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Clustering distributed Energy Storage units for the aggregation of optimized local solar energy

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Abstract

Active communities are emerging thanks to the necessity of creating a cleaner and safer energy system. The growing concern regarding climate change urges a solution to remove fossil fuels from the production equation. The Distributed Generation (DG) technologies are presented as a substitute, but the main resources' behavior is highly uncertain. Flexibility from the demand side is needed. In this way, the authors resort to mixed-integer linear programming optimization to schedule the active resources introduced by the Smart Grid concept: DG, Demand Response programs, and Energy Storage Systems. In this study, the last one is the focus where the impact of these technologies in an active community is analyzed and discussed. The authors performed a clustering method to identify patterns on Energy Storage System (ESS) profiles, finding the optimal number of clusters first. The results show the importance of ESS from both Aggregator and active consumer perspectives.

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Keywords: Clustering; K-means; Energy Storage; Scheduling; Prosumers

1. Introduction

The consequences behind greenhouse gases and air pollution created an urgent and essential movement on environmental awareness worldwide. The Smart grid concept works to find new ways to provide clean and safe energy in the energy sector. One of the main questions starts with the exchange of fossil fuels for a solution more environmentally friendly. So, increasing the penetration of Distributed Generation (DG), namely Renewable-based, such as solar and wind technologies, is considered a reliable solution [1]. However, these technologies are characterized by unstable and volatile behavior due to their primary sources. In this way, the demand-side must provide more flexibility to achieve system balance [2]. So, the consumers' role is changing act more directly on the market transactions. Smart equipment will be crucial to emerging active communities. First, allowing Demand

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Response (DR) programs, where the Aggregator will signal the participants to change their consumption, with the bidirectional communication [3]. After the redefinition of the consumers, now able to produce their energy — the so-called prosumers, can sell to the grid or used to suppress their consumption. And the Energy Storage System (ESS), widely used to cover and manage DG uncertainty [4].

With these tools, both Aggregator and the active consumers of the future should manage consumption/production to avoid discomfort and make a profit, keeping the system secure and reliable. In this way, the authors propose a method capable of dealing with all the resources mentioned above, resorting to a mixed-integer linear programming optimization. Being a continuation of previous works [5,6], the focus of the study presented in this paper is the ESS, understanding the impact on the active communities. A clustering method, k-means, was used to identify patterns in the ESS profiles. Also, since this method needs à priori the number of clusters, the Silhouette method was used to find the optimal number of clusters in each dataset.

The paper has five main sections. Firstly, a brief introduction to the topic and the work presented. After, a detailed explanation of the proposed methodology is followed by the case study definition. The results are analyzed and discussed in Section 4. And finally, the conclusions from this study.

2. Materials and methods

The present section details the proposed methodology schematized in Fig. 1. The goal is to minimize the operation costs, from the Aggregator perspective, regarding the interaction between active consumers and the external suppliers. Firstly, the scenario definition requires information from all the resources in the community. Besides generation means by the main network, the method supports DG, ESS, and flexibility provided by participants in DR events. The active community includes both consumers as well as prosumers — consumers with the capability of producing. In this way, the prosumers can use the generation to suppress their demand, battery charge, or inject into the main network considering a bidirectional interaction.

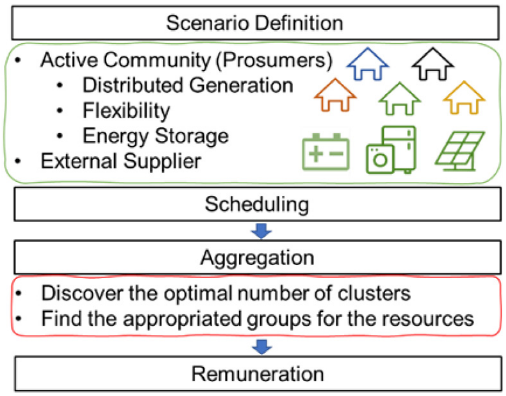

Fig. 1. Proposed Methodology.

