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From investment optimization to fair benefit distribution in renewable energy community modelling

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HIGHLIGHTS

- Renewable energy communities can properly contribute to a clean energy transition.
- Model novelty is the inclusion of different relevant aspects in integrated approach.
- Operational and investment optimization and Demand Side Management.
- Fairness Index to evaluate how fairly business models allocate benefits.
- Flexibility and composition impact on economic and environmental indicators.

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ABSTRACT

Energy communities are becoming a key topic in the decarbonization process as they can simultaneously guarantee economic, environmental, and social benefits. In this paper, an integrated method for the implementation of a linear bottom-up optimization model has been developed in order to address these aspects of an energy community: (i) definition of the dispatch and the best technology mix; (ii) assessment of the role of the Demand Side Management; (iii) definition of an original and fair method to allocate the benefit among the participants and of a Fairness Index to compare different business models. The developed method has been applied to an illustrative case study through the implementation of the Italian regulatory framework definitions and costs. The outcomes highlight how Demand Side Management and the energy community composition of the energy community impact on the overall investment: a case study, with heterogeneous composition and characterized by a 20% of flexible load, presents a reduction of 13% in photovoltaic and 93% in storage system capacity with respect to the case without Demand Side Management. The renewable source consumption with a more homogeneous case study decreases by around 20%–33% and bill savings by around 30%. These results impact also on each participant contribution, which underpins the introduced fair distribution method. Leading thus to a different and more proper distribution of the benefit, in order to guarantee everyone the fairest economic return. Moreover, a Fairness Index has been introduced to assess the consistency of other Business Models with respect to the fair distribution.

Abbreviations: ARERA, Italian Regulatory Authority for Energy; BESS, Battery Energy Storage System; BM, Business Model; BPP, Biomass Power Plant; DC, District Community; DP, Dispatchment Price; DSM, Demand Side Management; EC, Energy Community; ED, Excise Duty; EE, Energy Efficiency; EoS, Economies of Scale; EP, Energy Price; epc, Equivalent Periodical Cost; ESP, Energy Sharing Provider; FI, Fairness Index; FIPV, Façade Integrated Photovoltaic; GIS, Geographic Information System; HH, Household; HPP, Hydro Power Plant; JARSC, Jointly Acting Renewables Self-Consumers; LP, Linear Programming; LV, Low Voltage; MILP, Mixed-Integer Linear Programming; MiSE, Italian Ministry of Economic Development; MOO, Multi-Objective Optimization; MV, Medium Voltage; oemof, Open Energy Modelling Framework; OF, Objective Function; OSM, Open Source Model; PBP, Pay Back Period; PoD, Point of Delivery; PUN, National Single Price; PV, Photovoltaic; RES, Renewable Energy Sources; RE, Renewable Energy; REC, Renewable Energy Community; RPV, Rooftop Photovoltaic; RS, Reference Scenario; SC, System Charges; SGS, Shallow Geothermal System; SOO, Single-Objective Optimization; STE, Solar Thermal Energy; TC, Electricity Transport and Meter Management Costs; VAT, Value Added Tax; WT, Wind Turbines.

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Nomenclature

Indices

d	index of data points
i, l	indexes used for the energy community members
k	index of cluster
m_{tot}	total number of members in the EC
n	index of node set N
t	time-step index of set T
u	generation unit index of set U

Parameters and variables

BC_i	benefit contribution of member i
C_{AL}	avoided grid loss coefficient
$CAPEX_u$	capital expenditure of investment variable u
C_k	centroid of cluster k
Dcd,i	contribution distribution percentage of benefits for member i
Di	distribution percentage of benefits for member i
DS_k	total number of data points belonging to cluster k
Dw,i	worse distribution of benefits, according to the contribution distribution, for member i
$E_{n,u,t}$	electricity generation value of unit u of node n at time t
$E_{n,u,t}^{discharge}$	electricity provided by storage units
$E_{n,u,t}^{charge}$	electricity used for the storage charging
$E_{n,t}^{gridloss}$	electricity lost in grid transmission.
$E_{n,u,t}^{excess}$	electricity excess
epc_u	equivalent periodical cost of investment variable u
fi	frequency of the composition a certain member i
G	Gini coefficient
I	set of the energy community members
inv_u	capacity of investment variable u
K	total number of clusters
$L_{n,t}$	electricity load of node n at time t
$lifetime_u$	life expectancy of investment variable u
m	number of members for which Di > 0
NP^{flow}	nominal transmission value
NS	nominal storage capacity
$oemof$	Open Energy Modelling Framework
OF_{EC}	objective function of the EC model
OF_{kmeans}	objective function of the k-means clustering algorithm
$OPEX_u$	operating expenditure of investment variable u
OPT	savings of the EC if all members are included
$OPT\text{-}i$	savings of the EC if member i is not included
$P_{nom,u}$	nominal capacity of the generator unit
$P_{u,t}^{flow}$	power flow exchanged through a powerline
P_t^{charge}	power charging the storage at time t
$P_t^{discharge}$	power discharging the storage at time t
$P_{u,t}$	power supplied by each generator unit
S_t	storage state at time t
$S_{u,t}$	storage filling level
$vc_{n,u,t}$	variable costs of the generation unit u of node n at time t
$wacc$	weighted average cost of capital
$x_d^{(k)}$	data point d belonging to cluster k
Z_P	Zonal Electricity Price
η_{self}	storage self-discharge efficiency
η_{charge}	charging process efficiency
$\eta_{discharge}$	discharging process efficiency

1. Introduction

Renewable energy communities are becoming a relevant topic worldwide. For instance, in Beijing [1], Wuhan [2], Melbourne [3] there are examples of application of Energy Communities (ECs), also known as Prosumer Communities, where the notion of energy-sharing is central. In Europe with the EU RED II Directive in 2018 [4], ECs have become a key topic for distributed photovoltaic (PV) systems. When considering ECs, it dawns on all the opportunities (economic, environmental and social benefits) and the main challenges and issues regarding the applied schemes, the access to data, the technical limits, the communication to citizens and municipalities. Therefore, although the convenience of ECs might be clear, their introduction is not so rapid and, as it will be highlighted in this work, its best application is not necessarily granted.

Energy Community benefits have been well categorized in [5] after their identification in literature. Seven categories are defined: economic benefit; education and acceptance; participation; climate protection and sustainability; community building and self-realization; renewable energy (RE) generation targets; innovation. It is clear that ECs involve a wide variety of areas and they are seen as an opportunity to ease energy poverty, to increase social inclusion, to support for energy saving measures, and to switch to a more sustainable and healthier lifestyle. Besides all these effects, the direct financial benefit is the catalyst of these changes and it is the focus of this work.

Two main different Energy Community schemes can be identified when dealing with ECs. The first one aims at distinguishing the 'jointly acting renewables self-consumers' (JARSC) and the 'renewable energy community' (REC). JARSC are defined in [4] as *'[…] a group of at least two cooperating renewables self-consumers […] who are located in the same building or multi-apartment block'*, while the REC is defined as *'[…] a legal entity […] effectively controlled by shareholders or members that are located in the proximity of the renewable energy projects […]'*. Here we will be focusing on the second scheme which leads to the distinction between the "physical" and the "virtual" self-consumption scheme which are easily depicted, through a simplified approach - a housing building - in Fig. 1. The physical self-consumption scheme provides for a connection between the PV plant and both the private and the common utilities, with a single metering point or Point of Delivery (PoD).

On the contrary, in the "virtual" scheme the public network is used for the exchange of energy between the generation plant and the private utilities. [6]

There are many features involved in ECs: the evaluation of the impact of the regulatory schemes, the aspects regarding the optimal installation of systems for the production and storage of renewable energy, the composition of the energy community are just some of them. The main challenge taken up in this work is therefore to provide a tool to assess and study all these aspects, their relative advantages and disadvantages and thus also allow an effective and comprehensible communication to citizens and municipalities as well.

This tool should then have a twofold objective: (i) the modelling of the EC system which considers all the possible sectors, schemes, optimal technology-mixes, user characteristics and impacts and (ii) the identification of the relationships which characterize these aspects and of the best business models. It must also be considered that these objectives can be addressed both together and separate in different areas of interest (e.g. district, housing building, single final user).

Different studies present models which focus on the electricity sector, as [7], which includes also the modelling of reserve provision and distribution network constraints, or [8], which in addition applies the demand side management (DSM) strategies, or [2] which considers also aggregators agents, and [9], which, differently from the previous three, does not include a BESS. Some others assess sector coupling and also

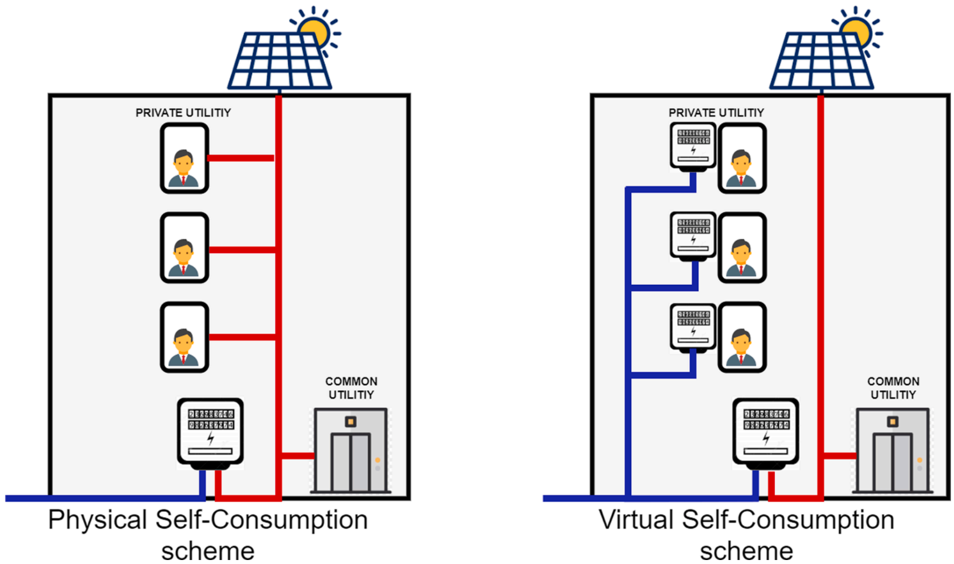

Fig. 1. Physical VS Virtual regulation schemes.

include the thermal sector as [10], or the transport sector as [3] or both [11]. Moreover, also the space resolution of interest can be different and it can vary from a multi-family housing building, as in [12,13], to several buildings, as in [14], and up to the scale of entire districts, as in [15]. Different areas can be assessed simultaneously, and the choice is clearly also linked to the regulation framework and the considered technical constraints. A further option emerging in EC existing models regards the simulation or optimization objective - there can be one or more objectives. Existing optimization objectives can be the minimization of energy from the grid [7]; the minimization of investments and cash flow [16]; the maximization of each user's saving [8] the minimization of the environmental impact [17] and of the health impact [9]. However, in these models, a correlation between EC characteristics and the relative model outputs is still missing.

