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Aggregation of Consumers and Producers in a Community with different Clustering Methods

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Abstract

The consumer concept is shaping up as the grid is improving to a smart way. Moving from an actor with little information about what was happening in the energy market, to player with an active and important role in its management. The term prosumer will revolutionize the way the electrical system operates. The possibility of the participation of distributed small-scale energy resources in the network infrastructure changes the current management model. The authors propose a model that optimally associates all concepts. Scheduling, aggregation and compensation are the main phases that compose this model. In this paper, the author focusses only on the second, being the main goal compare between being a consumer, a producer or a prosumer in this method. In this way, two partitional clustering methods were used, testing different k clusters.

Keywords: aggregation, clustering, market, prosumers, smart grid

1. Introduction

The era of smart grids has revolutionized the energy market and opens the door to new players. In this context, one of the main objectives is to move from a formerly centralized model to a more decentralized paradigm, allowing the participation of Distributed Energy Resources, [1]. In this way, the consumer concept can be updated according to this new change. This introduced the prosumer – making a combo between the consumer, storage and local level generator capabilities. Through the Smart Grids, there is the possibility of participation in the small-scale production market, enabling this new consumer, which now may have the possibility to produce its own energy. With this ability, doesn‘t need to request anything from the network and may also, in some cases, sell the excess. Most of them rely on, for example, solar energy sources, through photovoltaic panels, [2].

There are several benefits associated with this change for a smarter grid: reliability increase, carbon footprint reduction, increase in revenue and decrease in consumer energy expenses. However, the current transportation and distribution system is not ready for a successful implementation and hence there is still a long way to go. Right now, the grid presents challenges in terms of design, operation, control, energy storage technologies integration and regulatory issues. It is necessary to update and apply new Information and Communication Technologies so that the system can flow correctly and reliably, [3]. Overcoming these difficulties, prosumers and small-scale production will be allowed to make electrical and economic transactions in so-called local electricity markets (also known to micro-markets by some authors). They can feed consumers belonging to the local community, reducing, for example, transport losses, [4].

In this paper, the authors suggest a way of integrating these local and small-scale markets into the energy market through aggregation with clustering methods. This is the development of previous work, [5]. Thus, one of the main objectives will be to compare the benefit of being prosumer in this type of model: consumers and producers will be separately aggregated and then as prosumers. Throughout this paper two types of clustering methods and various k cluster will be tested.

The first section presents a brief introduction to the main topic addressed throughout this paper: prosumers. Next, the approach by which the authors decided to invest and the proposed model is described. The third section presents the case study and the fourth section the results coming from it, as well as its analysis. Finally, it presents the conclusion of the studied subject.

2. Approach

As discussed in the previous section, this paper deals with the development of previous work. In this section, the proposed model is presented in order to situate the reader in the context in which this article is developed. Therefore, the Fig. 1 presents an overview of the model, highlighting the part in which this work focuses. The three main phases are presented and then a general description of what the purpose of each of them will be presented.

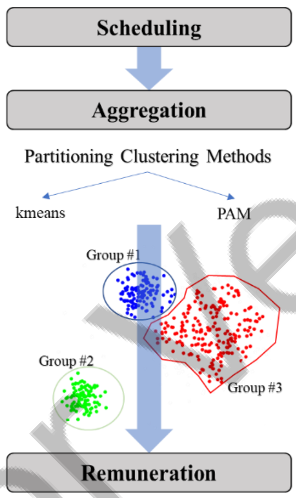

Fig. 21: Overview of the proposed methodology for this paper.

In the infrastructure of the electrical system, the aggregator may play a crucial role. This methodology presents the proposal of the authors of how it may be linked to the tasks belonging to the market of this sector.

First, the model proposes that an optimization should be made to schedule all the resources associated with a particular aggregator, in an optimal way - these resources may be small scale distributed production units, consumers that can be part of demand response programs and suppliers. Only if small-scale resources fail to supply the demand, the suppliers will be used. The input parameters for this optimization may, for example, consider the price elasticity of demand, the possibilities of direct control of the load or even the production of either heat or electricity. The objective function is to minimize operating costs from the Virtual Power Player (VPP) point of view and, in addition, to fairly remunerate all resources that are aggregated and actively participate in community management. In this way, price and operating restrictions are considered in this optimization as well as operational restrictions imposed by the VPP in order to achieve its objectives

Finishing the optimization, the second phase of the model imposes itself - aggregation of resources. The definition of groups is performed taking into account the results obtained previously. By grouping these small resources, the VPP will be able to enter the market with a considerable amount of energy. With this, it will also allow the entry, in a more direct way, of this type of consumers / producers in the transactions of the market.