The next phase, Scheduling, resorts to a mixed-integer linear programming optimization. Eq. (1) represents the objective function – ($P_{(t)}^{grid_{in}}.C_{(t)}^{grid_{in}}$) represents the costs when supplied by an external supplier, $P_{(t)}^{grid_{out}}.C_{(t)}^{grid_{out}}$, represents the revenues when injecting power to the main network, $P_{(c,t)}^{DR}.W_{(c,t)}^{DR}$ Represents the DR curtailment costs. The term Δt was introduced to adjust the consumption in a 15-min basis to the tariff basis, which is hourly. The parameter T represents the total number of periods.

$$\min EB = \sum_{t-1}^{T}\left[\left(P_{(t)}^{grid_{in}}.C_{(t)}^{grid_{in}} - P_{(t)}^{grid_{out}}.C_{(t)}^{grid_{out}}\right).\frac{1}{\Delta t} + \sum_{c=1}^{C} P_{(c,t)}^{DR}.W_{(c,t)}^{DR}\right]$$
$$\begin{cases} P_{(t)}^{grid_{in}} = P_{(t)}^{grid}, if\ P_{(t)}^{grid} > 0 \\ P_{(t)}^{grid_{out}} = P_{(t)}^{grid}, if\ P_{(t)}^{grid} < 0 \\ \forall t \in \{1, \ldots, T\} \end{cases} \tag{1}$$

The balance between consumption and generation is represented in Eq. (2). It is worth mention that was assumed regarding the $P_{(t)}^{grid}$ is positive when the energy is bought to the grid and negative when the energy is sold, as shown in Eq. (3).

$$\sum_{p=1}^{P} P_{(p,t)}^{PV} + P_{(t)}^{grid} + \sum_{c=1}^{C} P_{(c,t)}^{DR} + \sum_{s=1}^{S} P_{(s,t)}^{dch} = P_{(t)}^{load} + \sum_{s=1}^{S} P_{(s,t)}^{ch}, \forall t \in \{1, \dots, T\} \tag{2}$$

$$- P_{(t)}^{gridmax_{out}} \leq P_{(t)}^{grid} \leq P_{(t)}^{gridmax_{in}}, \forall t \in \{1, \dots, T\} \tag{3}$$

The flexibility provided by the DR participants is represented with $P_{(c,t)}^{DR}$, limited by Eq. (4). Another assumption was considered on Eq. (5) – the loads are connected to relays and, only when activated (status represented with the binary variable $X_{(c,t)}^{DR}$), the loads can be shed. The parameter C represents the total number of active consumers.

$$0 \leq P_{(c,t)}^{DR} \leq P_{(c,t)}^{DRmax}, \forall t \in \{1, \dots, T\}, c \in \{1, \dots, C\} \tag{4}$$

$$P_{(c,t)}^{DR} = P_{(c,t)}^{DRmax}.X_{(c,t)}^{DR}, X_{(c,t)}^{DR} \in \{0, 1\}, \forall t \in \{1, \dots, T\}, c \in \{1, \dots, C\} \tag{5}$$

Regarding the ESS, Eq. (6) represents the operation capacity limits, Eq. (7) the charge, and Eq. (8) the discharge limits per period. With Eq. (9), one can guarantee the impossibility of charging ($X_{(s,t)}^{ch}$) and discharging ($X_{(s,t)}^{dch}$) during the same period t. The parameter S represents the total number of batteries considered. Eq. (10) is introduced to maintain the power balance within the ESS — the previous state of what was charged and what was discharged.

$$E_{(s,t)}^{stormin} \leq E_{(s,t)}^{stor} \leq E_{(s,t)}^{stormax}, \forall t \in \{1, \dots, T\}, s \in \{1, \dots, S\} \tag{6}$$

$$0 \leq P_{(s,t)}^{ch} \leq P_{(s,t)}^{chmax}.X_{(s,t)}^{ch}, X_{(s,t)}^{ch} \in \{0, 1\}, \forall t \in \{1, \dots, T\}, s \in \{1, \dots, S\} \tag{7}$$

$$0 \leq P_{(s,t)}^{dch} \leq P_{(s,t)}^{dchmax}.X_{(s,t)}^{dch}, X_{(s,t)}^{dch} \in \{0, 1\}, \forall t \in \{1, \dots, T\}, s \in \{1, \dots, S\} \tag{8}$$

$$X_{(s,t)}^{dch} + X_{(s,t)}^{ch} \leq 1, \forall t \in \{1, \dots, T\}, s \in \{1, \dots, S\} \tag{9}$$

$$E_{(s,t)}^{stor} = E_{(s,t-1)}^{stor} + P_{(s,t)}^{ch} + P_{(s,t)}^{dch}, \forall t \in \{1, \dots, T\}, s \in \{1, \dots, S\} \tag{10}$$

