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# What makes an Energy Community? Features Impact in Collective Benefits

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**Abstract**—Energy communities (ECs) aggregate users within proximity, which have diverse assets and consumption/generation power profiles. Such a variety of user arrangements significantly influences the benefits expected from the ECs. From a vast pool of EC configurations, this paper investigates their composition regarding users’ profiles impact on collective benefits. To that end, clustering is performed for i) different features to characterize an EC and for ii) the performance metrics of the EC once managed. The paper discusses how the community setup impacts its performance, which enables identifying the most relevant features. Hence, 1000 ECs are formed from 10 users. Additionally, two study cases are tested, one with 100% users with PV and battery (i.e., 100% prosumers) and the second with 50% prosumers. The results suggest that in terms of investment, the photovoltaic installed capacity is a more significant asset than storage capacity.

**Index Terms**—Energy communities, prosumers, clustering, performance metrics, community self-consumption, natural self-sufficiency.

## I. INTRODUCTION

Residential users account for a noticeable portion of energy consumption, around 18% in Europe [1]). Users are increasingly encouraged to invest in photovoltaic (PV) and battery technologies, primarily driven by financial considerations and environmental concerns. These decisions can be made individually or collaboratively. When residential users with diverse assets aggregate together, they can form energy communities (ECs) [2]. Forming ECs can lead to technical and economic benefits, such as more efficient utilization of local generation, reducing the reliance on the upstream grid for imports and thus lowering energy bills [3].

Discussions in existing literature about ECs often focus on issues such as cost distribution [3]–[5], the complexity of trading within markets among users [6], and the optimal size of batteries and PV capacity for a given energy community [7]. Additionally, some analyses provide a business model to address possible losses of the EC manager (who supervises the EC and acts as an intermediary between the EC members and the retailer) and how to fairly allocate revenues to users [8].

However, in such studies, the obtained results directly depend on the use cases considered in terms of EC setup—i.e., the number/type of consumers and solar/storage capacities—which is oftentimes unaddressed. Determining the optimal size of an EC goes beyond just sizing, as it is imperative to consider the intrinsic characteristics of the

users forming such energy communities. Nevertheless, it can be challenging to define features that accurately characterize an EC, as these features may not effectively represent the assets or the composition of the EC members and may not provide any valuable insight into the ECs’ characteristics.

Therefore, this paper proposes an analysis of different EC configurations and how the EC setup may impact the potential benefits of the generated collective structure. Instead of answering the question of the optimal number of users for an EC, this research focuses on the following question: “What are the best features to achieve a high collective performance?” The contributions of this paper are listed as follows:

- 1) Three features are introduced to characterize ECs, followed by a clustering.
- 2) The ECs’ performance is assessed using an economic and technical approach, with two metrics: community self-consumption and bill savings.
- 3) Investigate the correlation between the features and the performance metrics in clustered ECs, illustrated on two study cases, one with 100 % of prosumers with PV and battery and the other with only 50 % of prosumers equipped.

The remainder of the paper is organized as follows: Section II describes the methodology, which includes the discussion on the energy communities’ features, the community model and its energy management, and the performance metrics to assess collective energy management. Section III draws the main results. Finally, Section IV discloses the conclusions.

## II. METHODOLOGY

To form diverse energy communities, this research uses the “drawing a sample with replacement” technique [9] for selecting users from a pool of  $J = 173$  individuals to form a set of  $i = 1000$  energy communities, each comprising  $N = 10$  users.

The features of each  $EC_i$  are computed based on the users’ assets and power profiles. After the formation of each  $EC_i$ , a centralized energy management strategy is applied, resulting in calculations of power imports ( $P_t^{c-}$ ) and exports ( $P_t^{c+}$ ). These values are then used to derive performance metrics for evaluation. This process is described in Fig. 1.

