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New Members Selection for the Expansion of Energy Communities

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Abstract: Energy communities are key enablers for end-users to actively participate in the energy transition in a more consumer-centric context. This paper focuses on the expansion of existing energy communities that may need to select new members among a pool of candidates. Selection is based on heuristic methods for better explainability and to promote a transparent selection process from end-users' perspectives. The proposed methodology is further verified with an accurate optimization-based energy management strategy. The member selection is performed in an iterative process where the best potential candidate is added as a new member of the energy community before running the same procedure over successive iterations. Simulations were performed for a complete month with a real community of six houses and nine potential candidates. The proposed rule-based method achieves similar ranks among candidates for two investigated metrics and return the same results as the more accurate optimization. Furthermore, the results show a hint on how to identify the best location (i.e., member) to install new assets that can contribute best to the energy community since it can boost the value brought by the candidates to the community. In that sense, the proposed method also serves as an investment decision support tool as well as a selection strategy for inhabitants of an energy community.

Keywords: local energy system; collective self-consumption; energy community expansion planning; new member candidates; member selection; optimization; scoring method

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1. Introduction

An energy community (EC) is formed by a pool of households located in a close geographical area with sharing production and possibly also storage asset at the community level. This group of people can be composed of citizens, but also local authorities, small and medium enterprises, and/or municipalities [1]. Energy communities are perceived as an evolution of both distributed generation and microgrid concepts [2] to provide positive environmental and economic impacts by using local development [3]. In the French context, a limitation of 2 km between two members and 3 MW of total installed generation has been imposed [4].

Heterogeneous household load and/or generation profiles in an energy community enable energy exchanges between members, which leads to higher self-sufficiency and self-consumption ratio, often denoted as load matching improvement [5,6]. The self-sufficiency ratio (SSR) is defined as the amount of consumption that is supplied by local assets, while the self-consumption ratio (SCR) is the portion of the local generation that is consumed locally [7].

In the topic of the local energy community, most literature focuses on the system design (i.e., solar and storage sizing) [8,9] and the topology/interconnection [10] of an EC as well as the control strategy [11,12] considering grid constraint and privacy issues [13]. Allocation and sharing strategy is also an interesting area that has been explored exhaustively [12,13] along with the local market [14] and peer-to-peer energy trading [9,15].

Some selection processes have been studied in the scope of energy communities. They include the selection of modeling tools such as HOMER, MATLAB, etc. [16] and community expansion planning in terms of generation and transmission energy sizing [17,18]. The considered distributed energy resources (DER) typically refer to renewable energy sources such as solar PV, wind, biomass, heat pump, etc. and its selection is presented in [19,20].

One identified limitation of the current literature on the energy community is that their expansion is oftentimes neglected. The members in energy communities are based on open and voluntary participation [21]. However, joining or leaving an energy community is not possible at any time [22]. The engagement of local citizens is perceived as a success factor in energy communities and the number of households is one of the evaluations used in their decision to continue the project [23]. The study in [24] identifies different factors that influence end-users willingness to adopt the energy community as their energy supply model. Assuming that legal constraints are satisfied, an existing energy community may want to expand, i.e., welcome new members such that the collective welfare increases. Individuals who live in the neighborhood of an energy community may indeed have a desire to join the community and experience the use of local, affordable, and clean energy [25] at a more profitable cost [12,26], especially when provided with adequate information on the financial aspect [27,28]. Moreover, the majority of households in the EU are expected to be active participants in the framework of sustainable energy transition [29].

Energy communities are often linked with fairness [30] and allow all participants to benefit from green energy, including those who are economically marginalized. In this context, the community manager needs a tool that helps determine the relevance of welcoming new members and also how to adapt their net load profile (for instance installing additional production or storage) to improve the shared benefits of the community or its reliability. Another possibility would be a decision support tool to select new members, based on similar criteria. However, this particular topic on new member selection in an energy community has not been found in the literature to the knowledge of the authors.

The present paper aims at developing several methodologies for existing energy communities to (i) select new member candidates while targeting improvement of the overall welfare or (ii) incentivize end-users to adapt their profile to a given community when considering investment options (e.g., by installing new local production or storage). This work proposes a heuristic method, keeping in mind that explainability is the key for end-users' acceptance. Indeed, trust is essential for the sustainability of an EC [25]. Importantly, the proposed rules and performance metrics are compared with results returned by a more accurate optimization-based method. Specifically, these methods can be applied to different household types regardless of the combination of individual energy assets.

The main contributions of this paper are the following:

- A heuristic method to discriminate new member candidates to join an existing community, which consists of production/consumption need and battery requirement;
- Two performance metrics to support the heuristic method;
- Validation of the proposed methodology with an optimization-based EMS which yields similar results;
- A discussion on the usage of such a method in terms of a decision support tool for inhabitants to select investment options before joining selected communities as a function of production and storage needs.

The rest of this paper is organized as follows. Section 2 introduces the EC model architecture of the members and their power exchanges. Section 3 presents the proposed heuristic method based on two performance metrics and its comparison with an optimization-based methodology. The use case is then described in Section 4, where results are analyzed in terms of ranking performances and value contribution of various candidates (based on their daily profile) for both methodologies. Finally, Section 5 concludes this paper and provides points for future works.

2. Energy Community Framework

An energy community is defined as an organization of several consumers or prosumers that may be equipped with local DER assets such as solar panels or energy storage systems. Individual members are the core of the existence of such community and their profiles are keys to the social and economic relevance of the community. Presenting heterogeneous energy profiles that can fill out each others' deficit or surplus of generation at certain times leads to more self-consumed energy at the community level, the so-called collective self-consumption (CSC) [31]. This may be translated in the form of benefits for the community members.