Since the ESSs are the aim of this study, the next phase, Aggregation, intends to find groups of batteries with similar behavior for each period t. The clustering method used was one of the well-known partitional methods — k-means. The algorithm aims to find a centroid value to represent each group, comparing the distance between elements until finding the minimum value. The k-means clustering method was already studied and widely used with various extensions in the literature [7]. One of the main problems refers to the initialization. This method needs the number of clusters from a dataset a priori, which, normally, is unknown. However, validity indices are used to find the optimal number of clusters for a dataset (kopt), and the one used in this study was the Silhouette method — the maximum value of silhouette score represents the kopt [5,6]. Having this value, k-means is applied to the ESS results, and groups are found. The idea is to understand which ones should discharge according to the status at the event period. The group with the ones with higher values is chosen, and a merit order is defined. The participants are then remunerated with lower tariffs in the following periods.

3. Case study

The present paper simulates 20 prosumers in an active community for this study. Following the current legislation from the Portuguese network, small consumers have the opportunity, with the local generation, to no just use the energy produced to suppress their demand necessities but also inject into the main grid. The contracts with the external suppliers' resort to Time-of-use (TOU) tariff have three different periods: peak, intermediate, and off-peak, as shown in Table 1. The table also presents the parameter W, which represents the DR weight according to the periods.

All of them have a PV Generation, ESS installed, and participants in DR events with three types of appliances: dishwasher, air conditioning, and water heater. The information regarding the community resources is on a 15-min interval basis, so 96 periods were considered throughout the day. Fig. 2 presents the community total consumption, the sum of all PV generation, and the DR flexibility from each type of appliance.

4. Results and discussion

The focus of this study is the integration of ESS into the active communities and the impact that will have on both Aggregators and active consumers perspective. All the ESS results found through the Scheduling phase were

Table 1. Active community characterization.

Transactions	Peak	Intermediate	Off-Peak
Sell (m.u./kWh)	0.1659		
Buy (m.u./kWh)	0.3326	0.1681	0.0930
Periods	10 AM–1 PM	8 AM–10 AM	10 PM–8 AM
	7 PM–9 PM	1 PM–7 PM, 9 PM–10 PM	
DR weight	0.000	0.2000	0.4000

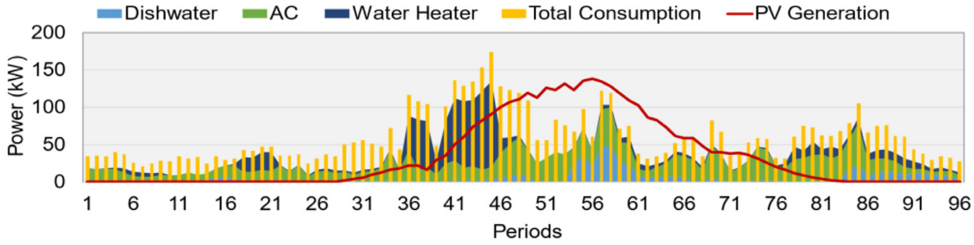

Fig. 2. Discriminated Consumption for the active community: DR flexibility, total consumption, and PV Generation.

analyzed and discussed to recognize a pattern behavior. Since the focus of this study is the Aggregation phase, the authors resort to the k-means method to find clusters within four datasets: $E^{stor}_{(s,t)}$ referred to as the Status curve, $P^{ch}_{(s,t)}$ referred to as the Pch curve, $P^{dch}_{(s,t)}$ referred as Pdch curve, and the combination from the charge and discharge curves, considering the discharge as a negative value — Profile curve. One of the main problems for the k-means method is finding the optimal number of clusters in a dataset. So, the authors resort to the Silhouette method, and the results found can be seen in Fig. 3. The kopt is found through the maximum value of silhouette score — for the Status dataset was 0.5686, for Pch dataset was 0.3409, for the Pdch dataset was 0.3041, and for the Profile dataset 0.2166. With this, the k=2 has the most appropriate clustering configuration for all the datasets.