It is worthwhile having a brief overview on the DSM, which has been mentioned above as it can be a further option to provide flexibility to the energy system in addition to the storage. The flexibility potential of the DSM , in buildings can be granted thanks to the several deferrable loads, e.g., laundry machines, dryers, or dish washers and, although it is well known and described in studies such as in [18], it is an option less commonly included in energy system modelling tools with respect to storage systems.

An effective DSM definition was provided in [19] as "the planning and implementation of those electric utility activities designed to influence customer uses of electricity in ways that will produce desired changes in the utility's load shape". In literature [19], the different DSM strategies, that are often used simultaneously, are defined and classified into Peak Clipping, Valley Filling, Load Shifting, Strategic Energy Conservation, Strategic Load Growth, and Flexible Load Shape.

Demand response programs are also used in microgrids to match energy generation and consumption and guaranteeing thermal comfort of the occupants as in [20] or to attain energy-efficiency in changing weather or occupancy conditions as in [21].

In this work the focus will be on Load Shifting, which involves shifting deferrable loads from on-peak to off-peak periods, as well as on Flexible Load Shape, when there is an advantageous option for the customer. Thanks to the activation of energy flexibility in buildings, the DSM is consequently recognized as effective for the integration and share of renewable energy sources (RES) and also for the reduction of the energy bill of the final user thanks to the adaptation of the energy demand to the PV intermittent production [22]. Price responsiveness is also emphasized, and the energy consumption costs are lowered by shifting the load profile to the time of low energy cost while keeping unchanged the overall energy consumption [23].

It is possible to go much more in the literature detail and compare the existing EC models outlined in Table 1.

From the literature analysis results that none of the existing model assess simultaneously all the listed aspects. For instance in [16] are assessed both the DSM role and minimization of global costs, while the benefit return for each user is missing; in [33] are minimized both the global and individual costs, but the DSM role is missing; in [17] are minimized the global costs and a clustering algorithm is implemented, but both the individual costs and the DSM role are missing. The other listed aspects, not mentioned, but equally relevant are the sector coupling, the regulation framework and BM schemes, the composition, the energy efficiency, and the benefit distribution fairness as well as the emissions.

The work presented in this paper aims to overcome the above gap and to innovatively contribute with a linear-programming, bottom-up optimization model, which addresses the mentioned aspects of an energy community. The evaluation of flows dispatches and definition of the best investment mix (capacity of PV and BESS) is performed based on the characteristics of an energy community by minimizing the economic expenditures according to applied regulation frameworks.

An open source model (OSM) has been used and the component of the DSM was also used. Additional features implemented and integrated are a clustering algorithm to reduce computational complexity and a function to assess the sharing of benefits.

An original allocation method is suggested in order to distribute the global benefit among the participants: the assumption is that the participants of an EC system can have different load demands and can also offer different services and energy production, therefore a fair allocation of the profits is based on their own contribution to the system. Then, also a comparison of this allocation method and of a few more viable methods – for reasons of privacy and complexity of access to data – through a specific index, represents a novelty as it allows the modeler to find out whether the participation of the final users is convenient and whether the profit distribution is more or less fair, but above all it permits to identify a relationship between composition and profit allocation.

Therefore, the work novelty consists in the implementation of the aspects above listed in the model: as mentioned, also the role of the Demand Side Management (DSM) is investigated and integrated as it provides flexibility to the household composition and impacts both the first optimization part which regards the technology mix, but it also affects the profits and, therefore, the allocation method.

Table 1
Literature overview on Energy Community system models.

Reference / case study	Energy Sector	RES	ESS	Implemented aspects	Sector	Time resolution / horizon	Model features	Objective	Software/ Environment
[7] 102 customers	Electric	RPV	BESS	• Reserve provision • Distribution network	Residential	30 min / 1 year	SOO	min. energy withdrawal	AIMMS CPLEX (solver) OpenDSS CREST
[8] 20 smart homes	Electric	RPV	BESS	• TOU tariffs • DSM strategy • ESP	Residential	1 min / 1 day	SOO	min. individual cost (Nash eq)	JADE MATLAB TCP/IP ports
[24] LMABs, SMABs, SFHs Austria	Electric Thermal	RPV FIPV	BESS	• Clustering	Residential	1 year / 20 years	SOO	max. NPV (investment optimization)	–
[10] 12 buildings University of Calabria	Electric Thermal	RPV	BESS	• TOU tariffs • ESP	University campus	1 h / 1 month	MOO	• min. energy withdrawal • max. individual profit	Power Cloud model
[9] DC Central Okanagan Regional	Electric	RPV BPP	–	• LCA • criteria suitability rating index	Residential	1 year / 25 years	MOO	• min. global costs • min. emissions, healt impact • max. RE	STELLA SimaPro
[16]	Electric Thermal	RPV	BESS	• TOU tariffs • DSM strategy	Residential	15 min / 1 day	MOO ABM	• min. energy withdrawal • min. global costs	Anylogic
[25] 50 domestic users London	Electric	RPV	BESS	• TOU tariffs • DSM strategy	Residential	5 min / 1 week	SOO	max. flexible loads	Python Gurobi (solver)
[3] 50 prosumers Melbourne, Australia	Electric Transport	RPV	BESS EV	• TOU tariffs • DSM strategy • local en. market	Residential	1 h / 1 day	MOO	• min. individual cost • min. en. sharing risk (CVaR)	MATLAB
[11] San Francisco	Electric Thermal Transport	–	BESS TES EV	–	Commercial EV station	1 h / 1 day	SOO MILP	min. operational, collaboration cost	GAMS ILOG CPLEX (solver)
[26] 9 households (3 hold RES) Helsinki	Electric	–	–	• TOU tariffs	Residential	1 h / 1 day	SOO LP	• 3 separated min.: • individual cost • coalitional cost for HH w. RES and ESS (Shapley eq.) • EC coalitional cost	MATLAB
[27] 5–25 prosumers China Southern Grid	Electric	PV	–	• ESP • DSM strategy • local en. market	Residential Commercial Tertiary	1 h / 1 day	SOO	min. individual cost	MATLAB
[17] Linz, Austria	Electric Thermal Transport	RPV STE	BESS TES	• GIS • EoS • EE • clustering	Residential	1 h / 1 year	MOO	• min. global costs • min. emissions	2 OSM: “urbs” [28] “rivus” [29]
[2] 32 prosumers Wuhan, China	Electric	PV	BESS	• ESP • EE	Residential	1 h / 1 day	two-phase SOO LP	• min. global costs (deriving en.-sharing profiles) • min. individual cost (inducing en.-sharing prices)	MATLAB
[30] 2 consumers, 3 prosumers	Electric Transport	WT	BESS	• DSM strategy	Residenial	1 h / 1 day	two-phase SOO	• min. global costs • min. individual costs (Nash eq.)	–
[31] multi-family building Athens	Electric Thermal	PV SGS	BESS TES	• LCA	Residential	1 yearly 1 month / 10 years	SOO	investment optimization (min. en. transactions)	–
[1] 3 households Beijing	Electric	PV	BESS	–	Residential	1 h / 1 day	SOO LP	max. individual profit (Nash eq.)	GAMS PATH (solver)
[32] 12 dwelling condominium; office building; supermarket; mall Turin, Italy	Electric Thermal	PV	–	–	Residential Tertiary Commercial	1 h / 1 year	SOO	investment optimization	MATLAB
[33] Chiou, Aosta	Electric	RPV HPP	BESS	• GIS	Residential Tertiary	1 h / 1 year	SOO	• max. global profit • savings redistribution (Shapley eq.)	Pyomo, Python Gurobi (solver)

(continued on next page)

Table 1 (*continued*)

Reference / case study	Energy Sector	RES	ESS	Implemented aspects	Sector	Time resolution / horizon	Model features	Objective	Software/ Environment
[12] 5 dwelling condominium Bolzano, Italy	Electric	RPV	BESS	• regulation framework schemes • BM schemes	Residential	1 h / 1 year	Simulation	Global, individual profit assessment	Python
[13] 5 dwelling condominium Bolzano, Italy	Electric	RPV	BESS	• EoS • BM schemes • criteria suitability index	Residential	1 h / 1 year	MOO	• min. global costs • min. fossil fuel consumption • max. fairness	Python
* REC Bolzano, Italy	Electric	RPV	BESS	• regulation framework schemes • BM schemes • DSM strategy • TOU tariffs • Clustering • Composition analysis • criteria suitability index	Residential	1 h / 1 year	two-phase SOO	• dispatch • investment optimization • max. global profit • savings distribution (contribution) • fairness evaluation	OSM: "oemof" Pyomo Python Gurobi (solver)

* this work.

Further scope of the paper is therefore to evaluate the relationship between the composition of the EC in terms of heterogeneity of demand profiles and this optimal distribution of the benefits.

The paper is structured as follows. Section 2 details the methodology behind the creation of the EC model: the two macro-themes of the model structure and the profit distribution can be identified. Section 3 provides an overview of the regulation frameworks and of the input data specific to the tested case study. Section 4 presents the results and the discussions about the comparisons which have been performed and Section 5 draws the wholesale conclusions.

2. Methodology

2.1. General model characteristics and structure

The EC_model developed in this work is a Single-Objective optimization model, based on a bottom-up approach and a linear programming technique, which implements a static approach focusing on a short-term target period of one year. The model is written in Python and mainly based on [34], which is a linear programming framework to model and analyse energy systems. Gurobi [35] was chosen as the solver for the linear optimization with a convex set of viable solutions.

The oemof framework is used to perform the dispatch optimization and the operational optimization, identifying the optimal use of sources to satisfy the load and also to determine the investment capacity of generation and storage systems of the REC under study by minimizing the economic expenditures.

The EC system is defined as a network made up of nodes (Components or Buses) and edges (Flows). A free number of nodes is allowed and consequently the space resolution can change depending on the application, therefore the model is flexible to implement any type of EC.

By the oemof-solph module, based on the Pyomo library [36,37], it is possible to create and solve linear programming (LP) or mixed-integer linear programming (MILP) optimization models.