A typical model of an energy community is illustrated in Figure 1 where the physical flows only lie in the house meter (import $P_{n,t}^{meter^+}$ and export $P_{n,t}^{meter^-}$) while different exchanges can contractually occur between the members and the community as well as between the members and their conventional energy provider. Exchanges with the main grid and/or the community are conducted through a virtual connection. In the model, the grid import and export of a member n at a time t are denoted by $P_{n,t}^{gd^+}$ and $P_{n,t}^{gd^-}$, respectively. Similarly, $P_{n,t}^{comm^+}$ and $P_{n,t}^{comm^-}$ are the internal import and export power from and to the community. Each household may own individual assets such as PV, battery, and electric car.

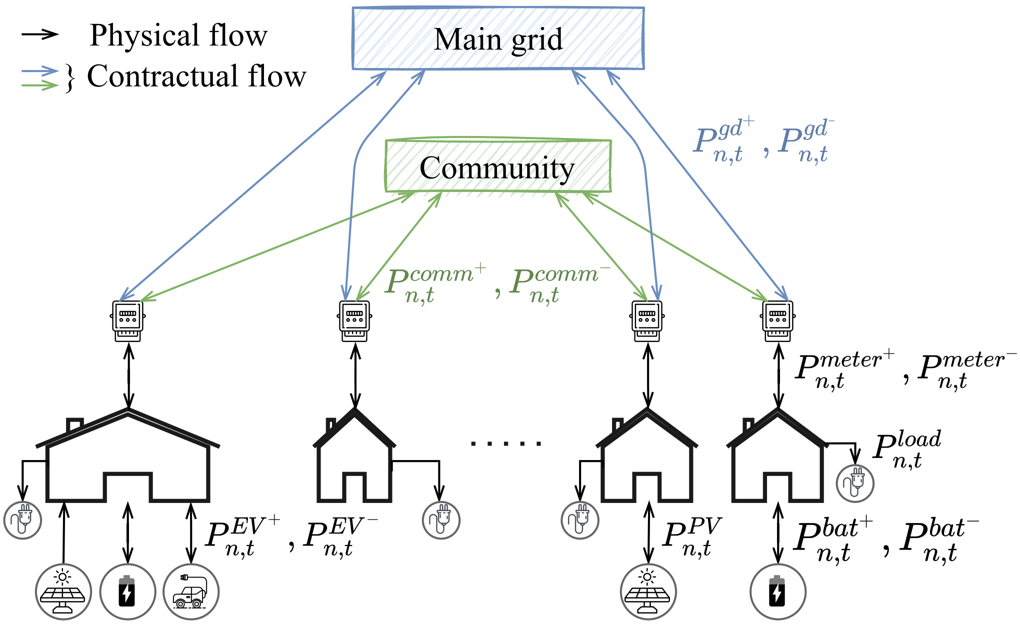

Figure 1. Typical energy community architecture.

3. Methodology for Candidate Selection and Ranking

New member candidates to join an existing community typically are end-users with specific demand profiles and potential local energy assets such as PVs, batteries, and/or EVs. From the perspective of an existing EC, the opportunity to add more production and consumption at the community level shall be investigated based on the community collective profiles at the current situation and the candidates' characteristics. The expansion process of an EC is done in an iterative way to select one best candidate and include him as a new member in the EC before taking another candidate, as shown in Figure 2. It means that at each iteration, the EC cannot take more than one candidate because the state of the existing EC evolves and it is important to have the right baseline of the community profiles (i.e., the needs of the evolved new existing EC may be different from the previous one).

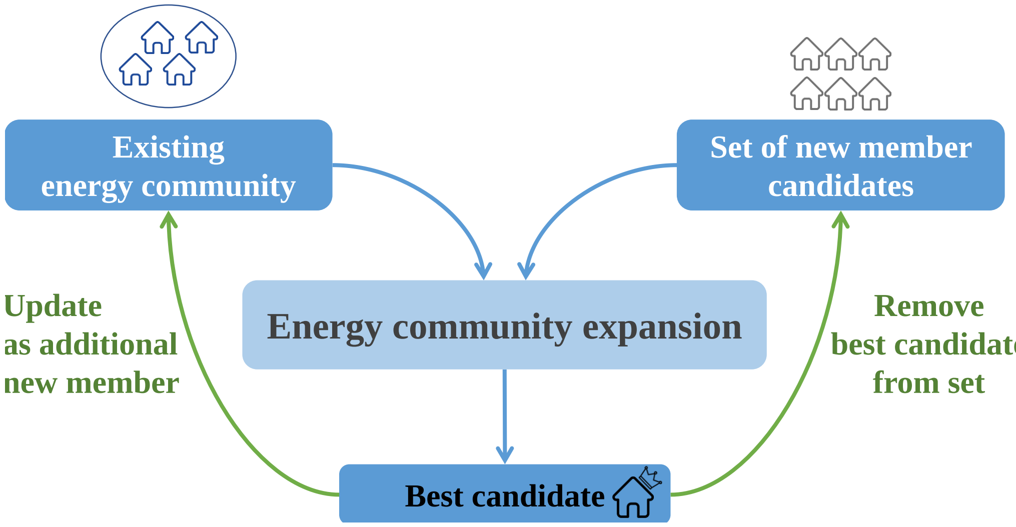

Figure 2. Iterative process of member expansion in energy community.

In this paper, the proposed member selection methodology relies on a simple rule-based approach regarding the existing energy community's current performance and successive tests for each new member candidate. This method differentiates between the needs for production/consumption (based on two metrics) and the need for storage. In particular, this profiling method allows giving a better idea of which new member candidate is the most suited for the existing community. This choice is due to the need of justification for future members of the energy community that may not be able to understand, thus accept, a selection based on a "black-boxed-like" algorithm.