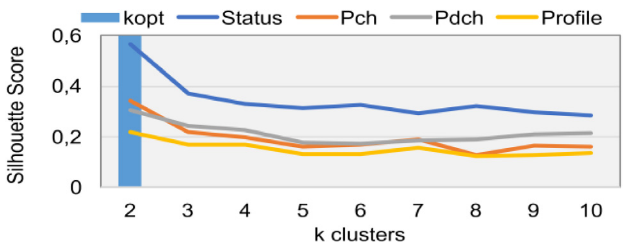

Fig. 3. Silhouette method for ESS Status dataset.

Considering this information, the k-means method was performed for each dataset, and the results can be seen between Figs. 4 and 5. First, the ESS status centroid has a similar behavior between both groups throughout the day. However, Cluster 1 aggregates the ones with higher values and has a total of 14 ESS. It should be noticed that high values of ESS status were recorded when the PV generation also has higher values — Fig. 4(a). Thus, when the PV system started to produce and low consumption value, the ESS was no longer needed and could charge until the max capacity — Cluster 1 centroid was near the 12 kW. From the Aggregators' perspective, the ESS capacity was useful to suppress the load consumption when there was no PV generation — intervals between periods 18 and 35 most of the ESS status had values near the lower limit. Moving to the ESS charging profile results, the group with more members was Cluster 2, as shown in Fig. 4(b). Two different intervals can be identified as the ones with more ESSs charging: interval 1 starting around 26 and finishing on 61 and interval two starting around 76 and finishing at the end of the day.

The first interval matches the growth of PV generation value, and the second refers to the periods where the external supplier price is lower than the remaining intervals. For the ESS discharging profile, the group with more elements is Cluster 1, with 11 elements, as shown in Fig. 4(c). Again, intervals with higher values of discharging