The objective function (OF_{EC}) formulation is reported in Equation (1) which is equal to the total cost of generation and investment. The model is completed by different constraints: Equation (2) reports the hourly power balance in each node.

$$OF_{EC} = \sum_{n\in N}\sum_{u\in U}\sum_{t\in T} E_{n,u,t}\bullet \mathrm{vc}_{\mathrm{n,u,t}} + \mathrm{inv}_{\mathrm{u}}\bullet \mathrm{epc}_{\mathrm{u}} \tag{1}$$

$$L_{n,t} = \sum_{u\in U}\left(E_{n,u,t} + E^{discharge}_{n,u,t} - E^{charge}_{n,u,t} - E^{gridloss}_{n,t} - E^{excess}_{n,u,t}\right) \tag{2}$$

Where:
OF_{EC} = objective function of the EC model
n = index of node set N
u = index of generation unit set U
t = time-step index of set T
$vc_{n,u,t}$ = variable costs of the generation unit u of node n at time t
$E_{n,u,t}$ = electricity generation value of unit u of node n at time t
inv_u = capacity of investment variable u
epc_u = equivalent periodical cost of investment variable u
$L_{n,t}$ = electricity load of node n at time t
$E^{discharge}_{n,u,t}$ = electricity provided by storage units
$E^{charge}_{n,u,t}$ = electricity used for the storage charging
$E^{gridloss}_{n,t}$ = electricity lost in grid transmission.
$E^{excess}_{n,u,t}$ = electricity excess

The storage balance constraints, reported in Equation (3) and (4), account for the charge, the discharge and the self-discharge and for the filling level of the storage $S_{u,t}$.

$$\left(P^{charge}_{t}\bullet \eta_{\mathrm{charge}} - \frac{\mathrm{P}^{\mathrm{discharge}}_{\mathrm{t}}}{\eta_{\mathrm{discharge}}}\right)\bullet \Delta \mathrm{t} - (\mathrm{S}_{\mathrm{t}} - \mathrm{S}_{\mathrm{t-1}})\bullet \eta_{\mathrm{self}} = \mathrm{S}_{\mathrm{t}} - \mathrm{S}_{\mathrm{t-1}} \tag{3}$$

$$S_{u,t} \le NS \tag{4}$$

Where:
P^{charge}_{t} = power charging the storage at time t
$P^{discharge}_{t}$ = power discharging the storage at time t
η_{charge} = charging process efficiency
$\eta_{discharge}$ = discharging process efficiency
S_t = storage state at time t
η_{self} = storage self-discharge efficiency
$S_{u,t}$ = storage filling level
NS = nominal storage capacity

Finally, the powerlines flow limit is expressed in Equation (5).

$$P^{flow}_{u,t} \le NP^{flow} \tag{5}$$

Where:
$P^{flow}_{u,t}$ = power flow exchanged through a powerline, at time t
NP^{flow} = nominal transmission value

Through the Investment mode, oemof performs the expansion capacity optimization considering the PV and BESS costs as input to evaluate their optimal capacity. For this purpose, we used the investment mode applicable to Source and Generic Storage.

The nominal PV generator capacity and the nominal storage capacity are therefore not inputs, but are the decision variables determined by the optimization problem. Therefore, all the parameters that usually refer to the nominal value or the capacity will now refer to the investment variables and will be characterized by the equivalent periodical cost (epc) for the investment which is calculated as in Equation (6).

$$epc_u = CAPEX_u \bullet \frac{\mathrm{wacc} \bullet (1+\mathrm{wacc})^{\mathrm{lifetime_u}}}{(1+\mathrm{wacc})^{\mathrm{lifetime_u}} - 1} + \mathrm{OPEX_u} \tag{6}$$

Where:
$CAPEX_u$ = capital expenditure of investment variable u
$lifetime_u$ = life expectancy of investment variable u
$wacc$ = weighted average cost of capital
$OPEX_u$ = operating expenditure of investment variable u

Then the oemof-network module is used: it contains the base classes as Source, Sink, SinkDSM, Generic Storage, to model generation sources, the electricity demand, the flexible electricity demand driven by Demand Side Management (DSM) and the storage and the links between these components as schematically shown in Fig. 2.

The variable costs considered are the ”energy price” (*EP*), the ”dispatchment price” (*DP*), which are both part of the expenditure on energy, the expenditure on system charges (*SC*), to cover costs for general activities of interest for the electricity system, the expenditure on electricity transport and meter management (*TC*), the excise duty (*ED*), the Value Added Tax (*VAT*), but also the incentives or refunded quota related to the energy sharing (*SH.I*). Fig. 3 shows the scheme of how each cost is associated to energy flows or objects: they are the purchased energy price (*PE*) expressed in Equation (7), the shared energy price (*SE*) in Equation (8) and the price of sold energy (*FE*) in Equation (9).

$$PE = EP + DP + SC + TC + ED + VAT \tag{7}$$

$$FE = EP \tag{8}$$

$$SE = DP + SC + TC + ED - SH_I + VAT \tag{9}$$

Another component used is the SinkDSM, one of the last implemented in oemof, which allows to simulate Demand Side Management (DSM) [38]. The global electricity demand remains unchanged over time, while some flexible load may be moved, for example, from periods with high power prices to periods with lower prices or from hours with low renewable generation to hours with higher renewable generation.

Essentially, SinkDSM models the flexible demand, while Sink is used for fixed loads. There are two constraints, (capacity_up and capacity_-down) and the shifted demand can vary between them. If the demand is reduced in a certain instant, there will be an increase in demand in another time-step in order to have a constant overall load to satisfy. For a more realistic scenario, it is also possible to associate a cost to the load increase or reduction.

Between the two implemented formulations available for the DSM, the “interval” mode where the demand can be shifted within the defined bounds of elasticity and not across days is adopted [39].

The depicted self-consumption model has a “physical” scheme for what regards each house or housing building: there is only one PoD with the network. Hence, the energy produced and self-consumed remains within the private building perimeter and would not be charged for the network system charges. While the energy shared in the REC – among buildings - uses the public distribution network.

2.2. Household profile generation and evaluation of EC heterogeneity

The load profiles of the residential users have been obtained through the LoadProfileGenerator (LPG) tool [40]. Then, each profile has been split into flexible and fixed load profiles, the former as input for the SinkDSM and the latter for the Sink.

Basically, the tool returns both profiles of each household as an aggregated profile or provides the consumption of every individual appliance. This latter aspect is usually detailed more precisely in the research on DSM methodologies [41]. Thanks to this, it has been possible to distinguish loads of time-shiftable domestic devices which can provide flexibility and those which cannot, thus obtaining realistic load profiles to enter as input for the model. The time-shiftable appliances, which have been taken into consideration, are dishwashers, washing machines, dryers and other comparable devices.

The different profiles have been generated by setting specific characteristics and compositions and by entering the examined city coordinates and temperatures for the selected year. Then, for each composition, more profiles have been generated in LPG by selecting a different number of members (which can vary from 0 to 6 +).

In EC composition it is possible to provide a scenario with an established energy community or to generate it randomly by setting the maximum number of involved buildings.

The definition of the energy community is implemented through python functions and its methodology is briefly shown in Fig. 4.

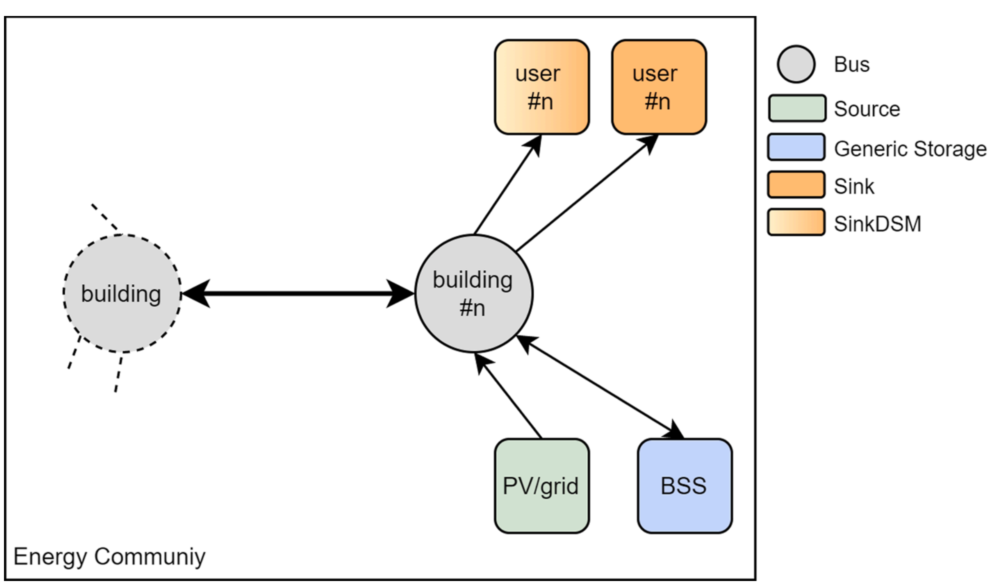

Fig. 2. Streamlined illustration of an energy community as an oemof-network.

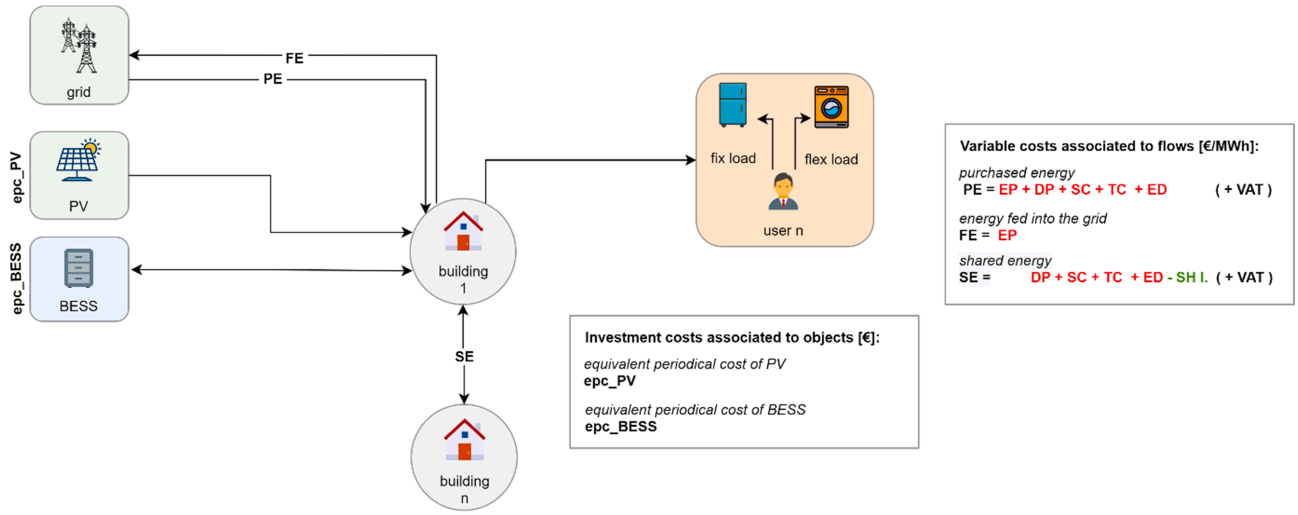

Fig. 3. Scheme of the costs associated to each flow and objects.

As indicator of the notions of heterogeneity and homogeneity of the energy community under consideration we have introduced the normalized Gini coefficient.

In [42] the Gini coefficient definition is provided (Equation (10)) and it is also reported how it can reply to the need of synthetic indexes, which are useful for the comparison of the socio-economic profiles (i.e. and in OECD to evaluate income inequality [43]).

This heterogeneity index involves the frequencies of the different compositions in the EC and it can vary between 0 and 1. It is maximum if the frequencies are equally distributed among all the modalities, while it is minimum if there is maximum homogeneity and all the frequencies are concentrated in a single modality.

$$G = \left(1 - \sum_{i=1}^{m_{tot}} f_i^2\right) \frac{m_{tot}}{m_{tot} - 1} \tag{10}$$

Where:
G = Gini coefficient
fi = frequency of the composition a certain member i
m_{tot} = total number of members in the EC
2.4 K-means clustering

One encountered drawback concerns the computational cost of the model as the number of buildings and members involved in the EC increases. To address this bottleneck, typical load profiles are recovered from data via the k-means clustering, one of the most effective clustering methods used in machine learning, belonging to the class of centroid-based clustering [44].