To assess the accuracy of the proposed method, a reference approach based on optimal energy management strategy (EMS) is run for each new EC formed after the addition of a new member candidate taken individually. The accuracy is here improved (optimality guaranteed) at the cost of explainability.

These methods could complement a decision support tool for investments of local production and/or storage assets for future members of a community (i.e., improve their fitting to the need of the community, thus maximize the shared benefits).

3.1. Heuristic Approaches

This section describes the main proposed methodology that consists of a simple heuristic and step-by-step decision method relying on two typical performance metrics. In this method, we distinguish two different conditions for the existing EC: (1) the need for more production/consumption; (2) the need for more storage.

3.1.1. Matching Production and Consumption

The characterization of production/consumption needs of an EC and the value contribution from each candidate depends on the two proposed metrics: matching score energy and collective self-consumption energy, described below. Both metrics are computed at each time step and the total contribution of each candidate is then the summation for the considered time horizon (typically a year).

Metric 1: Matching Score

The first metric option to differentiate the energy community's needs relies on the so-called 'community mismatch profile' (CMP). The CMP ($P^{CMP}_{comm,t}$) is computed based on the community surplus or deficit at each time step (1). Note that it does not consider storage power output as the need for storage will be investigated separately in Section 3.1.2. The set of existing members n in the community is denoted by $\mathcal{N}$ while for the new member candidate m is $\mathcal{M}$.

$$P^{CMP}_{comm,t} = \sum_{n \in \mathcal{N}} P^{PV}_{n,t} - \sum_{n \in \mathcal{N}} P^{load}_{n,t}. \quad (1)$$

The CMP is designed to help comparing new member candidates' load curve (or net load curve if the candidate possesses local productions) at each time step. The candidates' net load curve ($P^{net-load}_{m,t}$) is defined as the candidates' consumption minus production at each time step (i.e., remaining consumption that is not covered by its generation, ignoring battery control if any) (2) [32]. If a candidate has no individual DER asset, then the net load curve is obviously defined as the conventional load curve.

$$P^{net-load}_{m,t} = P^{load}_{m,t} - P^{PV}_{m,t}. \quad (2)$$

A scoring system is then proposed to estimate the matching degree between the community need and the candidates' profile with Algorithm 1. The contribution of each candidate m to the EC is based on the total score at each time step that is accumulated for the whole considered time horizon.

If at a time step the EC suffers from a deficit of production (negative CMP value) while a candidate displays a surplus (negative net-load), his score is the surplus production, as illustrated in the first arrow representing example of CMP scores in Figure 3. On the contrary, if the community has a surplus and the candidate has a deficit at the same time, then the score is the net load value, as shown in the last three arrows in Figure 3. Otherwise, at other times, the score's default value is zero. The illustration of this metric is shown in Figure 3.

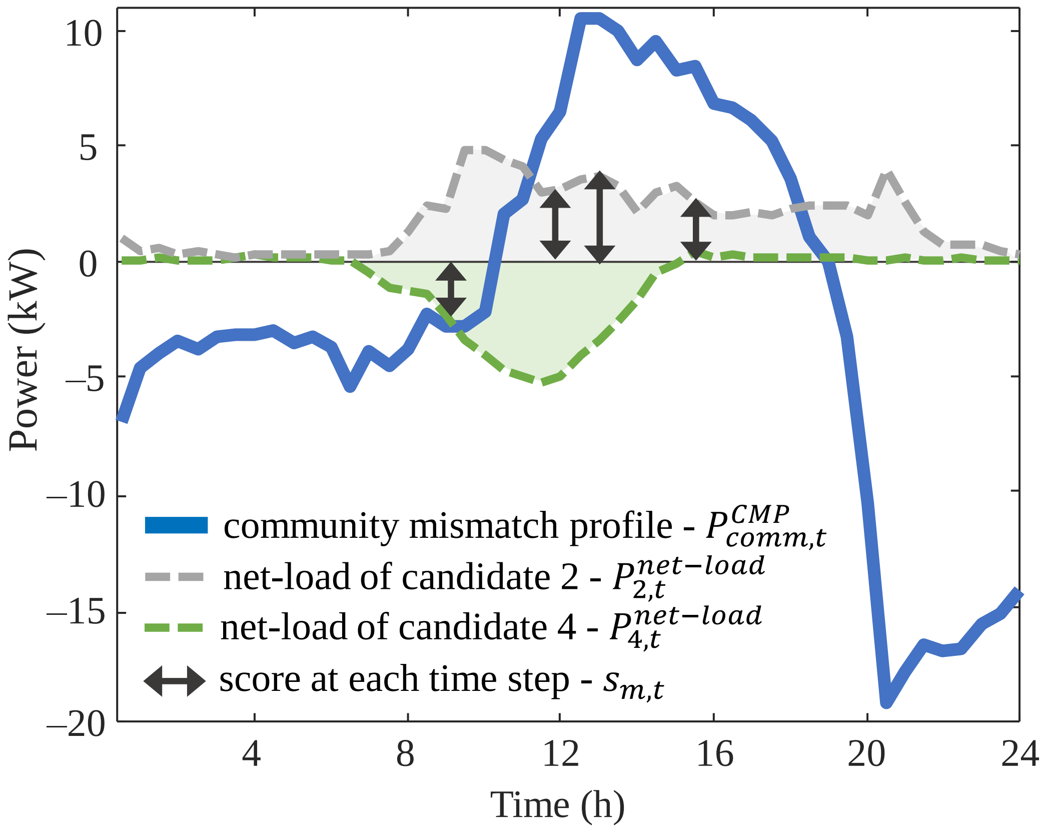

Figure 3. Sample score shown by the length of arrows.

