m ²]	67	67	100	100	134	167
Building geometry	Ceiling height [m]	2.8	2.8	2.8	2.8	2.8	2.8
	Windows to wall ratio [%]	18	18	20	20	25	25
	U-value of walls [W/m ² K]	1.4	1.4	1.4	1.1	1.1	1.1
Building thermophysical properties	U-value of windows [W/m ² K]	2.5	3.8	3.8	2.5	2.5	2.5

Table 3
PV systems characteristics, type and count of prosumers.

PV systems sizing			
Prosumer	Type #1	Type #4	Type #5
Rating power [kW]	0.7	1.75	2.98
Number of PV module [–]	4	10	17
Surface [m ²]	5.2	13	22.1
Number of end-users [–]	1	7	9

Technological characteristics of PV polycrystalline module					
$P_{MPP,STC}$ [W]	G_{STC} [W/m ²]	$T_{cell,STC}$ [°C]	$C_{t,P}$ [1/°C]	η_{BOP} [–]	$\eta_{shading}$ [–]
175	1000	25	–0.0043	0.79	0.75

3. Proof of concept

The suggested methodology's potential was assessed through a concept analysis targeting the design of an energy community, considered as case study, situated in a residential zone adjacent to the park of the Royal Palace of Caserta, Italy. Initially, the users of this area were categorized on the basis of occupant types and the geometric, thermophysical properties of their respective buildings. This classification allowed the establishment of building archetypes, enabling the energy simulation of the users. Table 2 presents the characteristics of the six identified building archetypes.

This table delineates the building characteristics and occupancy types for each user category, providing essential parameters used as inputs for estimating their electrical demands. The predictive methodology, relying on statistical analyses and the HNN hybrid model described in the previous sections (2.1 Building archetypes for EC users' energy modelling and 2.1.3. Sequential HNN model for heating / cooling demands), was employed to assess the electrical loads linked to equipment, lighting, and HVAC systems for these users. Additional inputs, necessary for this energy simulation, include occupancy profiles patterns sourced from analyses conducted by the national statistics institute (ISTAT) [59], as well as equipment and lighting utilization factors obtained from this specified reference [53]. Moreover, the weather data impacting the buildings' air conditioning demands - such as external air temperature, humidity, and solar radiation - were taken from Meteorism version 8 software datasets [60].

For a comprehensive analysis of the estimated electrical demands for the users within the investigated case study, refer to Appendix A.

The prospective users within the surveyed residential area willing on deploying a photovoltaic system belong to types #1, #4, and #5 (refer to Table 2 for specific categorizations). The primary parameters considered for sizing the systems tailored to these user types, alongside the user count per type are outlined in Table 3. The results related to the dynamic

performance and producibility of the photovoltaic systems of the investigated users are reported in Appendix B.

The design of this case study's energy community aims to optimise the energy resources management of these users equipped with a PV system (i.e., prosumers) by aggregating them with specific consumer types. This aggregation minimizes interactions with the central grid and maximizes energy exchanges among end-users (as described in paragraph 2.3 EC design methodology).

The initial step in the methodology adopted for the EC design involves introducing an end-user's aggregation scheme to create subgroups within the EC. The configurations of these subgroups were optimised using the first-level optimisation procedure described in the previous section (2.3.2 Optimisation of P2P cluster archetypes). This criterion aims to outline opportunities for each prosumer to align with specific consumer categories, emphasizing maximal self-sufficiency while minimizing investment pay-back time. As previously mentioned, subgroup configurations are characterized by a maximum of one user per user type. Subsequently, in order to enhance the self-consumption levels of the prosumers' PV systems and reduce dependence on the central electricity grid, a second level of aggregation was proposed. Finally, this criterion aims to offer guidelines for globally aggregating users and determining the optimal EC design.

The next section presents the results concerning energy management, as well as the energy and economic performance indices of the EC derived from the applied methodology.

4. Results

This section presents the main results concerning the performance and energy management of the EC designed in accordance with the proposed methodology and implemented for the analysed case study. The saving obtained by the proposed methodology have been evaluated comparing it with a reference scenario characterized by the users (both consumers and prosumers) acting independently and connected only to the national electricity grid.

The results section, aimed to investigate the reliability of the developed methodology, is organized as follows:

- Evaluation of the performance and accuracy of the innovative HNN hybrid model for estimating electrical loads associated with users' air conditioning demands.
- Assessment of energy inputs that encompass the electrical load profiles of the identified end-user types and estimates of electricity production from PV systems owned by users acting as prosumers (the results concerning the determination of these inputs are detailed in Appendix A Results of users' electrical load forecasting and Appendix B Results of PV systems production respectively).

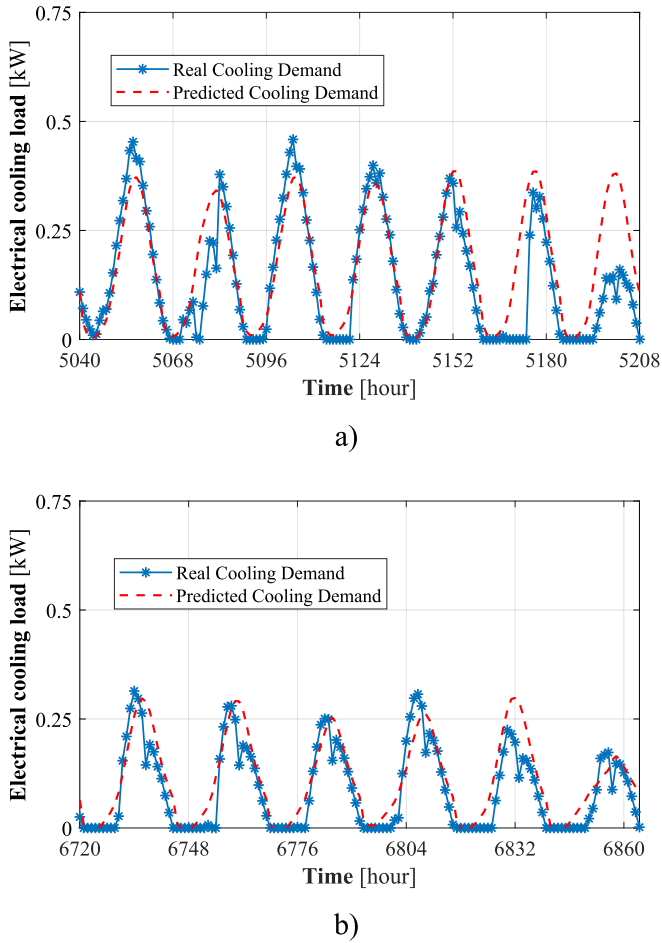


Fig. 5. Comparison between the real and predicted electrical cooling demand for building archetype 1: a) comparison from July 29th to August 4th; b) from October 7th to October 12th.

- iii) Results concerning to the proposed bi-level optimisation procedure aimed at determining the optimal configuration and design of the energy community.
- iv) Analysis of the energy management for each end-user, taking into account the effects associated with the adoption of a P2P energy sharing mechanism.
- v) Economic analysis conducted on individual EC users.
- vi) Assessment of the overall energy performance of the EC.

4.1. HNN model prediction accuracy

As documented in the literature, air conditioning requests often contribute significantly, sometimes up to 40%, to the total electrical demand of buildings [61]. Therefore, this study endeavours to address this by developing a precise model for predicting the electrical load linked to HVAC system requirements.