In these methods each cluster is represented by a centroid, which may not necessarily belong to the initial dataset. The algorithm takes the number of clusters (K) as input to partition the data points into K groups, so that the points contained in the same cluster are as similar as possible according to the Euclidian distance (Equation (11)). The K-means clus-

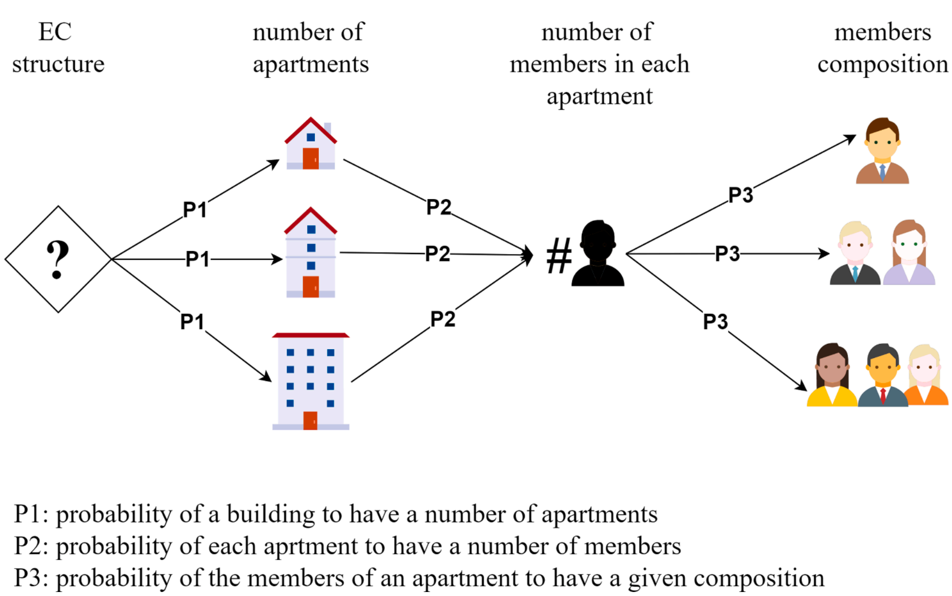

Fig. 4. Function scheme for the definition of EC.

tering algorithm, already implemented in python with scikit-learn, is the standard heuristic to tackle this optimization task.

$$OF_{kmeans} = \min \sum_{k=1}^{K} \sum_{d=1}^{DS_k} \left(x_d^{(k)} - c_k\right)^2 \tag{11}$$

Where:
OF_{kmeans} = objective function of the k-means clustering algorithm
k = index of cluster
K = total number of clusters
d = index of data points
$x_d^{(k)}$ = data point d belonging to cluster k
c_k = centroid of cluster k

However, in order to apply this method, it is necessary to select the desired number of clusters, denoted by K. A useful graphical tool to identify the right K for the dataset is the Elbow method [44].

Fig. 5 shows a graphical scheme of the K-means algorithm and the elbow method.

2.3. Costs, incentives, and regulations

If typical load profiles have to be identified by the K-means algorithm to lower the computational burden, also hourly cost profiles have to be reduced according to the same criteria. For clarification: the clustering algorithm is not applied twice, but the cost profile is adapted, keeping the exact same clusters that were identified for the demand profiles..

Another aspect concerns the modeling of the tax reduction taken into account in order to manage the investment costs given as input, which allow for a meaningful investment optimization. By setting the deduction value, (e.g 50% deduction for the expenses incurred for the installation of the PV system), the model input costs undergo a variation to consider the actual costs that will be paid by the final consumer after the deductible ones.

2.4. Optimization model outputs

Once the optimization has been carried out, the post-processing identifies how the overall demand of each building is met: how much electricity is purchased from the grid, how much it is self-produced and shared or self-consumed within the building. Furthermore, the overall benefit derived from the avoided electricity purchase and from the refunded amounts are assessed.The EC elements known before the optimization are the following:

- Gini index
- Overall electricity demand and profiles before applying DSM
- Shared energy inside the renewable energy community (instantaneous sharing, sharing taken from BSS)
- Investment costs

While, those known after the optimization are the following:

- EC system characteristics (renewable generation and storage systems installed capacities - decision variables of the model)
- Electricity demand profiles after applying DSM
- Overall PV production and excess
- Shared energy inside the renewable energy community (instantaneous sharing, sharing taken from BSS)
- Costs/savings (self-consumption savings, refunded costs)
- Renewables overview (self-consumption rate, energy sharing rate, consumption rate of renewables)

2.5. Benefit allocation scheme

The question concerning the benefit distribution among the EC members comes up. To answer it, [12] has introduced business models to guarantee a fair distribution and to prevent penalizing someone.

After these initial studies the focus shifted to the fairness of the benefit allocation. Fairness is indeed a relevant performance measure in allocation schemes and an appropriate quantitative measure is important. Therefore, a Fairness Index, which had already been introduced in [13], has been further developed.

A key point is that fair does not necessarily imply an equal

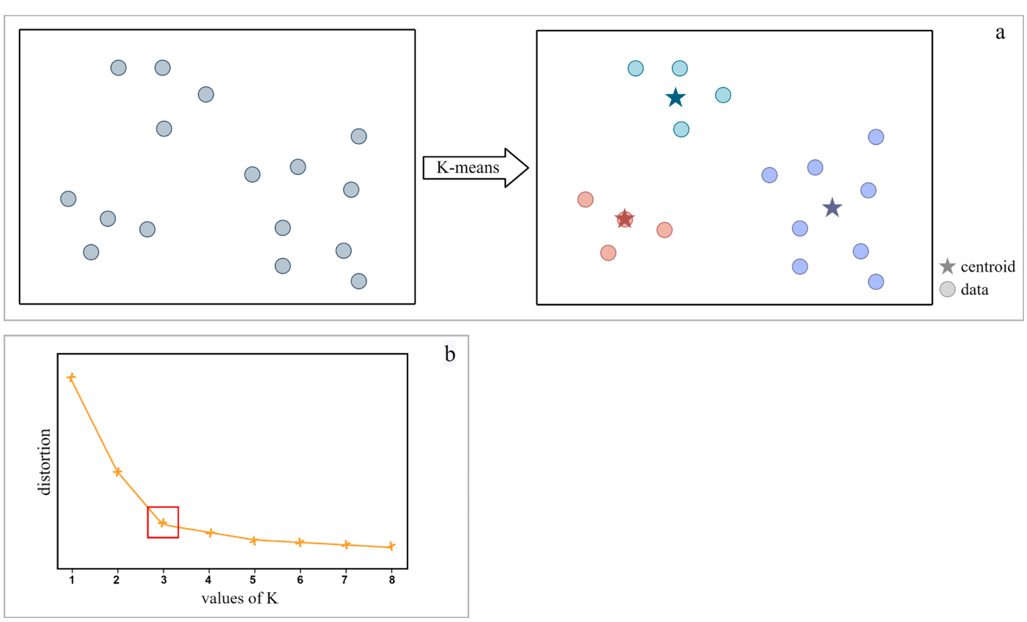

Fig. 5. K-means clustering (a) and elbow method (b) scheme.

distribution of the benefits. Sometimes, it is fair that a user is granted more benefits than another user; therefore, it is necessary to select the most appropriate allocation metric.

In this work, it is suggested the adoption of the Allocation Metric, hereinafter referred to as 'Contribution distribution'. The rationale behind this choice is that in an EC system, where members have unequal demand for resources and provide different services and production, the fairness may be based on the contribution of each member to the overall system.

Therefore, it is identified how the user contribution to the community can be quantified. In this case, the contribution is considered in economic terms. This is calculated by running the optimization several times – in addition to the already performed one – according to the number of the members of the energy community, without considering the building which the members belong to.

Each new optimization will evaluate the same EC system, excluding one member by member.

For instance, in an optimization one user is excluded, and, if his participation provides a contribution to the overall community, the results in terms of savings will be lower. The user contribution will be the difference in saving between the base case and the case without that user. This step will be performed for each member to assess every single contribution. Fig. 6 shows the above described procedure schematically, as well as Equations (12) and (13).

$$BC_i = OPT - OPT_{-i} \tag{12}$$

$$D_{cd,i} = \frac{C_i}{\sum_{l \in I} C_l} \tag{13}$$

Where:
I = set of the energy community members
i, l = indexes used for the energy community members
BC_i = benefit contribution of member i
OPT = savings of the EC if all members are included
OPT-i = savings of the EC if member i is not included
Dcd,i = contribution distribution percentage of benefits for member i

After finding all the contributions, it is possible to determine the benefit distribution, where the distribution among the users is weighted by their respective contribution. This should ensure that the benefit percentage assigned to a user does not trigger discontent among other members, who would not have equally access to that amount without that member participation. Moreover, here, the distributed savings among members, are recorded as net of investment costs.

Distribution may also have negative values if a member does not provide any benefit, thus showing further information regarding the optimality of the community composition. The best scenario is the one in which all members increase the overall common benefit.

This approach to the design of the contribution distribution is inspired by the Vickrey–Clarke–Groves (VCG) mechanism in auction theory [45]. The aim is to optimize global contentment, namely, to maximize the total of the bids.

The aspect considered in this work regards the assignment of benefits. In the future, when assessing the opportunity for new members to join the ECs, a truthful assessment could be extremely important. It would be even more useful if a personalized fee for community participation were applied.

Table 2
defined business models.

BUSINESS MODEL	DISTRIBUTION CRITERIA
BM **A**	homogeneous distribution among EC members according to the investment
BM **B**	distribution among EC members according to their DSM exploitation
BM **C**	distribution among EC members according to their PV self-consumption
BM **D**	homogeneous distribution among members of the same housing building
BM **E**	distribution among EC members according to their loads

2.6. Business models and fairness index

The distribution of benefits based on the contribution of each member has the limit of being unlikely applicable to reality. However, through the implemented model it is possible to evaluate what the optimal distribution for a CE with certain characteristics should be and to compare it, thanks to a specific Fairness Index, with business models (BMs) that identify further benefit distribution methods, which do not include any optimization and are more easily adopted in the real case.

Table 2 shows the BMs schemes for the distribution of the benefits. As the distribution of the incentives is decided within the EC by taking as a reference the method considered more suitable, additional BMs, not listed here, can be further tested. The only requirement is to define a function which must return the actual savings of each member as well as the distribution ratios.