Algorithm 1: Matching score rules.

Input: $P^{CMP}_{comm,t}$, $P^{net-load}_{m,t}$.

foreach $m \in \mathcal{M}$ **do**
  foreach $t \in \mathcal{T}$ **do**
    if $P^{CMP}_{comm,t} > 0$ ***and*** $P^{net-load}_{m,t} > 0$ **then**
      (surplus EC, deficit candidate)
      $s_{m,t} = P^{net-load}_{m,t}$;
    else if $P^{CMP}_{comm,t} < 0$ ***and*** $P^{net-load}_{m,t} < 0$ **then**
      (deficit EC, surplus candidate)
      $s_{m,t} = -P^{net-load}_{m,t}$;
    else
      $s_{m,t} = 0$;
    end
  end
  Total score for whole horizon: $S^{P/C,h}_m = \sum_{t \in \mathcal{T}} s_{m,t}$.
end

Metric 2: Collective Self-Consumption

The second investigated metric is another heuristic method that simply relies on the collective self-consumption energy. It is defined as the consumption within an energy community that is supplied by local generation, as expressed in (3) [33]. An additional member m to the community will change this collective-self consumption energy based on his load/generation profiles. Hence, the new collective self-consumption can be computed as in (4). The contribution of each candidate is valued as the difference between the collective self-consumption energy of the existing community before and after the addition of a new member candidate (5).

$$CSC^h = \sum_{t \in \mathcal{T}} \left(\min \left(\sum_{n \in \mathcal{N}} P^{load}_{n,t}, \sum_{n \in \mathcal{N}} P^{PV}_{n,t} \right) \right), \tag{3}$$

$$CSC^{h'}_m = \sum_{t \in \mathcal{T}} \left(\min \left(\sum_{n \in \mathcal{N}} P^{load}_{n,t} + P^{load}_{m,t}, \sum_{n \in \mathcal{N}} P^{PV}_{n,t} + P^{PV}_{m,t} \right) \right), \tag{4}$$

$$\Delta CSC^h_m = CSC^{h'}_m - CSC^h. \tag{5}$$

The two metrics in the heuristic method are used to investigate the needs for production and consumption for the community. The next section presents the methodology to evaluate the needs for the battery.

3.1.2. Battery Energy Storage

Besides the need for more production/consumption in an already existing EC, storage systems can also be of interest in order to manage local consumption and production more efficiently. The need for batteries in an EC is based on how much energy can be stored to be more independent from the main grid (i.e., increase the self-sufficiency ratio). The additional need for a battery (ΔE^{bat}_{comm} in kWh) can be defined as the minimum daily average energy between community surplus and deficit, taking into account the usable storage energy based on its existing capacity (6). The daily average surplus energy in the community ($\overline{E^{sur}_{comm}}$) is computed as the total surplus from each member per time step over the time horizon (7). Likewise, the daily average deficit energy ($\overline{E^{def}_{comm}}$) can be calculated from the total deficit from each member at each time step over the number of days in the whole horizon (8). The considered time horizon should last enough to capture consumption and production profiles as well as seasonality of the storage system. Ultimately, the value brought by each candidate depends on his battery capacity and the community needs (9).

$$\Delta E_{comm}^{bat} = \max\left(0, \left(\frac{\min\left(\overline{E_{comm}^{sur}}, \overline{E_{comm}^{def}}\right)}{\Delta SOC} - E_{comm}^{bat,exist}\right)\right), \tag{6}$$

$$\overline{E_{comm}^{sur}} = \frac{\sum_{t\in\mathcal{T}} \max\left(0, \sum_{n\in\mathcal{N}}\left(P_{n,t}^{PV} - P_{n,t}^{load}\right)\right) \times \Delta t}{n_{days}}, \tag{7}$$

$$\overline{E_{comm}^{def}} = \frac{\sum_{t\in\mathcal{T}} \max\left(0, \sum_{n\in\mathcal{N}}\left(P_{n,t}^{load} - P_{n,t}^{PV}\right)\right) \times \Delta t}{n_{days}}, \tag{8}$$

$$S_m^{bat,h} = \min\left(\Delta E_{comm}^{bat}, E_m^{bat}\right). \tag{9}$$

Finally, Equations (10) and (11) are defined in order to combine the value contribution both in production/consumption (Section 3.1.1) as well as battery side (Section 3.1.2).

$$V_m^{sco,h} = S_m^{P/C,h} + n_{days} \times S_m^{bat,h}, \tag{10}$$

$$V_m^{csc,h} = \Delta CSC_m^h + n_{days} \times S_m^{bat,h}. \tag{11}$$

3.2. Optimization-Based Approach

The most appropriate way to select new member candidates consists in running offline simulations of the final community (i.e., with existing members n in the set $\mathcal{N}$ plus a new member candidate m in the set $\mathcal{M}$) while estimating the benefits with an energy management strategy (EMS) that guarantees optimality. Such a simulation strategy relies on prior works [12]. The formulation here is expressed for the existing members n for the sake of simplicity. However, it shall also include a new member candidate m (in the final community) in order to estimate the final performances with each additional candidate taken individually.

This section proposes a more accurate and comprehensive scheme that considers all energy assets in the energy community at once, including the energy storage system. Unlike the heuristic method that relies on the practical calculation between PV production and load, the optimization-based EMS considers a whole time horizon that operates energy storage systems to maximize an objective, in our case the self-sufficiency ratio (SSR).