To characterize the energy communities, features are defined corresponding to the PV and storage installed capacity in comparison with the users’ power profiles. Moreover, two performance metrics are considered for this purpose when assessing the outcomes after forming ECs: the well-known

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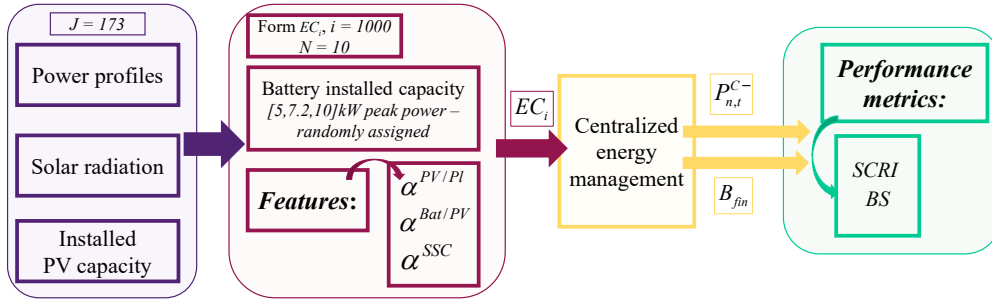


Fig. 1. Proposed framework.

concept of self-consumption and the community economic impact of such formations.

#### A. Energy Communities Characterization: Features

Determining the intrinsic characteristics of the formed energy communities derived from users' assets and power profiles is essential, as these directly impact group performance. This subsection presents the selected features for further analysis: storage capacity ratio, PV capacity ratio and self-sufficiency capacity.

1) *Battery Capacity Ratio*: The battery capacity ratio ( $\alpha^{Bat/PV}$ ) is a feature introduced to represent the storage size ( $\overline{P}_n^b$ ) as a function of the installed solar capacity ( $\overline{P}_n^{pv}$ ). A larger  $\alpha^{Bat/PV}$  means a higher capacity of storage over the PV generation, giving priority to storage over solar (local) production.

2) *PV Capacity Ratio*: The photovoltaic capacity ratio relates installed PV capacity ( $\overline{P}_n^{pv}$ ) over the aggregated peak load of the energy community ( $\sum_n \max(P_n^l)$ ). An  $\alpha^{PV/Pl}$  larger than one means the solar production can cover at least the collective peak load.

$$\alpha^{Bat/PV} = \frac{\sum_n \overline{P}_n^b}{\sum_n \overline{P}_n^{pv}}, \quad \alpha^{PV/Pl} = \frac{\sum_n \overline{P}_n^{pv}}{\sum_n \max(P_n^l)} \quad (1)$$

3) *Self-sufficiency capacity (SSC)*: The self-sufficiency ratio (SSR) is a key concept in this feature, which quantifies the amount of community load covered by the local generation and storage capabilities. Similarly, the "natural self-sufficiency (NSS)" quantifies the "alignment" of a load profile with the solar production over a defined period ( $\overline{P}_{t,n}^{pv}$ ) [10]. Therefore, the self-sufficiency capacity ( $\alpha^{SSC}$ ) relates the NSS with the installed PV capacity of the community ( $\overline{P}_n^{pv}$ ), normalized by  $N$  users. Equation (3) expresses the SSC feature which captures the average percentage of energy covered by PV production at every instant  $t$ .

$$SSR = 1 - \frac{\sum_t \sum_n P_{n,t}^{g-}}{\sum_t \sum_n P_{n,t}^{pl}}, \quad NSS_n = \frac{\sum_t \min(P_{t,n}^l, \widehat{P}_{t,n}^{pv})}{\sum_t P_{t,n}^l} \quad (2)$$

$$\alpha^{SSC} = \frac{NSS_N \times \sum_n \overline{P}_n^{pv}}{N} \quad (3)$$

#### B. System model for centralized energy management

An energy community is modeled as a set of  $N$  members equipped with a photovoltaic panel and a storage system tailored to their needs. Figure 2 depicts a scheme of an

energy community in which the dashed lines show the aggregated power. The EC management is modeled as an optimization problem aiming to minimize the grid interactions at the community level, i.e., reducing the collective bill, as defined in (4). The retail price for purchasing electricity is given by  $\pi^-$ ; similarly, the feed-in tariff is set to  $\pi^+$ . In this paper, both purchase and selling prices are considered flat. The EC acts as a single entity interacting with its supplier, purchasing ( $P_t^{c-}$ ) and selling the surplus ( $P_t^{c+}$ ). The energy storage states for charge ( $P_{t,n}^{b-}$ ) and discharge ( $P_{t,n}^{b+}$ ) allow a degree of freedom in the system to optimize the collective bill. Such operations influence the individual power interactions ( $P_{t,n}^g$ ) with the grid. Equations (5) to (12) model the constraints within the community and state of charge (SOC) update. Where (5) and (6) describe the power balance at the individual and at the community level, respectively. Moreover, (7)-(9) represent the power limits for the EC, the individuals and their batteries, respectively. Given that the objective is to reduce the bill's costs (i.e. ultimately the energy/the losses), then by design, there is no need of including binary variables for avoiding simultaneous import/export from/to the grid and charge/discharge of the battery. Finally, (10)- (12) model the state of charge of the battery, along with its limits and initial conditions.