The above mentioned Fairness Index (FI), additional output of the model for the evaluation of the fairness of BMs, has the following properties:

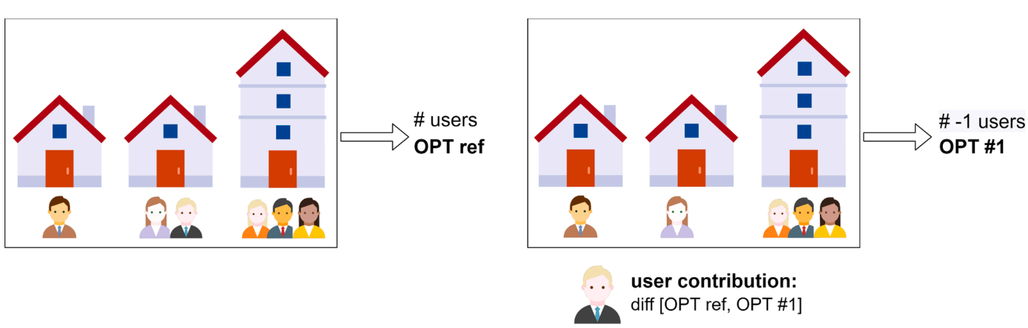

Fig. 6. Scheme for the evaluation of each user contribution.

- It is applicable to any EC of any size.
- Its value is between 0 and 1 if each individual member has a profit: $0 \leq \text{FI} < 1$. The closer the value is to zero the fairer and the more suitable is the applied BM
- It is meaningful also for distributions that allow negative values
- Its value corresponds to the number of members that would not be satisfied: FI = {1, 2, …, m_{tot} } where m_{tot} is the number of the members. E.g. FI = 4, 4 members have no economic advantage and will not partake.

Equation (14) shows the fairness index for the global community.

$$FI(m) = \begin{cases} \dfrac{\sum_{i=1}^{m} |D_i - D_{cd,i}|}{\sum_{i=1}^{m} |D_{w,i} - D_{cd,i}|} & \text{if } m = m_{tot} \\ m_{tot} - m & \text{if } m \neq m_{tot} \end{cases} \tag{14}$$

Where:

D_i = distribution percentage of benefits for member i

$D_{cd,i}$ = contribution distribution percentage of benefits for member i

$D_{w,i}$ = worse distribution percentage of benefits, according to the contribution distribution, for member i

m = number of members for which $D > 0$

m_{tot} = total number of members in the EC

The denominator of the FI can be determined by a function which allows to identify the worst case, the one that would lead to a distribution of the benefits the farthest from the reference metric distribution, thereby maximizing the denominator.

A simplified version of the model code is open source and available at [46].

3. Case study

The *EC_model* previously described is general: it can be applied to any Energy Community within any regulatory framework and can include different generation sources. In this work, it is tested to RECs placed in Bolzano, a city in the North of Italy and only PV sources are considered (average yearly *GHI* = 1434 kWh/m2, average *T* = 12.4 °C, *Lat/Lon*: 46.4936 / 11.3346; radiation database: CMSAF 2007–2016 [47]). The normalized PV profiles used are obtained from PV systems which orientation is south with an angle of a 30°.

Therefore, the variable costs of the model are calculated under the Italian regulations, however, the input values can readily be changed to suit different applications.

3.1 The Italian regulatory framework

The regulatory steps started with the adoption of the RED II directive [4], marking a European breakthrough in the EC as it introduced and distinguished the concepts of 'jointly acting renewables self-consumers' (JARSC) and 'renewable energy community' (REC). Later, IEM [48] promulgated further rules on the constitution of an EC.

Focusing now on Italy, the experimental stage started with the conversion into law of the Milleproroghe decree-law (D.L. 162/19 [49]). It was followed by the documents published by ARERA [50] - [51] and by MiSE [52], which were in charge of defining the regulatory framework and the incentive schemes, and the document published by GSE [53], which defined the operative rules later approved by ARERA [54]. In Table 3 the refunded amounts established by Arera and MiSE are defined both in case of JARSC and of REC: those referring to REC are adopted in this work.

In this work, the net metering mechanism will not be evaluated, in fact, it is not possible for ECs to access this mechanism and it is expected to be overcome in order to promote self-consumption.

Despite being currently not allowed in Italy, the investigated self-consumption scheme, which considers only one PoD for each housing building, is adopted to ease the methodology illustration. To read more about the energy sharing inside a multi-family housing building, we refer to [12].

The references of this section are in Italian since the EC model is applied to the Italian regulatory framework.

Table 3
Refunded amount for shared energy both in case of 'jointly acting renewables self-consumption' (JARSC) and of 'renewable energy community' (REC).

Model	Refunded amount (defined in [51] by ARERA)		Refunded amount (defined in [52] by MiSE)
JARSC	Variable transmission and distribution components (2019) 7,61 + 0,61 €/MWh	Avoided grid losses * C_{AL_MV}: 1,2% C_{AL_LV}: 2,6%	100 €/MWh
REC		–	110 €/MWh

* Zonal Electricity Price (Z_P) times the avoided grid loss coefficient (C_{AL}).

Table 4
Rooftop PV and battery data.

	Rooftop PV	Battery	Source
CAPEX 2020	1198 €/kW	587 €/kWh	[55]
OPEX	1.5 $\%_{CAPEX}$	5 $\%_{CAPEX}$	[56]
Discount rate	5%	5%	[56]
Lifetime	30 years	15 years	[56]

3.1. Investment costs

Table 4 shows the costs and the relative sources of PV and BESS. These data were given as input to the model to perform the optimization. Moreover, we have also considered the tax deduction of 50% for the CAPEX of the photovoltaic and storage systems as one of the options given by the Italian legislative framework.

The bill costs of this work take into account only the energy quota (€/kwh), while the fixed quota (€/year) and the power quota (€/kW/year) are not included. As we are focusing more on identifying the advantages of establishing an EC, the latter costs, which are still to be paid anyway, are not so relevant to this aim.

The 'energy price' (EP) has been assumed to be the 'National Single Price' (PUN which stands for Prezzo Unico Nazionale in italian), defined as the average electricity wholesale price, for year 2019 available on GSE website, while the other electricity bill component costs are available in [57].

3.2. ISTAT data on Bolzano residential building composition

The EC composition is based on the data available on the ISTAT registers [58] and on the data of the city taken into consideration. Each building may be composed of a certain number of apartments - ranging from 1 for a single-family house to 16 + for a multi-family house - and each apartment may host a certain type of household of one or more members. Table 5, which refers to Bolzano, shows the type of possible residential nucleus and their relative frequency. As mentioned, based on these compositions, more residential user load profiles were generated by LPG, by entering the coordinates of Bolzano and its temperature profiles in 2019.

4. Results and discussion

In this section the final results of the model applied to two case studies are introduced and discussed. In particular, the results will focus on the impact of the DSM and on the Fairness Index for case study #1 whose characteristics are depicted in Table 6.

Table 5
Household composition probability in Bolzano province (data elaborated from General population and housing census – 2011 [58]).

number of housing units	number of buildings	members per household	not a family nucleus	families with a single nucleus, without other residents: couple without children	couple with children	mother with children	father with children	families with a single nucleus, with other residents: couple without children	couple with children	mother with children	father with children	families with more nucleus
1	0.602	1	1	0	0	0	0	0	0	0	0	0
2	0.151	2	0.071	0.665	0	0.224	0.040	0	0	0	0	0
3 o 4	0.110	3	0.012	0	0.726	0.155	0.024	0.048	0	0.028	0.007	0
5 o 8	0.095	4	0.003	0	0.877	0.035	0.006	0.004	0.036	0.012	0.004	0.023
9 o 15	0.024	5	0.002	0	0.788	0.013	0.003	0.003	0.094	0.010	0.003	0.083
16+	0.018	6+	0.003	0	0.505	0.008	0.001	0.002	0.148	0.009	0.005	0.320

Successively, for the sake of comparison, a slightly different second case study is introduced to have a further focus on the EC heterogeneity impact.

4.1. With DSM versus without DSM

The comparison between the scenarios with and without DSM is now performed and also a reference scenario is introduced. Therefore, the scenarios we will be referring to are three:

- ***RS***: where the residents are not considered as belonging to an EC. Residents are independent and have to install their own PV and BESS system. The installation capacity is optimized (EC: false; DSM: false).
- ***noDSM_S***: where the DSM has not been applied and the optimization of the investment capacity has been performed (EC: true; DSM: false).
- ***DSM_S***: where the optimization of the investment capacity has been performed again and the DSM has been applied (EC: true; DSM: true).

Fig. 7 shows the structure of the mentioned above system through network graphs: the EC consists of 6 housing buildings and 21 households. The 2nd and 3rd subplots on the top - the EC network graphs - show the same system, but the size of PV and BESS changes. This is more evident in the bottom subplots, where PV and BESS capacities of all the REC members have been combined: the adoption of DSM for the same system means a lower investment both for PV (13%) and for BESS (93%).

Fig. 8 shows how the flexible energy demand is managed: the cumulative demand of each housing building has been plotted for one week in winter and one in summer.

Fig. 9 shows, for all the four scenarios a waterfall plot on the left, where costs and revenues are plotted and, on the right, there is the summary and the comparison of the net costs and the information about the Pay Back Period (PBP). On the contrary, Fig. 10 shows how the demand is satisfied and how the PV generation is used. It also shows the percentage of demand which is satisfied by renewable sources.

Therefore, not only the investment reduction is a relevant consequence of the DSM, but also the percentage reduction of the lost renewable production, which is also significant and equal to 91% (Fig. 10).

Table 6
Case study outline

Housing buildings	6
Households	21
Gini index	0.83
Flexible load	18.07%

The first scenarios (**RS** selling at 0 and selling at PUN) are the ones with the highest overall expenditure. By comparing the other two, ***noDSM_S***, and ***DSM_S,*** is noticeable that the DSM allows to increase savings by 8% and to decrease the investment costs by 40%.

The investments of scenarios RS and noDSM_S are comparable; however, in the second one, there is a slight increase in RES consumption. Scenario DSM_S presents a slight reduction in RES consumption with respect to noDSM_S, equal to 9%, but not so significant if we consider that the investment changes are significant.

In fact, observing the excess production from photovoltaics, we see that the share not used for self-consumption, or sharing is equal to 24.12% in the case without DSM and equal to 20.94% in the case with DSM.

4.2. Fairness

Fig. 11 and Fig. 12 summarize the contribution of each user's participation to the overall benefit of the EC system. They show who is providing a higher contribution to the community and consequently who should have a consistent result in savings. For instance, user B20 – represented by the green node which belongs to building E_cc - is contributing for almost the 13% of the overall benefit. Focusing on building D_cc, we see also that user B19 provides a lower contribution to the system (almost 6%) with respect to B20, but not as lower as e.g. B8, which provides less than a 1% contribution. However, it is a still positive contribution, which is not always granted, as it depends both on how much the demand profile matches with the PV production, with or without the DSM contribution, and affects the heterogeneity of the system.

Fig. 12 reproduces Fig. 11, but without the DSM. Therefore, the contribution of the users changes. User B20 is not anymore the one providing the higher contribution, but as shown by the color scale on the right, also the maximum contribution is lower. Focusing on B8 and B19 users, we see how their role is reversed: the one that in the first case contributed most to the benefit of the energy community does not maintain the same advantageous position in the second case.