SSR is defined as the ratio between the load that is supplied locally and the total consumption, as expressed in (12) [7,34]. Essentially, maximizing the SSR is equivalent to minimizing the energy import from the main grid (13).

$$SSR = 1 - \frac{\sum_{n\in\mathcal{N}}\sum_{t\in\mathcal{T}} P_{n,t}^{gd^+}}{\sum_{n\in\mathcal{N}}\sum_{t\in\mathcal{T}} P_{n,t}^{load}}, \tag{12}$$

$$f = \min \sum_{n\in\mathcal{N}}\sum_{t\in\mathcal{T}} P_{n,t}^{gd^+} \quad . \tag{13}$$

The decision variables considered in this optimization are all positive and semi-definite for every member n at each time step t as follows.

- *The individual self-consumption power $P_{n,t}^{indsc}$ and exchange power flows:* grid import $P_{n,t}^{gd^+}$, export $P_{n,t}^{gd^-}$ and community import $P_{n,t}^{comm^+}$, export $P_{n,t}^{comm^-}$.
- *The storage charge $P_{n,t}^{st^+}$ and discharge $P_{n,t}^{st^-}$*: batteries $P_{n,t}^{bat^+}$, $P_{n,t}^{bat^-}$ and electric vehicles (EV) $P_{n,t}^{EV^+}$, $P_{n,t}^{EV^-}$.
- *The storage state of charge $SOC_{n,t}^{st}$*: similarly refers to batteries and EVs.

Note that there is no binary variable considered here to ensure that concurrent flows do not occur simultaneously, but we check automatically that the optimization results are valid, i.e., no concurrent positive values for pairs ($P_{n,t}^{gd^+}$, $P_{n,t}^{gd^-}$); ($P_{n,t}^{comm^+}$, $P_{n,t}^{comm^-}$); ($P_{n,t}^{st^+}$, $P_{n,t}^{st^-}$).

The first set of constraints in this problem is the limitation of the power exchanged by the subscription power, both for the import energy (14) and export energy (15). Also, the peak power perceived by the grid cannot be higher than its original peak without any renewable assets (i.e., traditional load) (16).

$$P_{n,t}^{gd^+} + P_{n,t}^{comm^+} \leq P_n^{subs} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T}, \tag{14}$$

$$P_{n,t}^{gd^-} + P_{n,t}^{comm^-} \leq P_n^{subs} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T}, \tag{15}$$

$$\max\left(P_{n,t}^{gd^+}\right) \leq \max\left(P_{n,t}^{load}\right) \qquad \forall n \in \mathcal{N}. \tag{16}$$

The following set of constraints corresponds to the storage system [35]. Firstly, the storage power (17) and state of charge (SOC) (18) need to remain within the limitation. Next, the SOC calculation over time considering the storage's power ($P_{n,t}^{st^+}$, $P_{n,t}^{st^-}$) and efficiency (μ_n^{st}) is expressed in (19) with the determined SOC value at the start (20) and end of the horizon (21).

$$0 \leq P_{n,t}^{st^+}, P_{n,t}^{st^-} \leq P_{max,n}^{st} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T}, \tag{17}$$

$$SOC_{min,n}^{st} \leq SOC_{n,t}^{st} \leq SOC_{max,n}^{st} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T}, \tag{18}$$

$$SOC_{n,t+1}^{st} = SOC_{n,t}^{st} + \left(P_{n,t}^{st^+} \times \mu_n^{st} - \frac{P_{n,t}^{st^-}}{\mu_n^{st}}\right) \times \Delta t \times \frac{100}{E_{max,n}^{st}} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T}, \tag{19}$$

$$SOC_{n,1}^{st} = SOC_n^{init} \qquad \forall n \in \mathcal{N}, \tag{20}$$

$$SOC_{n,end}^{st} \geq SOC_n^{init} \qquad \forall n \in \mathcal{N}. \tag{21}$$

The next set of constraints is related to the individual and community power balance at each time step [12]. The overall production at the level of each member and its distribution is stated in (22). Similarly, the total individual consumption is expressed following (23). Next, the power balance at the community level is given by (24).

$$P_{n,t}^{PV} + P_{n,t}^{bat^-} + P_{n,t}^{EV^-} = P_{n,t}^{indsc} + P_{n,t}^{gd^-} + P_{n,t}^{comm^-} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T}, \tag{22}$$

$$P_{n,t}^{load} + P_{n,t}^{bat^+} + P_{n,t}^{EV^+} = P_{n,t}^{indsc} + P_{n,t}^{gd^+} + P_{n,t}^{comm^+} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T}, \tag{23}$$

$$\sum_{n \in \mathcal{N}} P_{n,t}^{comm^+} = \sum_{n \in \mathcal{N}} P_{n,t}^{comm^-} \qquad \forall t \in \mathcal{T}. \tag{24}$$

The optimization returns the best values for the decision variables such that we can compute the metric collective self-consumption (CSC). Since the storage is controlled in the optimization method, the CSC needs to consider it unlike the CSC formulation in the heuristic way. Referring to the SSR equation in the previous section (12), the CSC can be calculated equivalently as the total consumption minus total import energy from the main grid in case of non-sufficient local generation (25). The optimization problem is solved for the baseline (i.e., the existing energy community) and after the addition of a candidate m with the CSC value: CSC^{opt} and $CSC_m^{opt'}$, respectively. Ultimately, the actual contribution of the candidate m can be calculated with (26).

$$CSC^{opt} = \sum_{n \in \mathcal{N}} \sum_{t \in \mathcal{T}} P_{n,t}^{load} - \sum_{n \in \mathcal{N}} \sum_{t \in \mathcal{T}} P_{n,t}^{gd^+}, \tag{25}$$

$$V_m^{csc,opt} = \Delta CSC_m^{opt} = CSC_m^{opt'} - CSC^{opt}. \tag{26}$$

The contribution value by a candidate m using the optimization approach is then compared with the heuristic method (with two metrics: score and collective self-consumption). The next section describes the results of the proposed methods as a tool to evaluate new member candidates to join an existing community.