This hybrid model integrates the strengths of black-box neural network models with those of physical models used in building energy performance simulation (BEPS) tools, as previously mentioned. The resultant sequential HNN uses the gap between real and simulated data from the physical model as input for the neural network model. This approach enables the neural network to encompass all building physical effects, such as thermal inertia, solar exposure, and optical properties of window components. Concurrently, it retains the advantages of the black-box model in capturing events unattainable by the physical model, such as socio-behavioural influences of the occupants on HVAC system

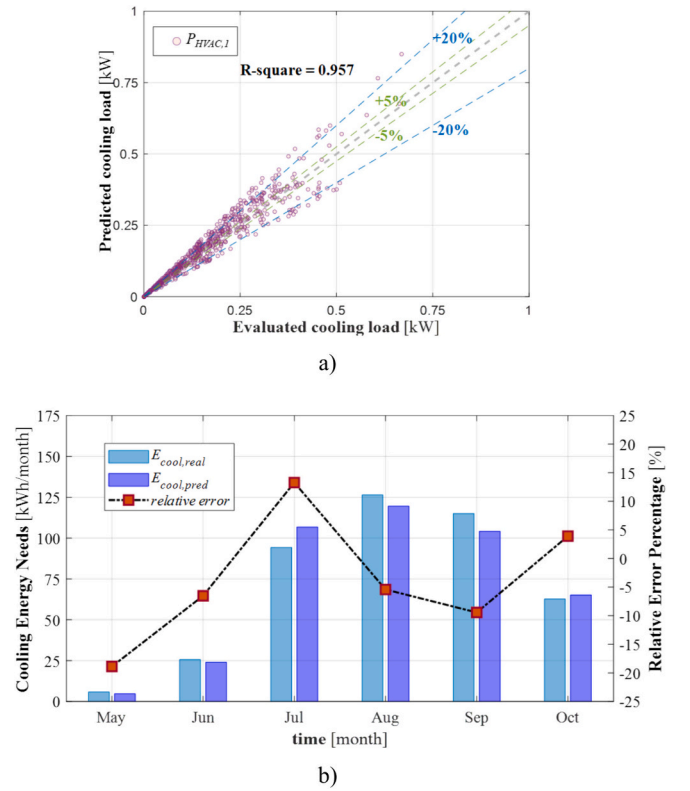


Fig. 6. Relative percentage deviation between simulated and real data: a) time series comparison of electrical load $P_{HVAC,1}$; b) monthly comparison of electrical cooling energy needs E_{cool} .

operation.

Six distinct hybrid models were developed for the various building archetypes identified in the analysed case study. Notably, these buildings rely on an air conditioning system (i.e., air-to-air heat pump) solely during the cooling season. The training process of the model was conducted using datasets associated with building typologies exhibiting similarities to those under examination, as outlined in Table 2. It is important to highlight that these datasets, obtained from open-source platforms [62], pertain to climatic locations distinct from those observed in the studied case. The robustness and the accuracy of the model were assessed by comparing the simulated electrical energy needs due to the HVAC operations with the actual data extracted from the aforementioned datasets. It is important to note that the data used for the model testing analysis came from a different time period than the ones used for the training process.

The results pertaining to the accuracy assessment of the developed model are shown in the following figures; for the sake of brevity, results relative to for the building type #1, characterized by a single occupant under the age of 64, are selected. In Fig. 5, a comparison of the dynamic electrical demand of HVAC systems is depicted (Fig. 5a: July 29th to August 4th, Fig. 5b: October 7th to October 12th), showcasing the simulation by the HNN model (red dotted line) against the actual data [62] (blue line). The comparison demonstrates a notable alignment between the predicted and dataset values.

In Fig. 6 it is illustrated the deviation between simulated and actual data throughout the entire cooling season. In Fig. 6a, the relative error of the time series of electrical load $P_{HVAC,1}$ for the archetype building #1 consistently falls within the range of $\pm 20\%$ across all data points, demonstrating a high R-square value of 0.96. This observation is supported in Fig. 6b, displaying the analysis of actual versus predicted monthly electricity demands for cooling (E_{cool}). The histogram reveals an increase in space-cooling electrical demands, particularly from July to October, and indicates the model's accuracy in estimating these

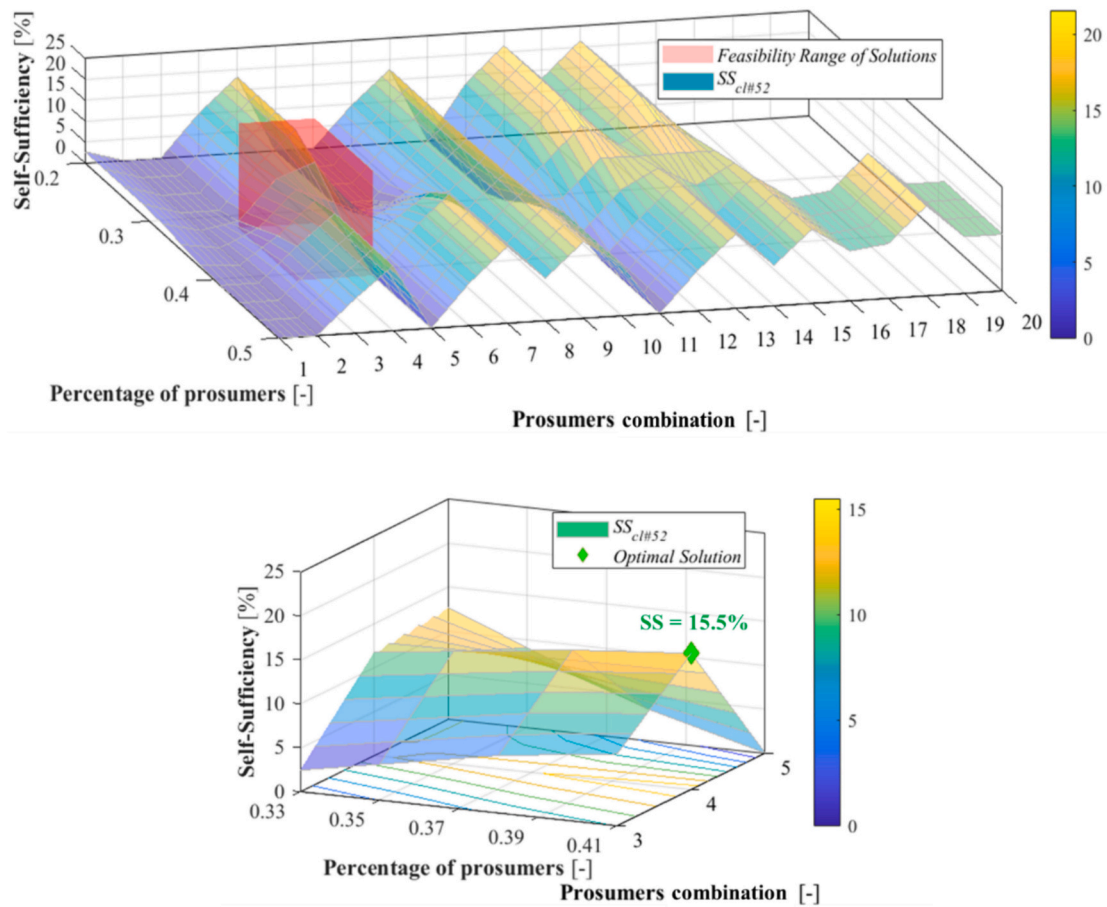


Fig. 7. Results of the first optimisation level referred to cluster archetype #52: top) self-sufficiency of all investigated solutions; bottom) choice of the optimal configuration within the feasibility range.

demands. Notably, minimal absolute energy deviations are observed, with relative error values within the $\pm 10\%$ range for the months of June, August, September, and October.