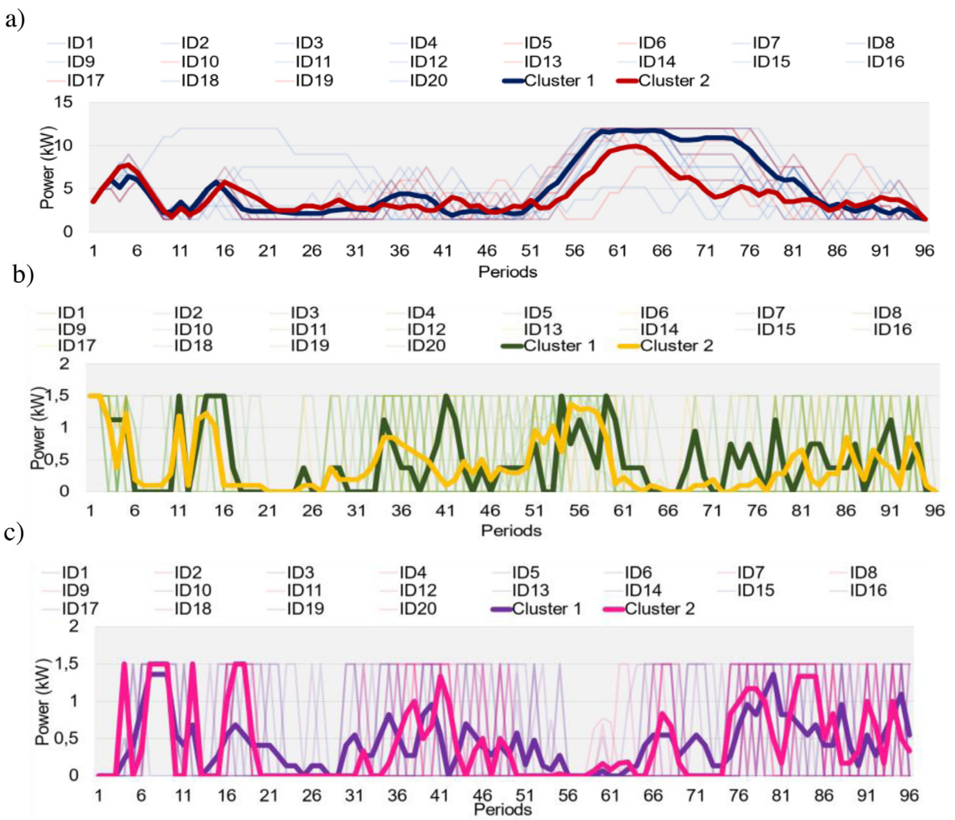

Fig. 4. Clustering Results for the ESS status (a), charging (b), and discharging (c) profile: Cluster 1, Cluster 2, and the ID in each group with a similar color.

can be noticed — mainly due to the lack of PV generation. However, this time should also be highlighted periods with lower values of consumption, like Off-Peak periods, it was worth sell to the grid — ESS was enough to satisfy the demand needs and sell to the grid, behind worth the difference from the consumer perspective — discharge with 0.1659 m.u./kWh and charge with 0.0930 m.u./kWh. With this approach, the consumers' revenue could achieve 0.0729 m.u./kWh. Finally, Fig. 5 summarizes the conclusions withdrawn in the previous results: charging during more consecutive periods around period 47 and period 61; discharging during more consecutive periods and more active consumers at the beginning of the day — following the strategy to achieve higher values revenue. According to the results obtained and DR events, ESS could be a solution to mitigate the intermittent nature of DG technologies, such as wind and solar, to fulfill the load consumption needs. The importance of active consumers' role in the future grid is more and more crucial — their participation will be essential to achieve the balance between generation can consumption.

5. Conclusion

In this paper, the authors proposed a method to successfully deal with the several uncertain resources introduced with the Smart Grids concept. In this way, four main steps were defined: Scenario Definition, Scheduling, Aggregation, and Remuneration. However, in the study presented, the focus was the Aggregation phase — analyzing and discussing the ESS profiles to understand the influence of these technologies in the active community balance. The clustering method used was k-means, where one of the main problems is the definition of the optimal number of clusters. To solve this, the authors resort to the Silhouette method for the several datasets created — ESS status, ESS charge, ESS discharge, and ESS charge/discharge. Two was the optimal number for all the datasets. The results show that ESS status reached higher values when the PV generation was also higher. ESS charging and discharging strategy were applied since there were different price intervals — during off-peak periods, the selling

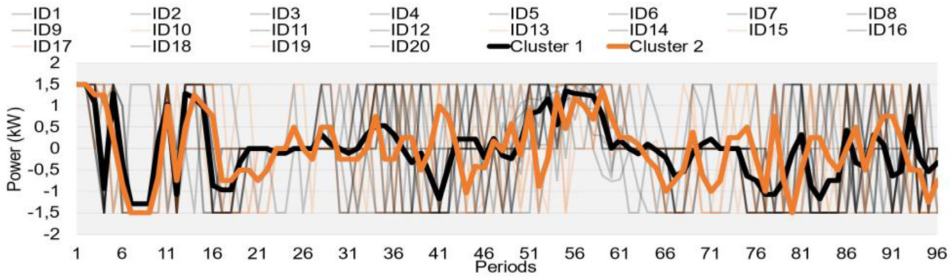

Fig. 5. Clustering Results for the ESS charging/discharging profile: Cluster 1, Cluster 2, and the ID in each group with a similar color.

price to the grid is higher than the buying price. With lower consumption values, the consumer tactic could result in high revenues. From the Aggregator perspective, the PV generation erratic behavior can mitigate by combining DR programs and ESS, resulting in lower requests to external suppliers and fossil fuels.

CRediT authorship contribution statement

Cátia Silva: Data curation, Formal analysis, Investigation, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Pedro Faria:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **António Fernandes:** Data curation, Formal analysis, Investigation, Software, Validation, Visualization. **Zita Vale:** Conceptualization, Data curation, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing.

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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