4. Results

4.1. Case Study

The heuristic (with two different metrics) and optimization methods are applied to an already existing pilot project of an EC located in Le Cailar, France which has been developed by our industrial partner, Beoga. We consider six households that have individual energy components as the baseline for an existing energy community. Table 1 provides the detail of the installed capacity of each asset and households' subscription power. The round trip efficiency for all storage systems in the community is assumed to be 95 %. The initial and final state of charge of the storage are set to 50 % [36]. Particularly, the period of EV availability is deterministic as follows: from 6 p.m. to 8 a.m. on weekdays, from 3 p.m. to 11 a.m. on Saturdays, and 24 h on Sundays.

The new member candidates are taken from an open database of household profiles [37]. From 20 household consumption profiles in Portugal and 30 in the UK, we use the Kmenoid method to create 9 clusters; thus, we obtain 9 central and representative profiles for each cluster. Those will be the load profiles for the new member candidates. The PV production profiles are also provided in the same source. Hence, different sets of candidates are described as follows (in total 3×9 candidates).

Table 1. Household parameters of the existing community.

House	PV (kW)	Battery (kW/kWh)	EV (kW/kWh)	Subscription (kVA)
1	3.2	5/9.8	11/40	18
2	12.24	5/9.8	-	36
3	-	5/9.8	-	9
4	3.2	-	-	9
5	3.2	-	-	9
6	6.4	-	-	9

(a) Load only (9 candidates);
(b) Load and PV (9 candidates);
(c) Load, PV and battery (9 candidates):
- Battery of 3 kW/4 kWh for candidate 1, 5, 7;
- Battery of 4 kW/6 kWh for candidate 8, 9;
- Battery of 4 kW/8 kWh for candidate 3, 6;
- Battery of 7 kW/10 kWh for candidate 2, 4;

(d) Mixed individual assets:
- Candidate 1–3 from sets (c) with load, PV and battery;
- Candidate 4–6 from sets (b) with load and PV;
- Candidate 7–9 from sets (a) with load only.

In order to have the right perspectives regarding the condition of the existing energy community as well as the candidates, the proposed methodology shall be run at least over a full year to capture all seasons' profiles. However, due to the limited availability and readiness data, frequently caused by the candidates, in this paper, we use one month profile in April 2022 with a 30-min granularity. The same methods can be applied to a larger time horizon without any modification. The optimization problem is modeled in MATLAB with the YALMIP toolbox [38] and solved with Gurobi.

4.2. Results and Discussion

In this section, the results of the heuristic methods (with two different metrics: matching score and CSC energy) are presented and further compared with the optimization method in the way they rank the potential candidate for the considered EC.

In order to distinguish clearly the performance of each method (heuristic metrics 1 and 2 as well as optimization), we normalize the contribution value by dividing every candidate's contribution by the maximum value observed in the dataset (27).

$$\hat{V}_m = \frac{V_m}{\max(V_m)}. \tag{27}$$

4.2.1. First Iteration—Selecting the First Candidate

The base case of the existing EC with six households yields a CSC energy of 564 kWh with the heuristic calculation and 1023 kWh with the optimization-based EMS. These values serve as the baseline to compute the improvement of the CSC energy with an additional member candidate in the EC (i.e., Metric 2: ΔCSC_m^h and optimization: ΔCSC_m^{opt}). Note that one computation process of the methods proposed here is aimed at selecting the best profile among the candidates in the considered set. It shall not be used to pick more than one candidate since the baseline of the EC after the addition of the first candidate will change accordingly (i.e., the need for this new baseline is different from the initial one). In such cases, the proposed procedure would have to be run successively several times, once per additional member.

Among all the candidates in the set, the maximum value of the different metrics is used as the normalization basis (refer to Table 2). The normalized value for each candidate of each set (set (a)–(d)) with the proposed methods (Metric 1: matching score, Metric 2: CSC energy, reference: optimization) is illustrated in Figure 4. Since the best candidate for all the considered methods is Candidate 2, the normalized values presented in the graphic are based on the ones from this candidate for each set and method.