After demonstrating the accuracy of this model and utilizing it to estimate the electrical load linked to HVAC systems for each archetype building type, it became feasible to determine the energy inputs concerning the overall electrical demands of the EC end-users, as detailed in Appendix A Results of users' electrical load forecasting.

4.2. EC design

This paragraph delves into the implementation results of the proposed bi-level optimisation procedure aimed at determining the optimal EC configuration for the investigated case study.

As initial step, the first user aggregation criterion is implemented. This stage aims to establish all end-users' connection combinations (referred to as *EC subgroups* or *cluster archetypes* within this manuscript) by adhering to the assumption of allocating a maximum of one building per type of end-user (as detailed in paragraph 2.3.1 Aggregation

Table 4
Optimal configuration of cluster archetypes.

Cluster Archetype configuration	User type #1	User type #2	User type #3	User type #4	User type #5	User type #6	Self-sufficiency
#35	prosumer	consumer	×	×	prosumer	×	10.5%
#52	prosumer	consumer	×	×	prosumer	consumer	15.5%
#55	prosumer	consumer	×	consumer	prosumer	×	12.7%
#56	prosumer	consumer	×	consumer	prosumer	consumer	10.1%
#60	prosumer	consumer	consumer	×	prosumer	consumer	11.5%
#6	×	×	×	prosumer	×	consumer	11.1%
#7	×	×	×	prosumer	consumer	×	12.3%
#14	×	×	consumer	prosumer	×	consumer	10.2%
#15	×	×	consumer	prosumer	consumer	×	14.3%
#29	×	consumer	consumer	prosumer	×	×	16.7%
#45	consumer	×	consumer	prosumer	×	×	9.9%
#11	×	×	consumer	×	prosumer	×	12.2%
#19	×	consumer	×	×	prosumer	×	24.4%
#27	×	consumer	consumer	×	prosumer	×	14.2%
#28		consumer	consumer		prosumer	consumer	11.1%
#32		consumer	consumer	consumer	prosumer	consumer	10.2%
#51	consumer	consumer			prosumer		25.1%

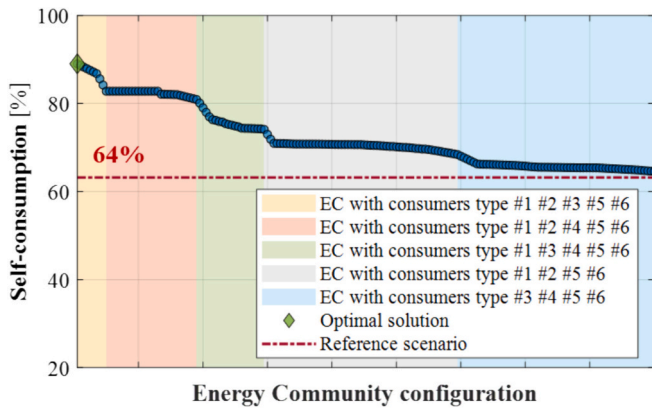


Fig. 8. Selection of the optimal energy community configuration maximizing the global self-consumption.

criteria). Consequently, with the identification of six distinct end-user types within the studied residential area, the total possible combinations of EC subgroups amount to 64. However, out of these 64 combinations, seven will be excluded as they consist of fewer than two users.

The first level of the optimisation problem focuses on determining the optimal configuration for each of the 57 cluster archetypes, maximizing annual self-sufficiency as the number and type of prosumer varies (refer to 2.3.2 Optimisation of P2P cluster archetypes). The problem is solved using a MILP-type algorithm that adopts a linear function to constrain the choice of the optimal solution. This function is aimed at determining the range of configurations that ensure revenues for each prosumer greater than or equal to the minimum threshold that guarantees a return on investment of the PV system of <3 years. The energy sharing model between users of the cluster archetypes investigated is based on P2P mechanisms (explained in paragraph 2.2 Peer-to-Peer model for users' energy sharing).

In Fig. 7 it is shown the results of this first optimisation level. To streamline the analysis, investigation was solely conducted for the cluster archetype of the #52 combination, which includes users of types #1, #2, #5, and #6. In Fig. 7 top it is reported the annual self-sufficiency of all configurations by varying both the percentage of prosumers and the prosumer type. The red-highlighted area outlines the feasibility range of solutions, representing the set of configurations adhering to the constraints imposed within the optimisation problem.

The analysis of Fig. 7 bottom is focused on investigating all the feasible solutions. Among these, the optimal configuration, indicated by the green diamond, achieves maximum annual self-sufficiency. This configuration involves 40% of prosumers, specifically represented by the building types #1 and #5.

The process of establishing optimal configurations (referred to as $P2P_{CA}$ in the manuscript) was conducted for all 57 combinations. Upon determining these configurations, each prosumer is offered various subgroup possibilities to unite with other residential area users, aiming to minimize their return on investment through energy sharing. In Table 4 the $P2P_{CA}$ configurations, that include the types of prosumers in the case study, namely types #1, #4, and #5, are reported.

As indicated in Table 4, $P2P_{CA}$ are categorized into subsets that present the same type of prosumer in their cluster configuration.

Following this categorization, the subsequent stage of the optimisation problem concentrates on defining the optimal design for the entire EC. The second aggregation criterion (detailed in paragraph 2.3.1 Aggregation criteria) aims to connect the previously determined subgroups to enhance the management of community energy resources. This aggregation involves implementing a secondary layer of P2P energy sharing mechanism, this time among different $P2P_{CA}$ users.

By combining all the subsets outlined in Table 4, a total of 180 potential EC configurations can be determined. An iterative procedure is

Table 5

Optimal configuration of Energy Community.

Aggregation of Cluster Archetypes	
Cluster Archetype	Number
#52	1
#15	7
#19	3
#51	5

Number of prosumers by type			
Cluster Archetype	N _{pros,type,#1}	N _{pros,type,#4}	N _{pros,type,#5}
#52	1	✗	1
#15	✗	7	✗
#19	✗	✗	3
#51	✗	✗	5

Number of consumers by type						
Cluster Archetype	N _{cons, type,#1}	N _{cons, type,#2}	N _{cons, type,#3}	N _{cons, type,#4}	N _{cons, type,#5}	N _{cons, type,#6}
#52	✗	1	✗	✗	✗	1
#15	✗	✗	7	✗	7	✗
#19	✗	3	✗	✗	✗	✗
#51	5	5	✗	✗	✗	✗

performed for all these combinations to ascertain the number of $P2P_{CA}$ occurrences required to encompass the entire prosumers of the case study within the EC. It will also ensure conformity with constraints related to the number of consumers by type present in the investigated residential area.

The second level of optimisation aims to identify the configuration that maximizes annual self-consumption from the available options. The reference self-consumption value, depicted by the red dotted line in Fig. 8 (64%), corresponds to the scenario without EC implementation.

The investigated EC configurations are then categorized based on the types of consumers they incorporate, with each coloured band in Fig. 8 characterized by solutions with different number of consumers. Subsequently, comparing all investigated EC configurations, each comprising the same number and type of prosumers, reveals that the optimal configuration achieves an annual self-consumption level of 89%, represented by the green diamond in Fig. 8. This configuration includes consumers of types #1, #2, #3, #5, and #6.

This categorization underscores the significance of appropriately grouping consumers with prosumers within an EC. The optimal energy community configuration attained through the exploitation of the proposed methodology is expressed in Table 5.

In the next sections, the energy performances obtained, the potential economic benefits of individual users will be analysed.