Fig. 13 gives some details about the fairness for each user on the adopted BM. According to the contribution distribution taken as reference (in Fig. 11), each user should receive a consistent benefit. In case the benefit is lower than expected and the user is suffering a disadvantage, there will be a negative deviation from optimal distribution (represented by a purple bar), while there will be a positive deviation from optimal distribution (blue bar) when the user is having an advantage.

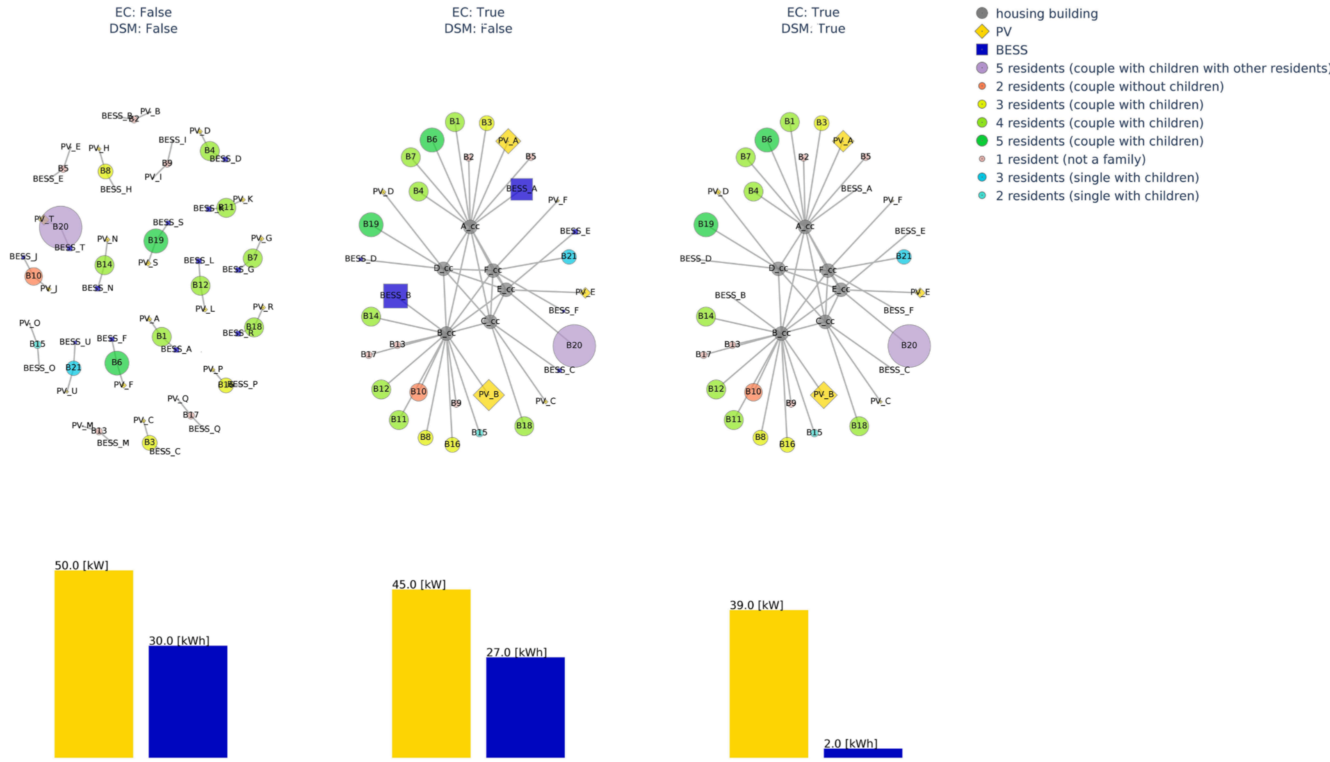

Fig. 7. Comparison reference scenario and EC scenario w/wo DSM.

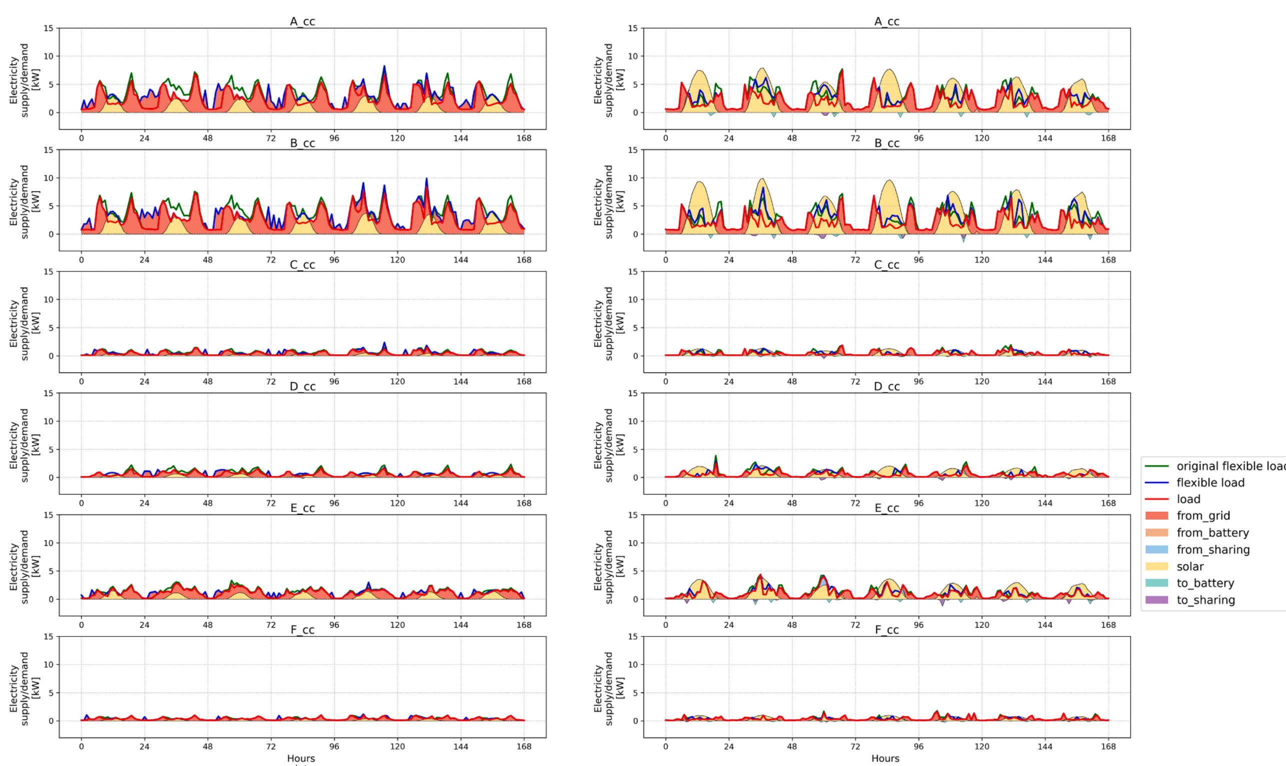

Fig. 8. Dispatch (one week in winter and summer).

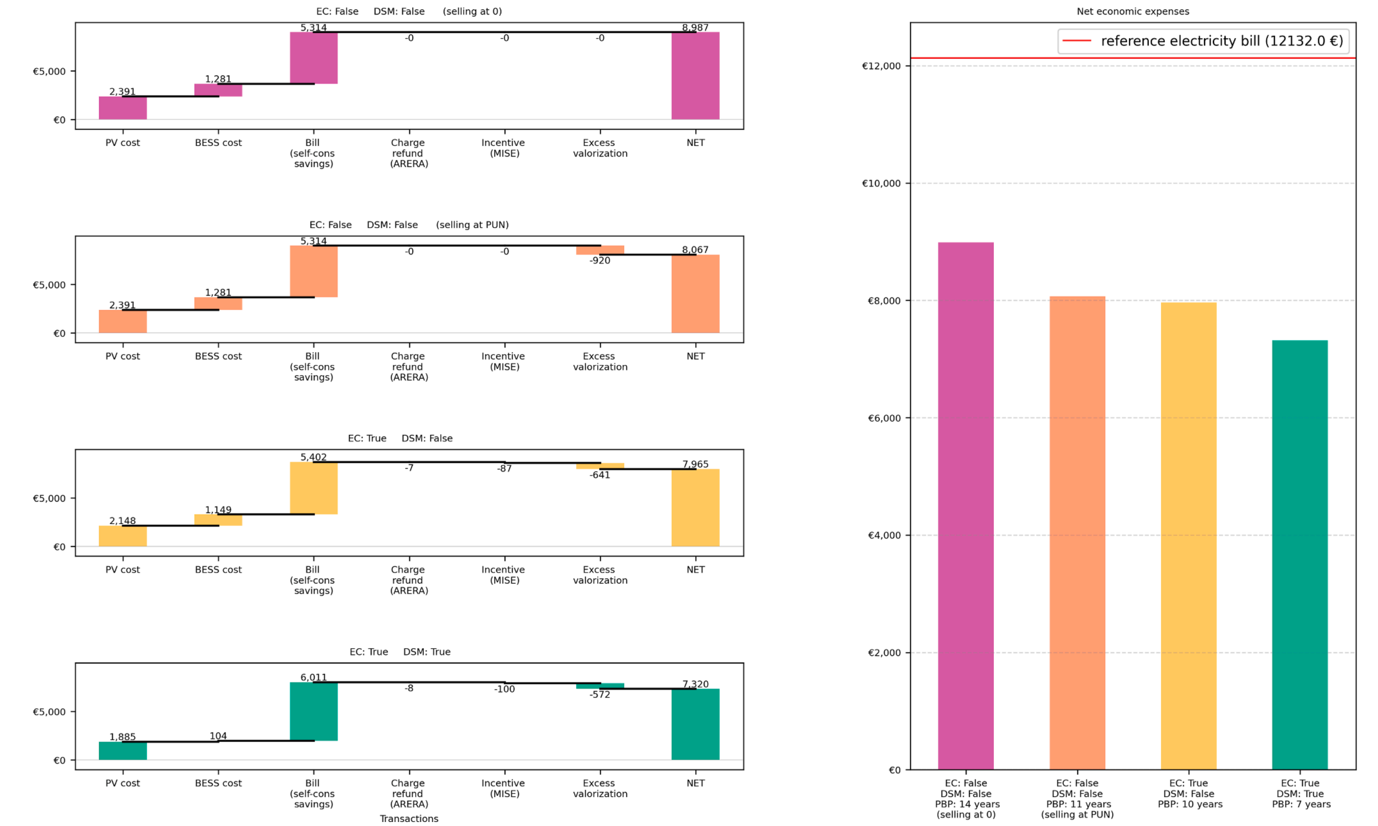

Fig. 9. Waterfall plot of investment costs and saving in base case selling at 0/selling at PUN and w/wo DSM (left) summary of net cash flow (right).

Fig. 13 shows that the same users of Fig. 10, who are guaranteeing the highest savings to the EC, would expect a greater return based on their contribution. E.g. user B20 is experiencing the highest negative deviation from the optimal distribution by applying BM B, even if there is an overall satisfaction (FI = 0.036). Applying BM C, the user is experiencing a positive deviation. For each BM introduced in Table 2, the standard deviation is reported, together with the FI, in Table 7 to estimate how much the distribution is far from the optimal one (which is visible in Fig. 13 in a more immediate way for BM B and BM C). The higher the deviation, the higher is the FI. FI could also state how many users do not get any benefit and therefore if the BM is unsuitable.