The optimization problem is described as follows:

$$\min B_{fin} = \sum_t (\pi^- \times P_t^{c-} - \pi^+ \times P_t^{c+}) \times dt \quad (4)$$

s.t.

$$P_{t,n}^g - P_{t,n}^{pv} - P_{t,n}^{b+} + P_{t,n}^{b-} + P_{t,n}^l = 0 \quad \forall \{t,n\} \in \{T,N\} \quad (5)$$

$$P_t^{c+} - P_t^{c-} = \sum_n P_{t,n}^g \quad \forall t \in T \quad (6)$$

$$0 \leq P_t^{c+}, P_t^{c-} \leq \overline{P}^c \quad \forall t \in T \quad (7)$$

$$\underline{P}_{t,n}^g \leq P_{t,n}^g \leq \overline{P}_{t,n}^g \quad \forall \{t,n\} \in \{T,N\} \quad (8)$$

$$0 \leq P_{t,n}^{b+}, P_{t,n}^{b-} \leq \overline{P}_{t,n}^b \quad \forall \{t,n\} \in \{T,N\} \quad (9)$$

$$SOC_{t+1} = SOC_t + \left( \eta \cdot P_{t,n}^{g-} - \frac{P_{t,n}^{b+}}{\eta} \right) \times \frac{dt}{E_{max}^b} \quad \forall \{t,n\} \in \{T,N\} \quad (10)$$

$$\underline{SOC} \leq SOC_{t,n} \leq \overline{SOC} \quad \forall \{t,n\} \in \{T,N\} \quad (11)$$

$$\begin{aligned} SOC_{t=0,n} &= SOC_n^{ini} \\ SOC_{t=T,n} &= SOC_{n,t=0} \end{aligned} \quad \forall n \in N \quad (12)$$

#### C. Assessing ECs' Performance

Two metrics are considered to assess the performance of a given energy community once it is optimally managed

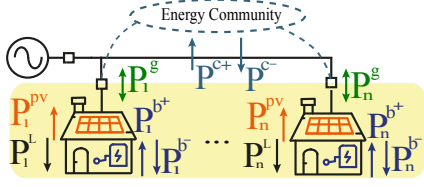


Fig. 2. Energy community scheme.

following the optimization problem previously presented. One metric is related to the technical performance, the community self-sufficiency ratio and the other evaluates the economic performance by calculating the collective bill savings relative to the baseline scenario. The baseline scenario entails users solely selling their energy production and adhering to conventional consumption practices.

1) *Self-consumption ratio (SCR)*: It is a metric that quantifies the amount of community generation that is consumed locally. As such, the SCR at the community level denoted all the energy that supplies the load and not exported to the upstream grid but produced and consumed locally. The SCR for the base case scenario (i.e., users with no battery) is shown in (13). This is compared to the final SCR from (14) in the SCR increase (SCRI) given in (15).

$$SCR_{ini} = \frac{\sum_t^T \min \left( \sum_n^N P_{t,n}^l, \sum_n^N (P_{t,n}^{pv}) \right)}{\sum_t^T \sum_n^N P_{t,n}^{pv}} \quad (13)$$

$$SCR = 1 - \frac{\sum_n \sum_t P_{n,t}^{g+}}{\sum_n \sum_t P_{n,t}^{pv}} \quad (14)$$

$$SCRI = \frac{SCR_{ini} - SCR}{SCR_{ini}} \quad (15)$$

2) *Bill savings (BS)*: The economic performance of the different combinations of users forming ECs is assessed by comparing the increment/decrement in the bill from the base case (users trading individually and solely with the grid) with the bill after forming such groups. Therefore, the initial bill considers the users' power consumption and PV profiles, as in (16). Moreover, the final bill is computed after the collective energy management, as described in Section II-B. Thus, the bill savings can be calculated by the difference between the initial and final bills, as in (17).