4.3. Users' energy management

The energy management results presented in this section refer to each end-user type of the $P2P_{CA}$ subgroups aggregated in the optimal EC configuration. It's important to note that the energy analysis investigated for each $P2P_{CA}$ is identical for all the subgroups belonging to the same $P2P_{CA}$ type. In Fig. 9 it is illustrated the dynamic trends of end-user energy management. To streamline the analysis, only one prosumer and one consumer were examined, specifically, prosumer type #5 from cluster archetype #19 and consumer type #6 from cluster #52. In Fig. 9a, the distribution of surplus energy generated by the prosumer PV system is showcased. Initially, any surplus is shared with users from the same cluster archetype (for this specific case represented by the consumer type #2) according to the 1st DL of the P2P mechanism. Subsequently, the remaining surplus is available for sharing with users from

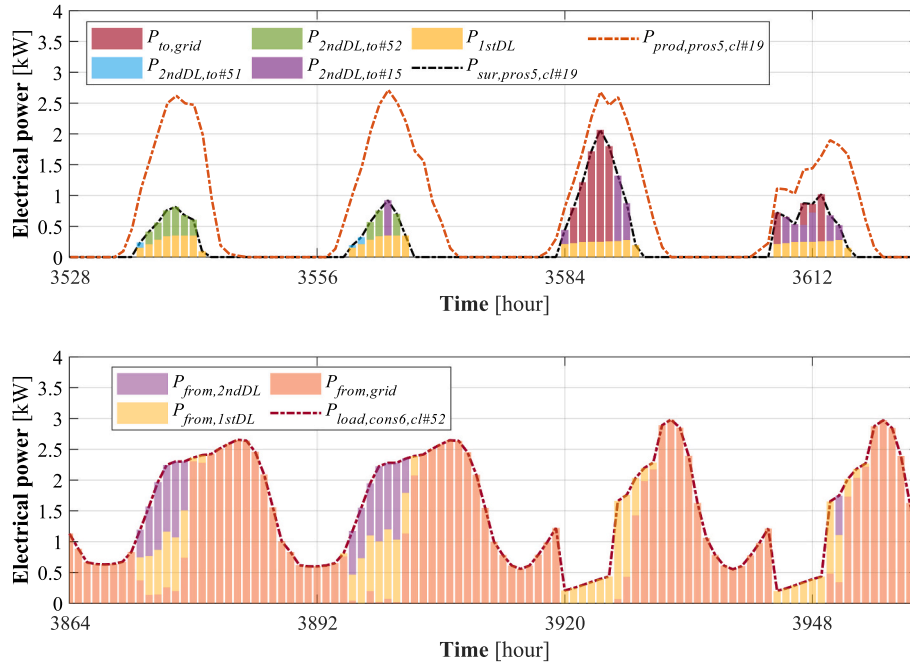


Fig. 9. Dynamic trend of single user energy management from 10th to 13th of June: top) PV production dispatching of prosumer #5 of cluster #19; bottom) electrical load of consumer #6 of cluster #52.

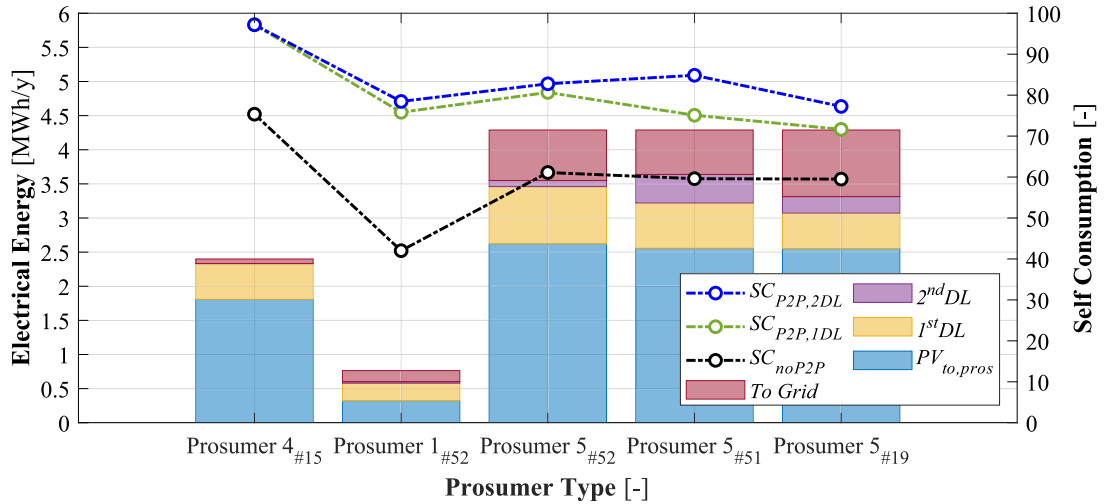


Fig. 10. Annual PV production management for each prosumer type of the EC's cluster archetypes.

other clusters, as stated with the P2P 2nd DL mechanisms. The coloured bars in Fig. 9 top precisely delineate the quantities of excess energy shared within the cluster (P_{1stDL}), shared with other clusters (P_{2ndDL}), and sent to the central grid ($P_{to,grid}$).

The analysis of Fig. 9 bottom demonstrates the fulfilment of the electrical load for the investigated consumer. The figure highlights that during periods of peak solar radiation, the consumer's load is effectively met by the excess energy generated by prosumers. The coloured bars in the figure represent the quantified energy acquired by the consumer: sourced from the EC prosumers in the 1st DL, from prosumers of other clusters via the 2nd DL, and from the central grid.

On the annual basis, PV production management for each prosumer type of the EC's cluster archetypes is reported in Fig. 10. Additionally, it is assessed how self-consumption levels are influenced by P2P mechanisms. For example, among the prosumers under investigation, the one of type #4 in cluster #15 achieves the highest levels of self-consumption, which is equivalent to 75% of the energy produced,

even before taking into consideration the energy shared with the P2P system. Additionally, it uses the P2P sharing mechanism of the 1st DL to its advantage to sell energy to consumers inside its cluster, increasing the self-consumption rate to 98%. Otherwise, the prosumers in clusters #51 and #19 with a self-consumption rate of 60% enhance their levels to 84% and 76% respectively, further benefiting from P2P energy sharing across other clusters.

The result of Fig. 11 provides an in-depth analysis of how each prosumer distributes its energy, quantifying the energy shared with the six types of consumers. In particular, the analysis of Fig. 11 top is referred to the 1st DL mechanism, while Fig. 11 bottom focuses on interactions with members from other EC clusters. Notably, prosumers from clusters #51 and #19 emerge as the primary contributors in the 2nd DL, sharing approximately 410 kWh/year and 235 kWh/year respectively. Moreover, both Fig. 11 top and Fig. 11 bottom depict a dotted black line, estimating the percentage contribution of energy shared in each of the two dispatching layers compared to the total energy sold to