4.3. Heterogeneity impact

In this paragraph the case study considered so far is launched again but applying a variation to the composition.

Few residents are substituted in order to decrease the Gini Index from 0.83 to 0.71 as visible in Table 8. The rate of flexible load has not

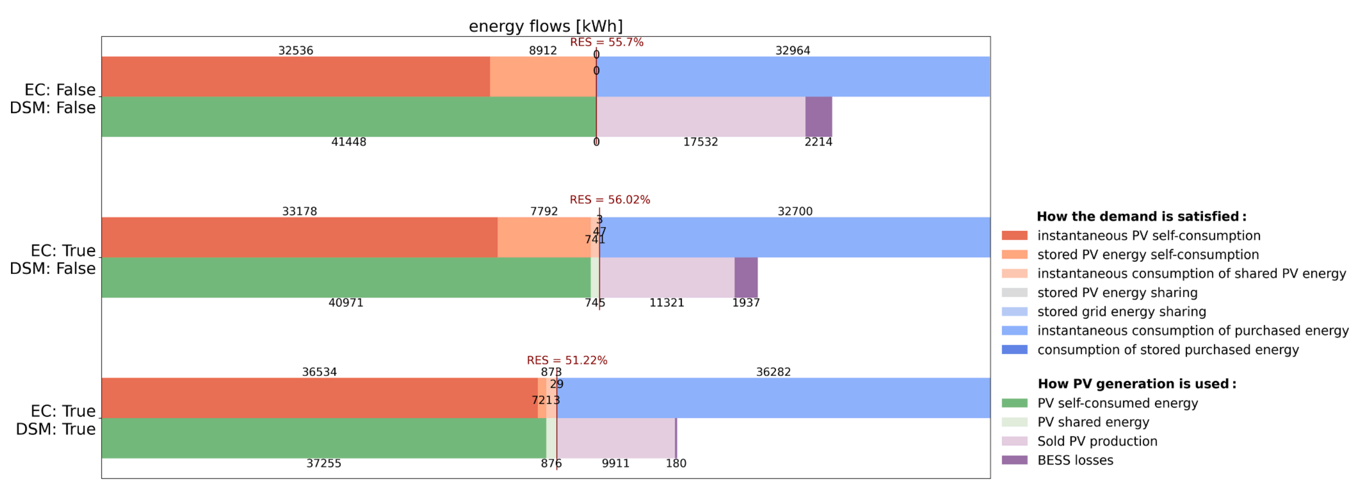

Fig. 10. Scheme of energy flows. Answer how the demand is satisfied and how PV generation is used in three cases.

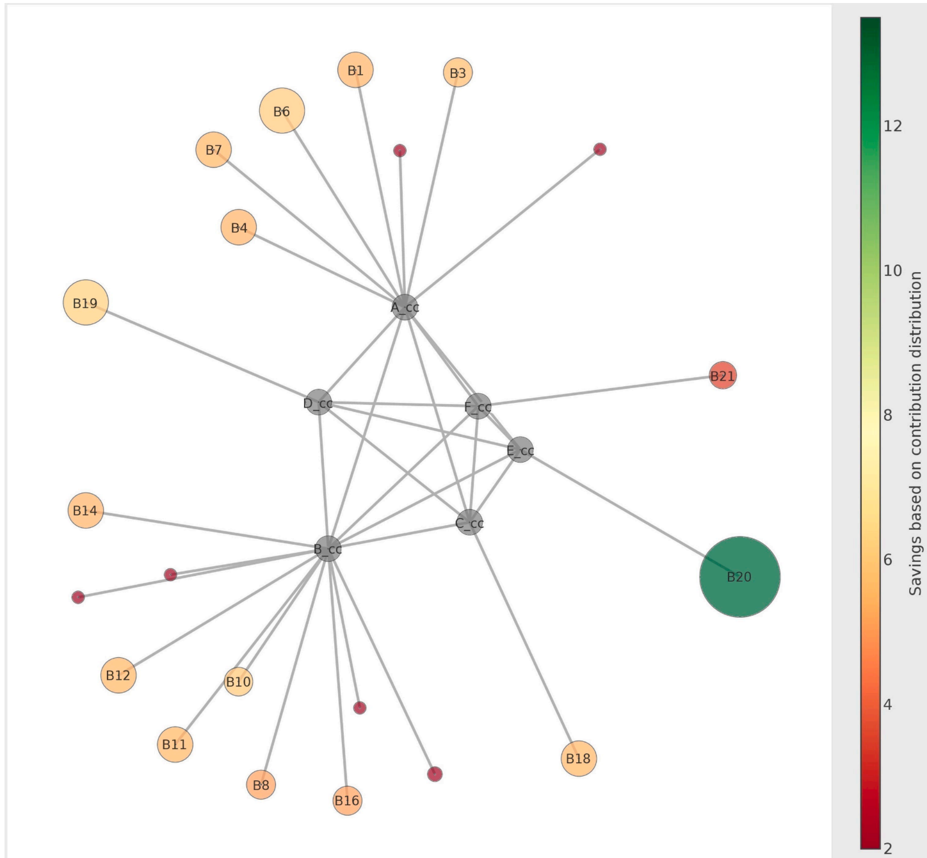

Fig. 11. Saving distribution according to each EC member's contribution –with DSM.

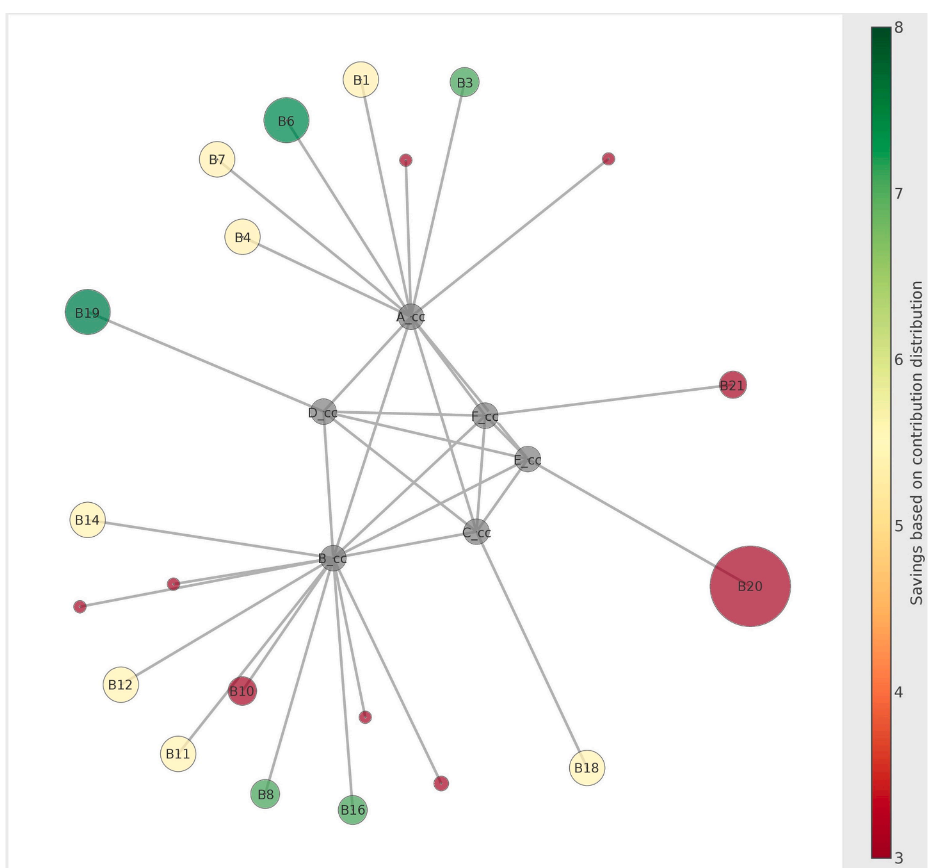

Fig. 12. Saving distribution according to each EC member's contribution –without DSM.

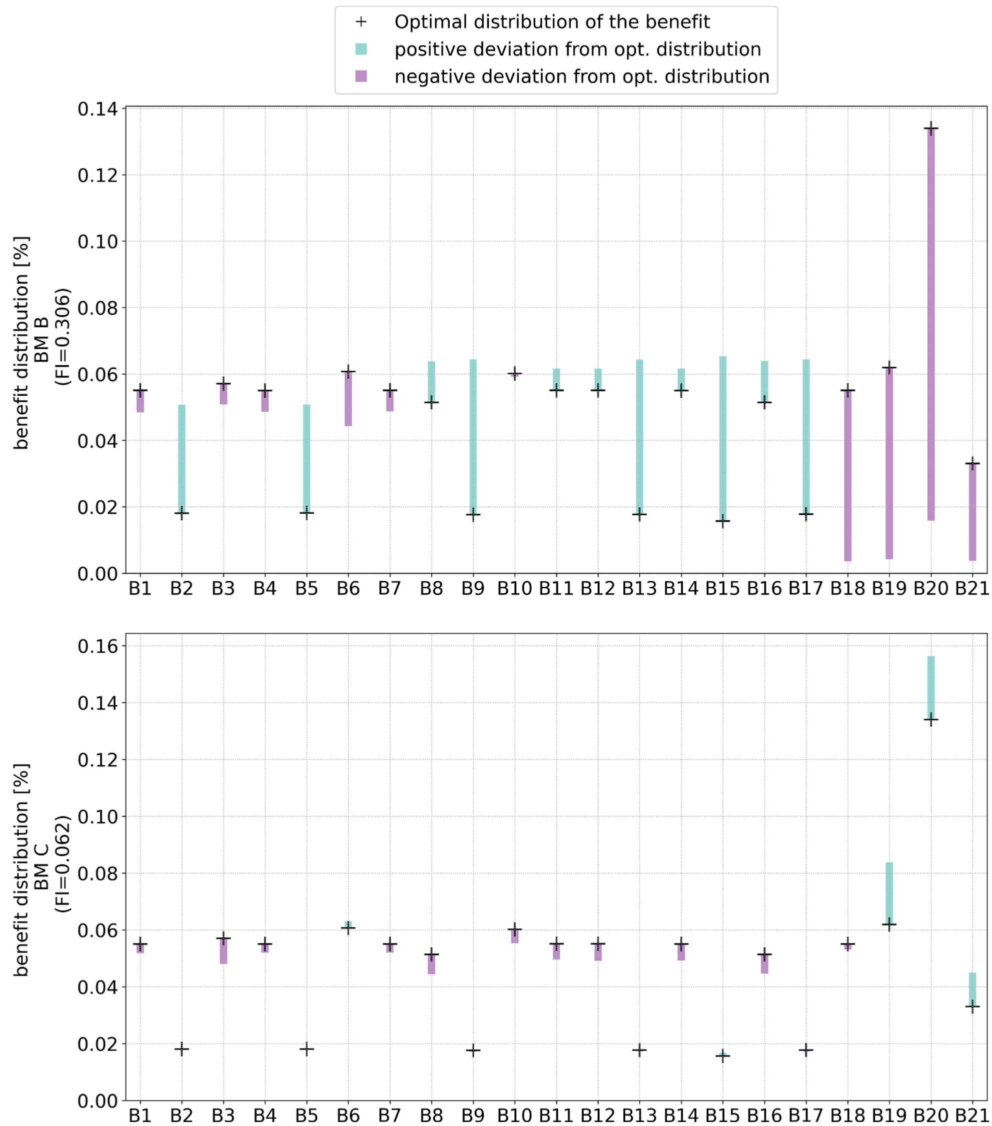

Fig. 13. BM fairness from the single member's point of view.

changed significantly, and the heterogeneity impact of the system have been assessed.