$$B_{ini} = \sum_n \sum_t (\pi^- \times P_{n,t}^l - \pi^+ \times P_{n,t}^{pv}) \quad (16)$$

$$BS = \frac{B_{ini} - B_{fin}}{B_{ini}} \quad (17)$$

### III. RESULTS

The results are based on the dataset provided by [11] for the power consumption  $P_{t,n}^l$  profiles spanning one year. We employed clustering techniques to select two representative days per month for simplification. This approach ensures that the energy representation across the 24 days remains equivalent to the entire year. Hence, the simulation runs over 24 days, representing one year. Moreover, all users are assumed to invest in photovoltaic (PV) and battery installations. The PV power profiles  $P_{t,n}^{pv}$  are taken from [3] and

reproduced for  $J$  users. The battery specifications are given by the categorical distribution:  $[5, 7.2, 10]kWh$  peak power, with a capacity of  $13.5kWh$ , and are randomly assigned to each user while forming various energy communities. The retail prices correspond to  $\pi^- = 10c€/kWh$  [12],  $\pi^+ = 25c€/kWh$  [13]. Additionally, two study cases are tested, one with 100% users with PV and battery (i.e., 100% prosumers) and the second with 50% prosumers.

#### A. Clustering Features:

We use the definitions discussed in section II-A to evaluate each energy community's features. The set of  $i = 1000$  energy communities is clustered based on the three dimensions of the selected features, using the K-means method [14]. Moreover, we utilize the elbow method [15] to determine the optimal number of clusters to initiate the clustering process, this is shown in Fig. 3. The elbow method aids in determining the optimal number of clusters graphically. This is achieved by calculating the within-cluster sum of squares (WCSS), which is the sum of the squared distances between points in a cluster and the cluster centroid. Additionally, the silhouette method [16] was also tested to offer further insight into the decision-making process on the number of clusters. Both methods concur in selecting four clusters based on the features.

Figure 4 shows the features within the selected clusters. It provides an insight of the ECs assets compositions. It suggests that the clusters can be defined appropriately in the storage and PV ratios. However, the self-sufficiency capacity seems to be blended among the clusters, given that the values exhibit proximity to one another, this is visible in Fig. 4.

Nevertheless, the Fig. 4 alone does not suggest any particular finding, it describes the ECs features and indicates a clustering mainly associated to  $\alpha^{PV/P^l}$ . Hence, it is essential to correlate the features with the performance metrics.

#### B. Clustering the Performance Metrics

The performance metrics are evaluated similarly to the clustering approach used for the features. The elbow method [15] is used as well to determine the optimal number of clusters, which is subsequently corroborated by the silhouette method [16]. The outcome also identifies four clusters. After

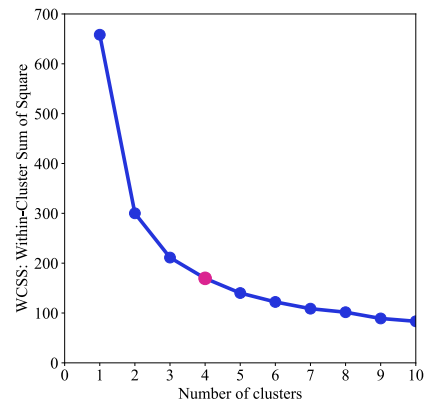


Fig. 3. Elbow method to determine the number of clusters for the features.

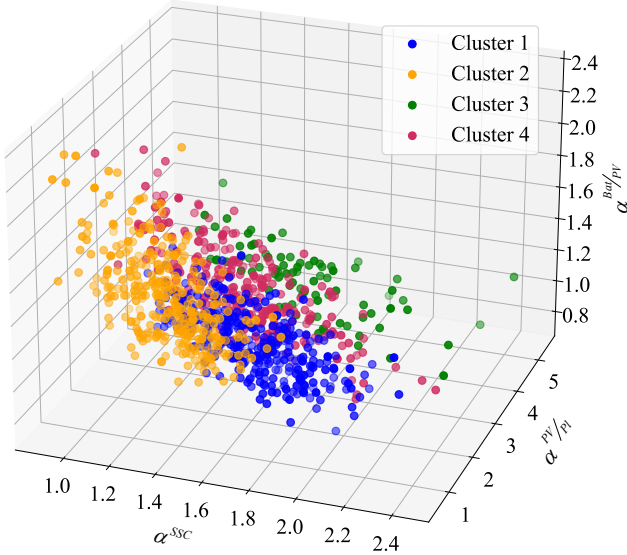


Fig. 4. Features' clusters.

determining the appropriate number of clusters, the performance metrics are clustered. This is done for both cases: 100% prosumers as depicted in Fig. 5, and 50% prosumers shown in Fig. 6. The figures display the self-sufficiency increment after the centralized energy management in the y-axis, and the bill savings described in (17) in the x-axis. It is shown that all tested ECs get an economic benefit when forming such groups, regardless of the percentage of prosumers. The clusters are classified according to the percentage of bill savings.