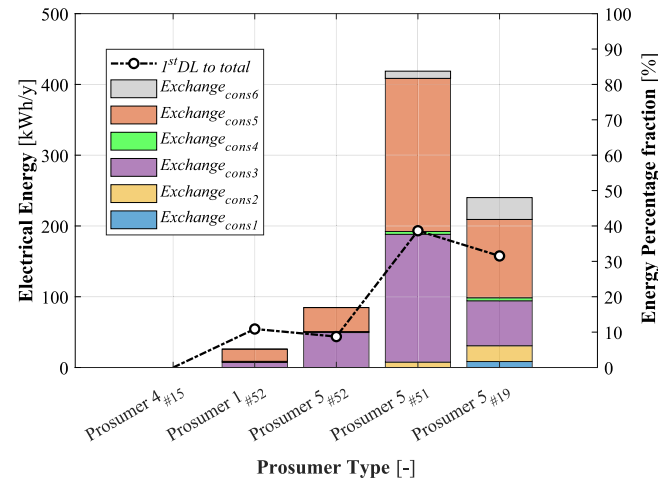
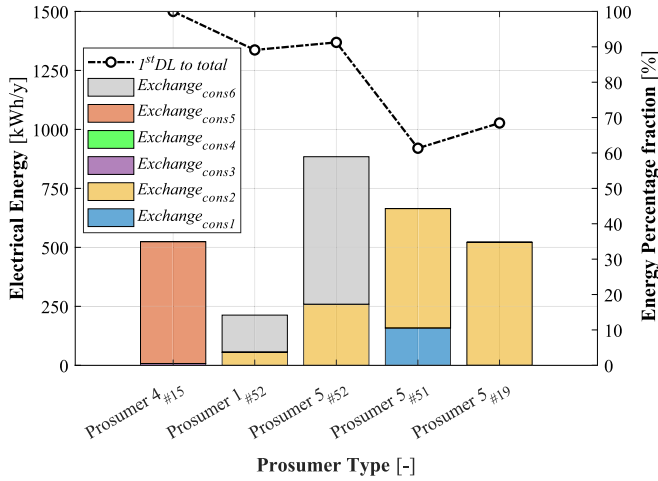


Fig. 11. Rates of energy exchanged with the different types of consumers: top) 1st DL; bottom) 2nd DL.

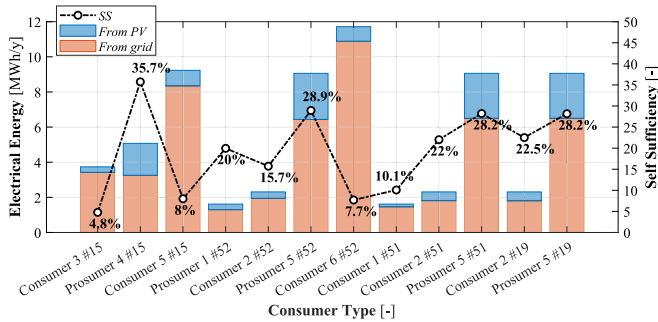


Fig. 12. Annual analysis of coverage of electricity needs and self-sufficiency by type of EC user.

consumers.

Finally, the energy results of Fig. 12 analyse how the annual requests of each EC consumer and prosumer are satisfied. Additionally, it reports the annual self-sufficiency value for each user, highlighting the percentage of the load covered by the renewable energy source.

4.4. Cost analysis: Prosumers and consumers

The method employed to calculate the cost of electricity shared by prosumers with consumers is founded on the balancing of the supply and

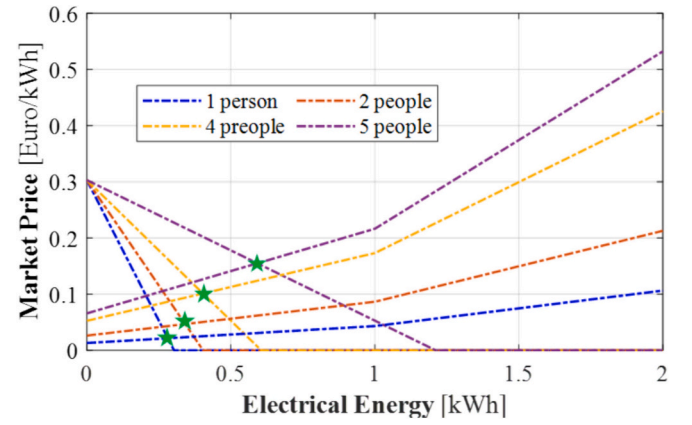


Fig. 13. Energy pricing strategy, balancing of demand and supply curves.

demand curves (refer to paragraph 2.2.1 Pricing strategy). In Fig. 13 it is described the strategy used to determine the price within the *local energy market*. Notably, the purchase price is influenced by the building occupancy and the quantity of electricity requested or offered. Additionally, as previously outlined, the demand curve is impacted by the maximum cost of electricity sourced from the grid, set at 0.31 Euro/kWh [63] for this case study (according to the Italian energy market price). Conversely, the offer curve is influenced by the maximum retail selling price from the grid, fixed at 0.10 Euro/kWh [63]. The results indicate purchase prices for users consisting of 1, 2, 4, and 5 occupants at 0.02, 0.05, 0.10, and 0.15 Euro/kWh respectively.

It is analysed in Fig. 14 the economic outcomes concerning prosumers' revenues, derived from energy sales, and the savings obtained by consumers. Fig. 14 top displays the bi-matrices depicting the quantity of shared energy and the respective revenues for each type of prosumer, considering the interaction with the six distinct types of EC's consumers.

The illustration of Fig. 14 bottom delves into the costs associated with electricity purchases for both consumers and prosumers of the EC. The grey and green bars represent the annual costs of energy purchased respectively from the grid and prosumers. Notably, even prosumers themselves, when acting as consumers, procure energy from other prosumers. The percentage savings depicted in Fig. 14 bottom indicate the economic advantages gained by each user through the procurement of energy from prosumers. These saving have been evaluated in comparison with the reference scenario where the consumers and prosumers are connected only to the national electricity grid.

Finally, in Table 6 it is presented the pay-back time estimation for each prosumer, considering a unit investment cost of 600 Euro/kW_{PV} for the purchase and installation of polycrystalline PV systems. The calculation of payback time includes considerations for costs avoided by purchasing electricity from the grid, revenues from selling electricity to users within the same cluster, and those related to sharing with users from other clusters within the EC. Additionally, it's assumed that surplus energy sent to the grid does not yield any remuneration. The results outlined in Table 6 underscore that the proposed methodology for optimising end-user aggregation allows for investment returns of fewer than 3 years for each prosumer.

4.5. Energy performance of EC

The investigation aimed at assessing the benefits resulting from the application of the proposed aggregation criteria involved conducting an energy analysis of the optimised EC configuration. The outcomes depicted in Fig. 15 pertain to the energy management of the EC. In Fig. 15 top, a monthly analysis illustrates how the requested electricity is fulfilled. This analysis includes the quantity self-consumed by the prosumers, that met through energy sharing mechanisms of the 1st DL and 2nd DL, and the portion purchased from the central grid. The dashed