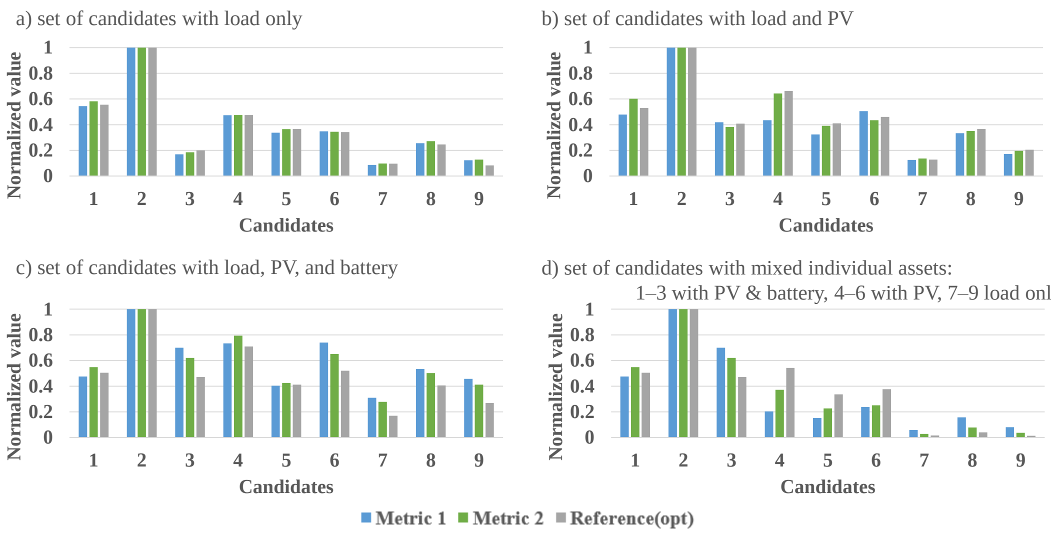

Figure 4. Normalized contribution value for every method of each candidate in the set of candidates: (**a**) with load only. (**b**) with load and PV. (**c**) with load, PV and battery. (**d**) with mixed individual energy assets.

Table 2. Maximum-base value of normalization for each method in kWh.

Set of Candidates	Metric 1	Metric 2	Optimization
Load	198	173	98
Load, PV	225	348	489
Load, PV, battery	478	602	597
Mix	478	602	597

Note that the value contribution (in kWh) of the candidates in Figure 4 between Metric 2 (ΔCSC_m^h) and the reference (ΔCSC_m^{opt}) cannot be compared properly because the CSC of the existing community is computed differently in both metrics. One can argue that the CSC value reached with the optimization is higher due to the storage control, but the heuristic method can fully capture all the potential contributions since there is no constraint, as observed in the optimization formulation.

Most noticeably, the ranking of candidates (from the best to the worst) in each set is respected between the proposed methods (Metric 1, Metric 2) and compared to the reference optimization-based approach, see Figure 4. The best candidate in every method is Candidate 2 and the worst is Candidate 7.

In the set (a), see Figure 4a, the value brought by each candidate when using Metric 1 (matching score) is higher than with Metric 2 (CSC) because we account for the whole potential energy that can be given by a candidate (i.e., regardless of the actual need from the community, see Algorithm 1). This computation is proposed since we can only select one best profile for each iterative process, as the baseline of the existing EC will evolve after a new member joins. While in Metric 2, we rather take the actual contribution, i.e., the minimum between what is needed and what is offered.

For other sets of candidates (i.e., the last three), the observed Metric 2 (CSC) may be higher than Metric 1 (matching score) since the individual self-consumption is excluded in the net-load power used in the matching score. On the contrary, the Metric 2 CSC energy consists of the candidate's individual self-consumption energy besides the main additional contribution to the existing community.

In Figure 4b, the normalized values among methods are still similar, except for candidate 4 since he presents quite a large amount of individual self-consumption that is considered in the CSC energy metric (Metric 2 and optimization) but not in the matching score (Metric 1).

The investigation of the battery need is based on the daily average need of the existing EC compared with the availability from the candidates. The baseline of the existing EC requires more batteries at the community level, with ΔE_{comm}^{bat} as big as 8.4 kWh. This value comes from (6) (in this case, the average community surplus) mostly indicating that the existing EC presents a surplus that can be stored rather than exported to the main grid.

For the sets of candidates with PV and battery, see Figure 4c, the batteries clearly improve a candidate's value such that it significantly alters the overall ranking. The higher the battery size, the higher the value of the candidates. See for example candidates 3 and 4 with a large battery and candidates 1 and 5 with a smaller battery in Figure 4b,c.

Figure 4d distinguishes the DER assets owned by a candidate. Candidates 1–3 have high normalized values, followed by candidates 4–6, then very small values for candidates 7–9. It shows that the production and/or storage seem to always improve the relevance of a candidate for the considered EC.

Table 3 compares the total computational time for all nine candidates in each set for different metrics proposed and optimization strategies. The computational time is very low for both metrics with the heuristic method (only 1.1 to 12.2 ms) but extremely higher when computed with the optimization method (2 to 3 min). This duration is still acceptable as this selection process is done in an offline mode and not aimed at operational purposes. However, in the case of a bigger existing energy community and/or a larger pool of candidates, it is recommended to use the heuristic method to save time as the ranking result among candidates has been shown similar to the optimization strategy.

Table 3. Computational time for the three methods.

Set of Candidates	Metric 1	Metric 2	Optimization
Load	4.8 ms	1.1 ms	130 s
Load, PV	7.7 ms	1.2 ms	138 s
Load, PV, battery	10.4 ms	3.9 ms	163 s
Mix	12.2 ms	4.6 ms	146 s

4.2.2. Second Iteration and More—Evaluating the Remaining Candidates

In this section, we select Candidate 2 (with PV) as a new member of the EC such that its baseline evolves from six to seven members. We then perform the next iteration of candidate selection. This new EC baseline results in a CSC value of 912 kWh computed heuristically and 1511 kWh with the optimization-based EMS. The need for more batteries in the community is 13.9 kWh. Similarly, we calculate the value brought by each candidate using the three methods: Metric 1 (matching score), Metric 2 (CSC energy) and the optimization.

Similar to the previous results with the first iteration, normalized values are used in order to compare methods easily based on the maximum value observed in the set of candidates. The maximum values observed for each method and each set of candidates are shown in Table 4. These normalized base values may refer to different candidates for each set of candidates (e.g., Candidate 1 for the set (a) and Candidate 4 for the set (c)) as shown in Figure 5.

Table 4. Iteration 2. Maximum-base value of normalization for each method in kWh.