From the perspective of the bill savings, in the case of 100% prosumers (Fig. 5), the 36.9% of the formed ECs belongs to the cluster with lower BS ( $19\% < BS < 47\%$ ), and only 5% of the tested ECs get bill savings larger than 90%. In contrast, in the case of 50% prosumers (Fig. 6), the bill savings of the clusters are much reduced than that of 100% prosumers. The lowest BS cluster ranges between ( $7.7\% < BS < 20.7\%$ ) corresponding to 37.7% of the total tested ECs, and the highest BS cluster renders savings between 45% and 73.2%, corresponding to the 5.2% of the total tested ECs. Similarly, self-consumption increases in all tested ECs compared to the base case (which considers users solely exchanging with the grid -before forming ECs). In the case of 50% prosumers, the SCR reaches up to 3.6% of increase compared to the base case. Conversely, for the case of 100% prosumers the self-consumption increase reaches up to 10%. Nevertheless, these results are expected since ECs are designed to increase technical and economic benefits. Therefore, correlating the features' influence on the performance metrics is imperative to understanding which characteristics drive the ECs' outcomes. Mapping the intrinsic characteristics of ECs and their performance will provide a deeper perspective.

### C. Features' impact on the Performance Metrics

This paper proposes to assess the correlation of the performance metrics' clusters with the defined features in order to comprehend the impact of the features on the performance metrics.

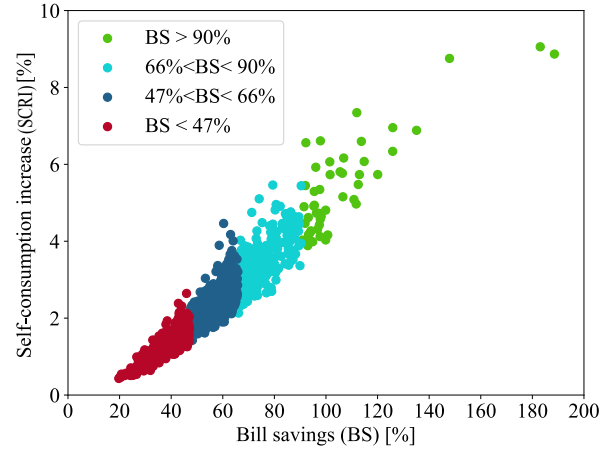


Fig. 5. 100% Prosumers in the ECs: Performance metrics' clusters

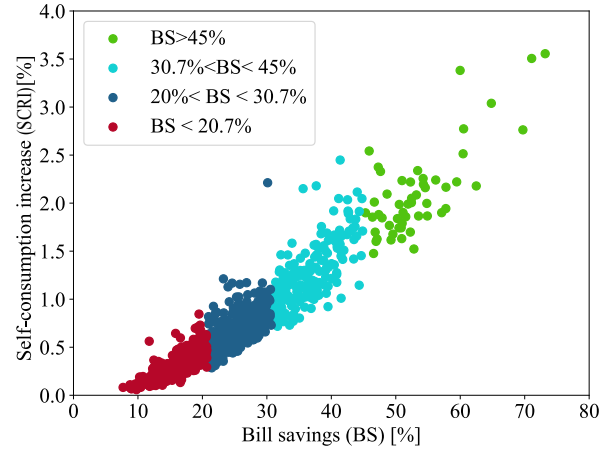


Fig. 6. 50% Prosumers in the ECs: Performance metrics' clusters

The features of the performance metrics' clusters are shown in Fig. 7 for the case of 100% prosumers forming ECs. It is visible that the PV capacity ratio has the most impact, especially on the highest bill savings. This suggests that investing in PV installation is more important than investing in large batteries. In contrast, the bill savings seem to decrease when the battery capacity is high. This is better displayed in the case of 50% prosumers, where the performance metrics show that the battery capacity ratio highly impacts on decreasing the bill savings. The features of this case are shown in Fig. 8. If we compare both figures, there is a proportional relationship between the PV installed capacity and the bill savings, while an inverse proportionality exists between the battery installed capacity and the bill savings. Likewise, for the self-consumption ratio, since the bill savings are proportional to the SCR.