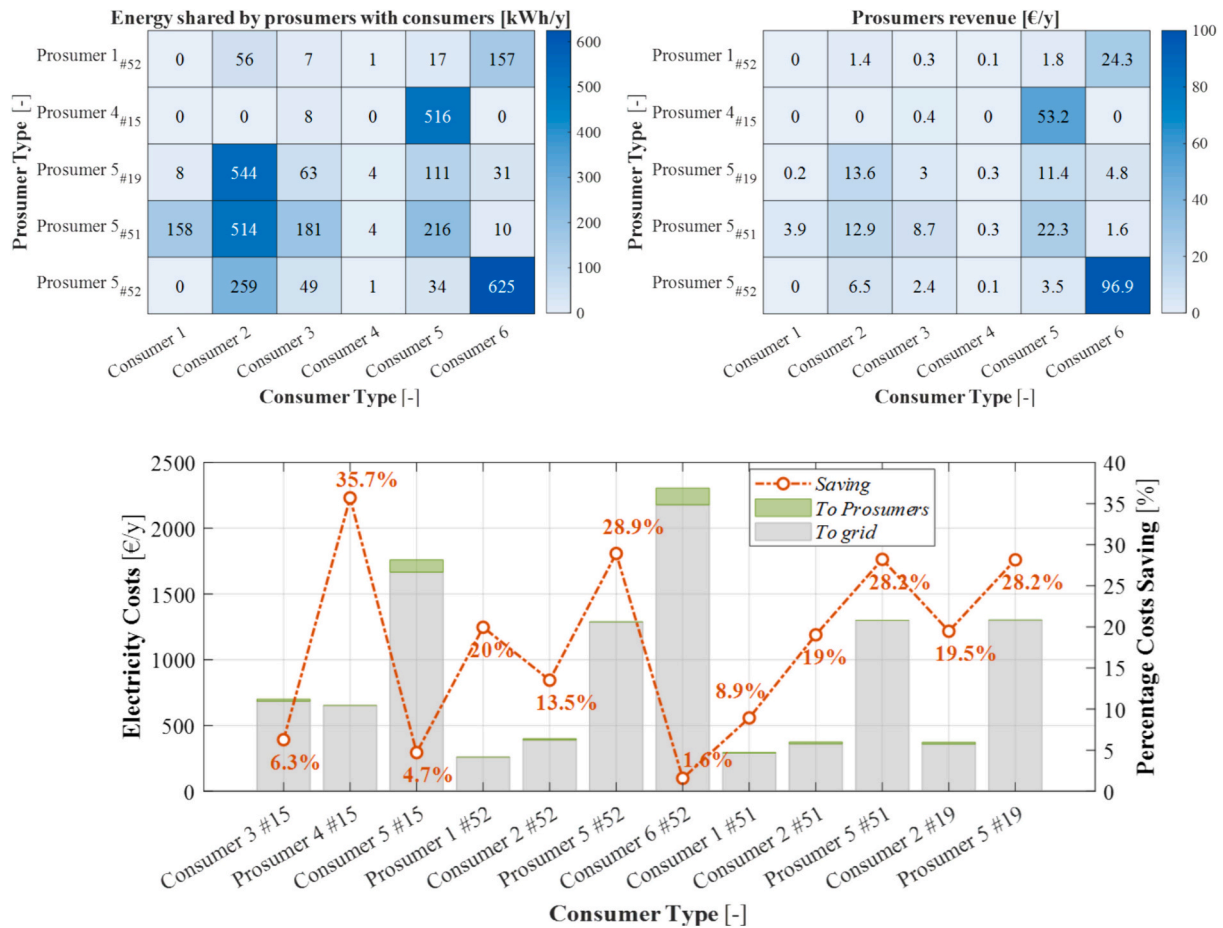


Fig. 14. Economic analysis: top) prosumers' revenues; bottom) users saving.

Table 6

Pay-back time of prosumers investments.

Prosumer Type	Prosumer 4 CA#15	Prosumer 1 CA#52	Prosumer 5 CA#52	Prosumer 5 CA#51	Prosumer 5 CA#19
Cost of Investment [Euro]	990	320	1780	1780	1780
Pay-back time [year]	2.2	2.7	2.4	2.6	2.8

black line represents the self-sufficiency levels, which notably peak during the summer months. Additionally, self-consumption, depicted in blue dotted line, exceeds 75% for each month.

The annual self-consumption and self-sufficiency indices for the entire EC stand at 89% and 21% respectively. As regard the reference case scenario where photovoltaic systems were solely used to fulfil individual prosumer demands and they are connected only to the national electricity grid, the self-consumption is 64%. The rise in self-consumption of the proposed case contributes positively to balancing the central electricity grid. In fact, it is worth noting that surpluses from individual user systems can frequently lead to imbalances in grid frequency and voltage.

The analysis of Fig. 15 bottom assesses the management of surpluses generated by the global photovoltaic systems of the community, grouped based on their archetype cluster types. The cumulative analysis underscores that 48% of the surplus is allocated for sharing within users of the same cluster, while 37.5% continues to be directed to the grid. Additionally, 14.5% of the surplus is designated for sharing energy with users across different clusters. Overall, the proposed strategy facilitated a transition from the reference case (with users connected only to the national electricity grid), where grid injections amounted to 20.1 MWh/year, to the proposed scenario yielding 7.5 MWh/year, resulting in a

reduction of 62%.

5. Discussions

The growing necessity to streamline the management of decentralized renewable energy resources parallels the increasing development of incentive policies driving the establishment of energy communities [10]. Energy communities primarily aim to: i) optimize the integration and management of energy resources, ensuring self-sufficiency for independent communities unconnected to the electricity grid (e.g., island communities) [64]; ii) enhance self-consumption of distributed production systems within a community by implementing innovative electricity sharing mechanisms among users (e.g., P2P, collective self-consumption, etc.) [65].

This study emphasizes the second type of energy communities, often defined as collective self-consumption groups. In the existing literature, the attention frequently gravitates towards optimising energy-sharing mechanisms. This includes exploring various control strategies (e.g., centralized, decentralized [66]), employing different trading methodologies among users (often employing game theory approaches [67]), and leveraging diverse demand management and storage technologies to bolster the community's energy flexibility [68]. Conversely, the

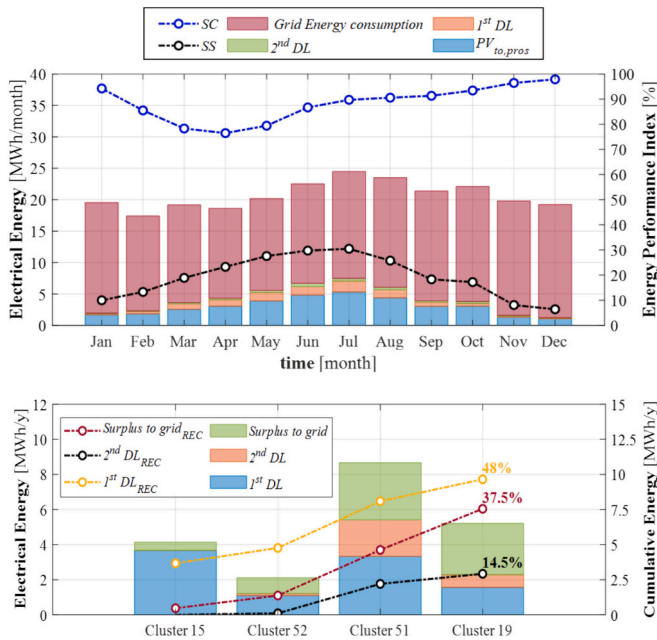


Fig. 15. Energy community management: top) monthly energy analysis of global electrical loads satisfied by PV production, energy sharing mechanisms (1st and 2nd DL), and power grid; bottom) energy analysis of PV production surplus for each cluster archetype.

proposed study is focused on an earlier phase: designing an energy community through a flexible methodology adaptable to real-world applications.

Challenges associated with community design often stem from insufficient data on user energy behaviour and improper user aggregation, which directly impacts community performance. To address the data-lack issue, this study proposes a sequential HNN model to simulate a building's electrical demands, merging the advantages of physical and neural network models. Inputs such as weather features, occupancy patterns, and appliance usage frequencies were obtained from statistical analyses. To minimize the potential limitations – such as input data not always reflecting real conditions – this study introduces a user classification into archetypes, based on human behavioural patterns, to enhance the accuracy of electricity demand estimation. The users demand assessment methodology, for the investigated case study, reaches a high level of accuracy comparing the simulated data with the real ones. The data agreement is demonstrated by a relative percentage error that falls within the range of $\pm 20\%$, and R-square values higher than 0.96.