Set of candidates	Metric 1	Metric 2	Optimization
Load	113	108	64
Load, PV	106	206	276
Load, PV, battery	321	457	499
Mix	314	356	366

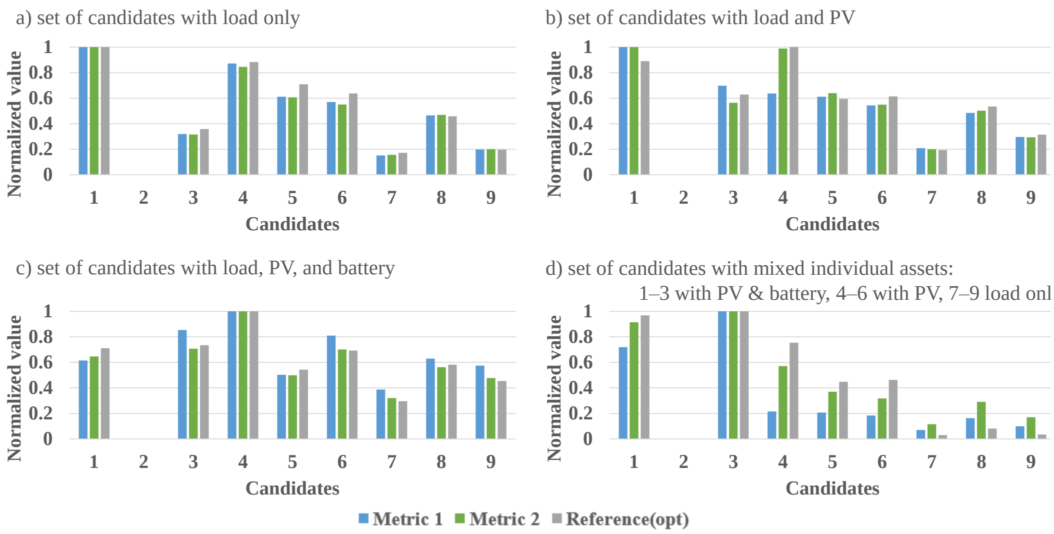

Figure 5. Iteration 2. Normalized contribution value for the three methods of each candidate from the set of candidates: (**a**) with load only. (**b**) with load and PV. (**c**) with load, PV and battery. (**d**) with mixed individual energy assets.

The result of the second iteration shows similar ranks between the methods (regarding the best candidate). In the set (a), Candidate 1 is the best while it is Candidate 4 in the set (c) and (d). In the set (b), the best candidate using the heuristics (Candidate 1) and optimization (Candidate 4) is not the same but their difference is not significant (see the value of candidate 1, 4 with Metric 2 and optimization). Note that the gap between the matching score (Metric 1) and CSC energy (Metric 2, optimization) is due to the individual self-consumption that is accounted for in the computation of CSC but not in the matching score (see analysis in Iteration 1).

4.2.3. Investment Decision Support Tool

The result of the different sets of candidates can also give an idea of where to install the DER assets in the most rewarding candidate's household, for instance in the form of an investment decision support tool. For example in Figure 5, Candidate 4 can yield a higher value than Candidate 1 if he has PV and/or battery (i.e., Candidate 4 has the potential to be the one selected). Similarly, Candidate 3 is better than Candidate 1 if he installs a battery storage system. Hence, this methodology on candidate selection provides the results on the best profile to include as a new member and possibly also the position/location recommendation on the generation/storage expansion. Based on those results, it is then possible to compute the levelized cost of energy of a new PV or storage system assuming the integration in an EC and an anticipation of the upcoming shared benefits, which can be investigated in further works.

5. Conclusions and Perspectives

This paper proposes a methodology for an existing energy community (EC) to properly select a new member candidate or to help them decide on potential investment that would maximize their chance to get shared benefits of this EC. Two heuristic metrics, matching score (metric 1) and collective self-consumption energy (metric 2), are presented to differentiate whether the EC needs more production/consumption and how to evaluate the relevance of each new member candidate to the EC. The assessment of more battery capacity is also performed heuristically which computes the daily average energy storage needed.

The need for an existing EC for more DER assets is then compared with the value offered by the candidates. Further, these methods are verified with optimization-based EMS where the storage control is optimal and, as such, constitutes a reference. Especially, the ranking of potential candidates with heuristic metrics is very similar to the optimization method but obtained with a much shorter computational time and with a much better explainability.

A real case study in Le Cailar, France has been used that consists of six existing members. Then, a total of 3×9 potential candidates are compared in terms of DER assets (i.e., set of load only; set of load and PV; set of load, PV, and storage; set of heterogeneous assets). The results of the proposed heuristic method are consistent after normalization and aligned with the collective self-consumption energy from the accurate optimization-based strategy. After the best candidate has been included as a new member in the existing EC, the second iteration is performed and shows similar results that the simple heuristic ranking system is reliable (compared with the accurate optimization method).

The result of metric 2 is closer to the optimization in the first iteration while it is metric 1 in the second iteration. Therefore, the authors believe that there is no better method to recommend in terms of technical performance between the two metrics as the result depends significantly on the profiles of existing members and potential candidates. However, metric 1 is considered to be more explicable and easy to understand from the viewpoint of end-users, mainly using visualization support.

The results in the second iteration also show that this method can be an investment decision support tool to install a new DER asset in the interest of the overall community. In our case for instance, the value offered by candidate 4 can be higher than candidate 1 (the best candidate if no DER installed) if he integrates PV. This can be used as an investment argument for candidate 4.

Future work will investigate the role of the energy community in the flexibility market and the sizing of assets in long-term planning. The provision of energy from the community to support the grid, mainly in the tertiary reserve can be activated manually from the residential storage. Also, it could be interesting to study the proper size of the different types of DER installed in the households such that it would achieve better community performance (higher rate of SSR and SCR).

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