The significance of photovoltaic production outweighs that of battery-installed capacity. It is essential to emphasize the critical role of selecting appropriate metrics to accurately characterize and define parameters influencing the performance of energy communities, particularly in relation to self-consumption and bill savings. The feature: self-sufficiency ratio was anticipated to offer insights into factors affecting increased self-sufficiency, yet it did not yield a definitive conclusion.

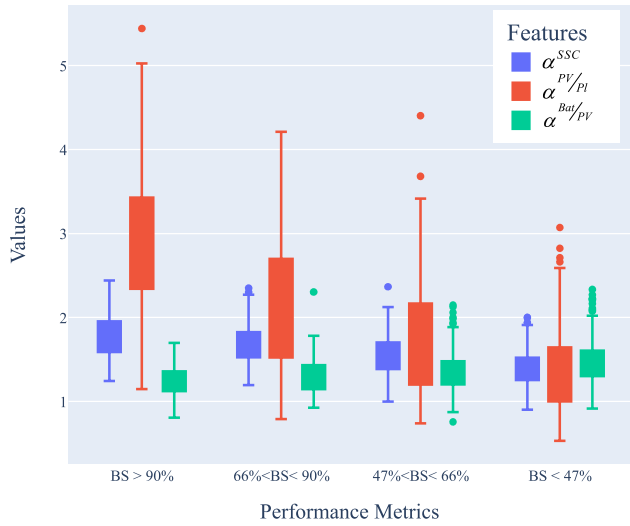


Fig. 7. 100% Prosumers in the ECs: Proportion of Features within the clusters of the Performance metrics.

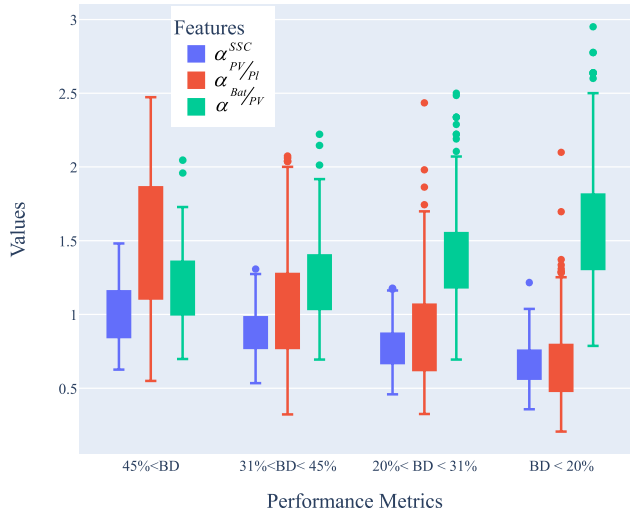


Fig. 8. 50% Prosumers in the ECs: Proportion of Features within the clusters of the Performance metrics.

#### IV. CONCLUSIONS

This paper deals with the collective formation of energy communities, understanding the assets composition and evaluating the outcomes through economic and energy metrics. We assessed the intrinsic characteristic of the formed ECs through features defined as self-sufficiency capacity, photovoltaic and battery installed capacity ratio. Furthermore, a set of 1000 ECs underwent testing, with energy storage randomized for each user. This randomization ensures that no predetermined number or fixed capacity is imposed on any user from the outset, allowing for flexibility in testing various group formations. The results were measured through metrics such as community self-consumption and bill savings, which were compared to the scenario where users did not form ECs. Furthermore, two cases with different percentage of prosumers was tested, one with 100% prosumers and the other with 50% prosumers. The results suggest that features related to PV installed capacity and the potential of covering more than the maximum consumption should be given high relevance. On the

contrary, having a higher battery installed capacity over PV production considerably influences the decrease of the bill savings, this was particularly visible when comparing the 50% prosumers case.

Further analysis will focus on an individual perspective rather than a collective one it will touch ground on the inner motivations for users to form ECs. Moreover, the proposed analysis could be compared to a base case where individuals implement local energy management (i.e., including storage in both cases).

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