Moreover, to optimise user aggregation within an energy community, a bi-level optimisation methodology is proposed and exploited with the aim at focusing on the aggregation i) between prosumers and consumers into subgroups by maximizing their self-sufficiency and economic benefits (first level optimisation); ii) among these subgroups to determine the optimal energy community configuration that maximizes total energy resource self-consumption (second level optimisation). In a real scenario, the first optimisation level of the developed methodology tailors to the prosumer's perspective. It aims to provide guidelines on the prosumers' possible choice of aggregating with different consumer types of the energy community. This choice can be made by a potential benchmark obtained with the first optimisation level that provides the energy and economic performance indices achievable through various combinations of users' aggregation. Conversely, the second level aligns with the stakeholder's viewpoint (represented by the electricity grid management company). Upon identifying the location of interest and characterizing its prosumers by type and number, this optimisation procedure strives to identify the best energy community configuration.

Its goal is to maximize self-consumption while limiting surplus injection into the grid, which represents the main cause of its voltage and frequency imbalance. For the investigated case study, the obtained results highlight that the optimisation of the EC design guarantees an annual collective self-consumption and self-sufficiency equal to 89% and 21% respectively.

For this reason, this study fosters a smart urban planning through the development of an innovative approach to aggregate energy objects within a buildings district by properly exploiting the potential of renewable energy sources. This approach is aimed at providing guidelines to stakeholders based on the development of a modelling tool capable of predicting the electricity demand of users of building clusters, implementing innovative energy sharing schemes and market strategies, as well as optimising the EC design considering proper aggregation methods.

6. Conclusion

This study focuses on pioneering methodologies developed for the establishment of energy communities, with a specific emphasis on Peer-to-Peer (P2P) models. The devised P2P strategy employs a centralized control logic to optimise connections between prosumers and consumers, aiming to maximize the energy exchange within the community. Furthermore, the pricing strategy in the energy market is formulated based on balancing supply and demand curves, thereby determining electricity unit costs tailored to individual user characteristics.

This research has yielded a precise model for predicting the electricity demands of users within the community. This model is pivotal when energy behaviour information about users is unavailable for designing energy communities. The developed model is a sequential hybrid neural network (HNN), integrating aspects of both white-box and black-box models. Respecting to white-box models, it incorporates physical attributes and defines building archetypes, while from black-box models exploits the peculiarity of predicting how occupant behaviour impacts electrical demands.

Subsequently, criteria for user aggregation were proposed to optimise the energy community configuration through a bi-level optimisation process. The first optimisation level focuses on grouping users into subgroups, aiming to maximize self-sufficiency by varying the integration of prosumers based on quantity and type. The subsequent optimisation level determines the global configuration of the energy community by aggregating the previously identified subgroups, thereby maximizing the community's self-consumption.

To demonstrate the efficacy of this methodology, a case study was conducted in a residential area of Caserta, Italy. The study identified six user types within the community, classified their building archetypes, and predicted their electricity demands using the HNN model. By identifying the number of prosumers in each residential area type, the optimisation methodology was applied to determine the optimal EC configuration. The obtained results facilitated an estimation of economic benefits for each user. Compared to the reference scenario where the users are connected only to the national electricity grid, the consumers achieve economic savings ranging from 1.6% to 19.5%, thanks to the partial fulfilment of their energy needs from prosumers' surplus. Prosumers, benefiting from avoided energy purchase costs and revenues from energy sales, realized a return on investment (SPB) in <3 years. Additionally, through optimised user aggregation, the energy matching between prosumers' surplus and consumer requests maximized annual self-consumption to 89% compared to 64% of the reference scenario (represented by the absence of energy community mechanisms). The achieved collective annual self-sufficiency is equal to 21%, where the amount of the available surpluses generated by the global photovoltaic systems of the community is shared for a rate of 48% among users of the same cluster, while 14.5% is exploited for sharing energy with users of different buildings clusters. Overall, it results in a reduction of the energy amount send back to the grid equal to a rate of 62%

compared to the reference scenario.

Finally, this optimisation effectively mitigates risks associated with voltage and frequency imbalances in the network resulting from frequent surpluses injected by prosumers.

CRedit authorship contribution statement

G. Barone: Writing – original draft, Investigation, Data curation. **A. Buonomano:** Writing – review & editing, Visualization, Supervision, Methodology, Investigation, Data curation, Conceptualization. **G. Cipolla:** Validation, Investigation. **C. Forzano:** Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **G.F. Giuzio:** Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization. **G. Russo:** Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization.

Appendix A. Results of users' electrical load forecasting

The users' electrical loads were estimated considering the rates due to lighting, equipment, and the HVAC system, as indicated in Eq. (4). The calculations for the electrical powers consumed by equipment (Eq. (6)) and lighting (Eq. (5)) are based on utilization factors, $f_{use,eq}$ and $f_{use,lights}$, sourced from ISTAT (Italian National Statistics Institute) datasets [59].

Fig. A.1.c and Fig. A.1.d illustrate the dynamic trend of these utilization factors, differentiated by weekdays and weekends, depicting the typical statistical behaviour of residential users at the investigated location. Additionally, Fig. A.1.a displays a table presenting nominal powers obtained from the research of Paatero et al. [53], outlining commonly used utilities in these residential buildings.

Finally, Fig. A.1.b exhibits occupancy factor given by the number of occupants that influence the daily usage of household appliances.