In Fig. 14 it is also possible to see how investments change showing an overall reduction, which is also partly due to a reduced electricity demand (-11%). Again, with the DSM, there is less need of storage and no BESS investment is made here. This scenario, characterized by a lower heterogeneity, highlights a decrease in RES consumption and an increase in excess as can be seen in Fig. 15.

This second case study has a less heterogeneous composition, which affects the contribution of the DSM. The DSM leads again to a significant reduction in the BESS capacity. However, with this lower heterogeneity, Gini Index equal to 0.71 against the previous 0.83, the DSM impact is higher and there is an increase of the renewable energy covering the demand equal to 9.22% although the installed PV capacity remains the same and no BESS is installed. However, in general with this more homogeneous case study, there is a decrease of the renewable source consumption by around 20%–33% and of the bill savings by around 30% compared to the one with higher Gini Index.

Table 7
Standard deviation and Fairness Index of applied business models

BM	A	B	C	D	E
σ	0.026	0.04074	0.008	0.018	0.010
FI	0.198	0.306	0.062	0.186	0.074

Table 8
outline of modified composition

Housing buildings	6
Households	21
Gini index	0.71
Flexible load	19.38%

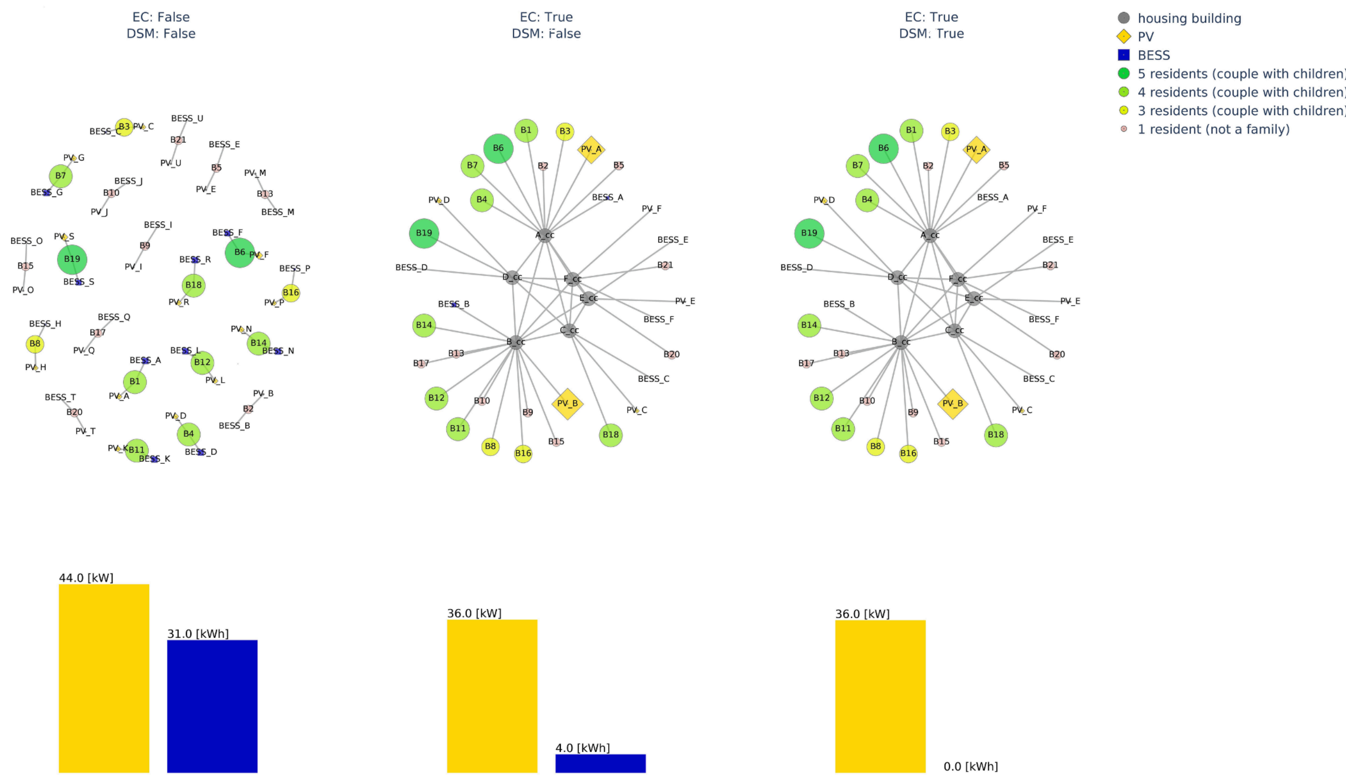

Fig. 14. Comparison reference scenario and EC scenario w/wo DSM (modified case study).

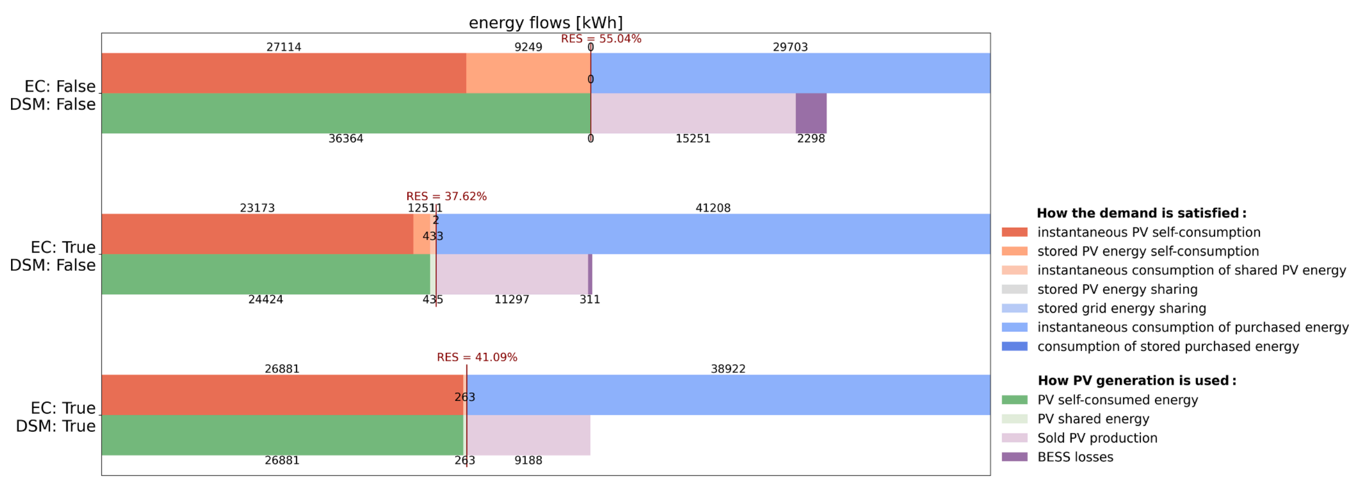

Fig. 15. Scheme of energy flows. Answer how the demand is satisfied and how PV generation is used in three cases (modified case study).

5. Conclusions

This work aimed at developing a methodology to assess the potentialities of the energy communities. A considerable diffusion of energy communities requires an increase of the awareness on their importance: clear messages and an effective communication of advantages and disadvantages are imperative. This work moves towards this direction as it combines a dispatching and investment model with linear programming, which is coupled to a function for evaluating the contribution of each household to the overall benefit, and its subsequent distribution.

The literature review has shown that several studies exist on the modelling of energy communities. However, the literature review has also highlighted the lack of a modelling approach for energy communities including all the following relevant aspects: the expansion capacity optimization taking into account both global and individual interests, the Demand Side Management, the community composition, the benefit distribution business models and their suitability and fairness as well as different regulation schemes (e.g. by changing the investment deductions, the bill components and the refunded amounts for energy sharing). The model presented in this work covers all the above aspects through an integrated approach.

The model can also be easily used for different applications by setting the most appropriate input data for the case to be analyzed, but in this work is applied to different renewable energy community case studies placed in Bolzano, Italy.

The Demand Side Management produces relevant consequences such as the investment reduction and the increase of RES share. The results of the case study with a 20% of flexible load show that applying Demand Side Management the investment is significantly lower especially for Battery Energy Storage System (-93%) and there is also a reduction in the percentage of the lost renewable production (-91%).

The results show also that the lower the heterogeneity of the composition, the higher the impact of the Demand Side Management. Two cases studies, with similar percentage of deferrable load, and a Gini Index equal to 0.83 and 0.71 respectively, show that by adopting the Demand Side Management strategy the renewable energy covering the demand of the first case decreases by 8.57%, while the one of the second case increases by 9.22%, although the installed PV capacity remains the same and no Battery Energy Storage System is installed. However, the renewable source consumption of the second case study with lower heterogeneity (Gini Index equal to 0.71) decreases by around 20%–33% and the bill savings by around 30% compared to the one with Gini Index equal to 0.83.

By the introduction and adoption of a Fairness Index it was then possible to evaluate the fairness of the distribution with respect to a method which suggests distributing the benefit according to each user's contribution.

The main message is therefore that it is important not only to identify the technological mix of the energy community, but also the weight of the composition of users. In fact, the participation of a user does not always bring a benefit, but, on the contrary, a user can be more significant than others. In order not to disadvantage anyone, especially because the participation is free and voluntary, it is essential to have an idea of the role of each energy community aspect and of each participating user and consequently to identify the most suitable business model.

It is possible to develop further the described method by focusing both on other technical details and by dedicating more space to environmental and emissions-related aspects.

For example, an aspect, which should be further analyzed, concerns the integration of multiple sectors into the model, as this is important to achieve a sustainable development of an energy system. Specifically, we refer to the thermal and the transport sector electrification, with a particular focus on the role of the heat pumps [18] and the introduction of electric vehicles. Also the modeling of buildings included in the energy community goes beyond the objective of this work, however it is a relevant aspect, which could be addressed in future studies to assess further technical limits.

CRediT authorship contribution statement

Valeria Casalicchio: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Giampaolo Manzolini:** Conceptualization, Writing – review & editing, Supervision. **Matteo Giacomo Prina:** Conceptualization, Formal analysis, Writing – review & editing, Visualization, Supervision. **David Moser:** Conceptualization, Writing – review & editing, Supervision.

Declaration of Competing Interest

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

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