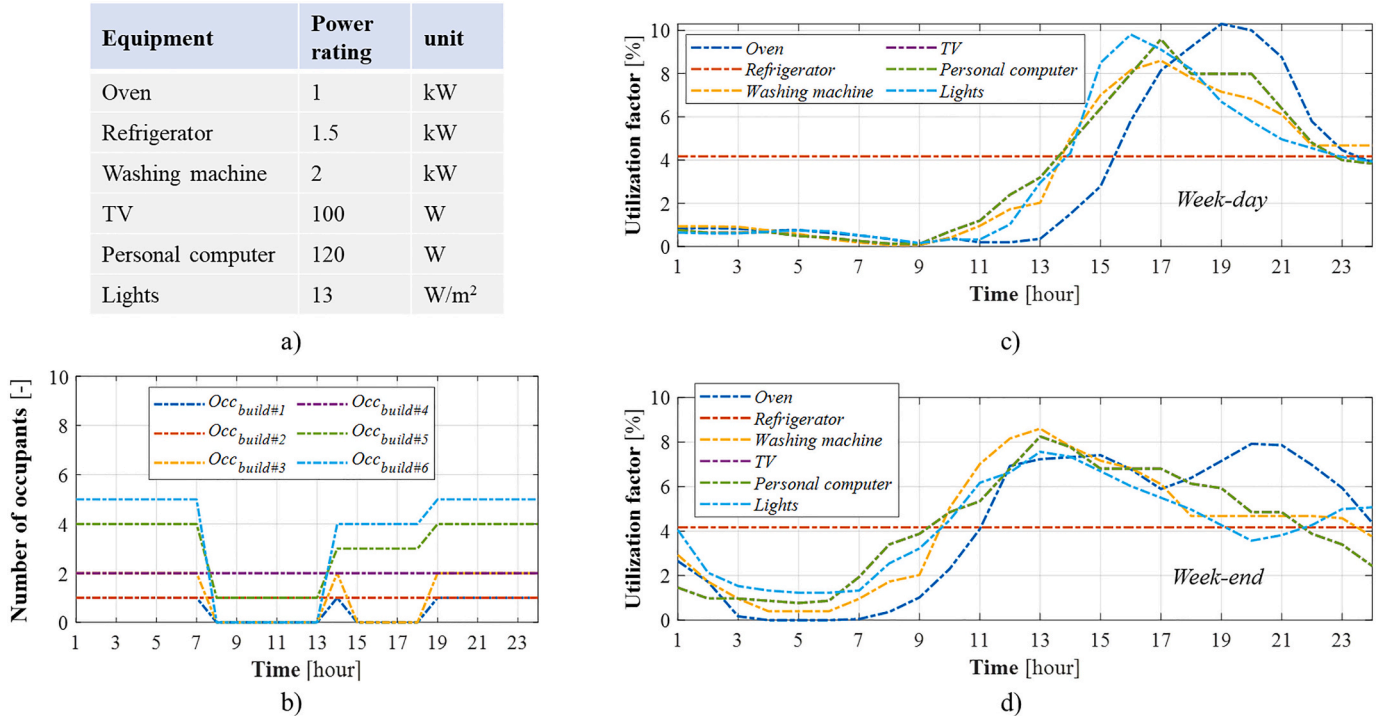


Fig. A.1. Equipments and lights electrical load:

a) power rating; b) occupancy factor given by the number of occupants of the 6 buildings archetypes of investigated EC; c) utilization factor of equipments and lights during weekdays; d) utilization factor of equipments and lights during week-end days.

This analysis enables the determination of dynamic electrical absorption profiles for various user types within the community. Concerning the users' air conditioning-related electricity consumption, it was assessed using the hybrid model detailed in the section (2.1.3 Sequential HNN model for heating / cooling demands). In the context of the case study, users are assumed to have an electrical absorption system solely for cooling needs.

Fig. A.2.a presents a dynamic illustration of the global electrical load profile from July 8th to July 11th for the six user types identified within the investigated community. Fig. A.2.b highlights the annual electricity consumption for each user type. Notably, the building's electricity consumption increases with the number of occupants, and the occupants' age also plays a significant role, impacting electricity consumption due to socio-behavioural characteristics.

Declaration of competing interest

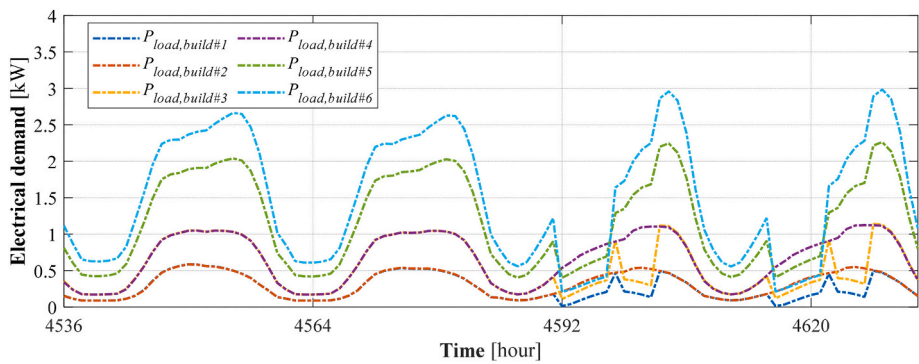
None.

Data availability

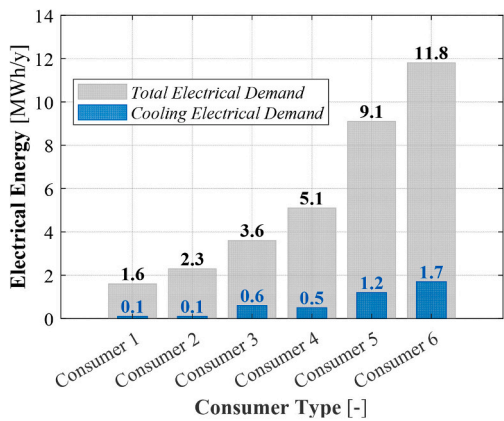
Data will be made available on request.

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a)



b)

Fig. A.2. EC's users electrical load:
a) dynamic profile of total electricity consumption from July 8th to July 11th; b) annual electricity consumption for different users' types.

Appendix B. Results of PV systems production

The PV systems producibility of the energy community's users acting as prosumers was determined using the mathematical modelling outlined in the section 2.1. Building archetypes for EC users' energy modelling.

Fig. B.1.a depicts the dynamic trend observed during a simulation period from July 8th to July 11th. Notably, the obtained power values correspond to the size of the installed systems. The weather characteristics affecting producibility, such as air temperature and solar radiation, were sourced from Meteonorm datasets.

Additionally, Fig. B.1.b presents cumulative annual data showcasing the electricity production from these PV systems of each prosumer type.

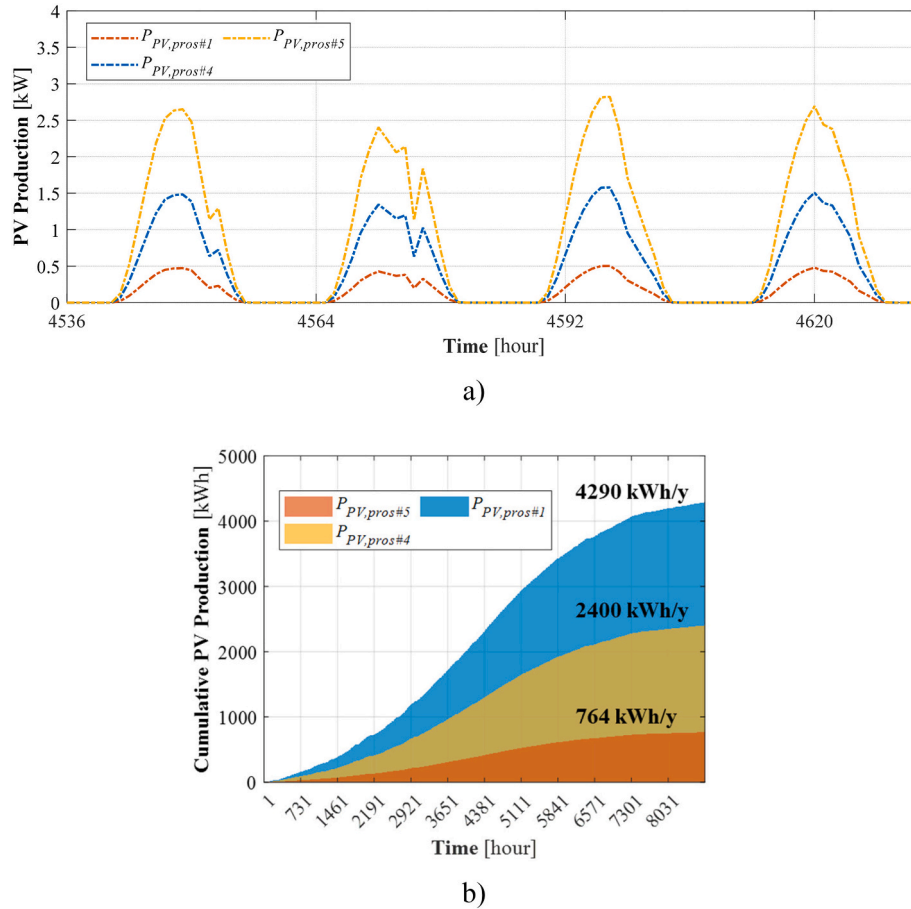


Fig. B.1. PV systems production for each prosumer type:

a) dynamic profile of electricity production from July 8th to July 11th; b) cumulative annual electricity production for different prosumer's types.

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