In this paper, the authors chose to use a clustering method that is one of the most famous of unsupervised machine learning when it comes to partitioning – kmeans. The model created by Hartigan-Wong in 1979 defined one of the possible variations for this method. The total variation within a cluster is then taken to the sum of the squares of Euclidean distance between a point and the center of the cluster, and then assigns the point to the nearest cluster, [8]. This study was carried out using software R.

In the end of this paper, the authors propose to compare the results obtained for kmeans with another clustering method belonging to partitioning – Partitioning Around Medoids (PAM). PAM is a method that looks for objects to represent a cluster – medoid. At each iteration, it is considered the exchange of the current medoid by a non-medoid in the case of some improvement. The criteria of the objective function - the minimization of the sum of the dissimilarities of all objects relative to the nearest medoid, [6]. However, PAM has a disadvantage relative to larger datasets. The problem of finding relatively small clusters in the presence of large clusters in the data set is a difficulty for this method. In the case of databases being greater than thousands of observations, Clustering Large Applications (CLARA) is an extension of this method to deal with this type of problems, [7].

Regarding the last phase of the model, the remuneration step, after aggregation, resources will be rewarded by continued collaboration with the aggregator. This phase serves as a motivation and as a advertising for new potential candidates for the aggregation. Through the cooperation of all resources, the management of network operation flows optimally.

3. Case Study

In this section it is detailed the case study that will be studied throughout this paper. The objective is to apply the second phase of the presented model - aggregation, to a data base constituted by 100 consumers and 100 producers. With the introduction of the concept of prosumers, the authors include it in this study. In this way, and with the existing players in the database, the hypothesis of each of them was tested to form a prosumer. Thus, in the end, the aggregation of 100 prosumers will be tested.

This database was provided by the company Discovergy, which through its smart meters can obtain different types of information, important for this type of study, from its clients. In this paper, only the energy consumed and produced were used. For each of the elements of the database, there is data with intervals of 3 minutes. In this paper, the authors opted to use 175 210 values of those collected in order to provide the method with a high set of elements.

4. Results

This section presents the results obtained by applying the model proposed to the case study presented previously. In a first phase, the idea would be to compare different k clusters through the kmeans clustering method. At Fig. 22 the results for the aggregation of consumers are presented. To aggregate this type of player, the values of energy consumed (kWh) were used by each of the 100 consumers studied for a total of 175 201 periods (with intervals of 3 minutes).

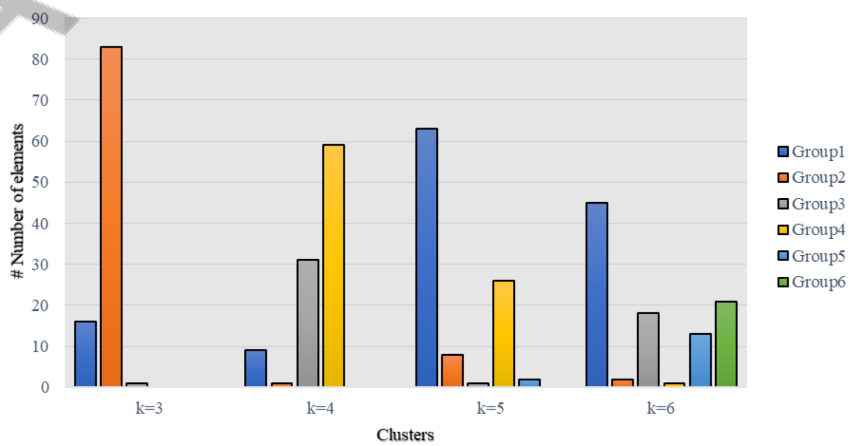

Fig. 22: Consumers – Results from clustering method kmeans for different k clusters.

Table 4: Consumers – Detailed results from clustering method kmeans for different k clusters

	k=3	k=4	k=5	k=6
Group1	16	9	63	45
Group2	83	1	8	2
Group3	1	31	1	18
Group4	0	59	26	1
Group5	0	0	2	13
Group6	0	0	0	21

Through the analysis of the Fig. 22 e da Table 1, for k = 3, the method agglomerated most of the consumers in Group 2. Regarding k = 4, the group that led the previous test was divided into Group 3 and Group 4, the latter group with most of the elements. Already in k = 5, the 63 elements that form Group 1 were also in the referred groups. Finally, at k = 6, the elements are more dispersed, emphasizing that the Consumer 25 has been kept in a separate group in all tests performed.

Turning to the analysis of the Producers, the logic was the same as that presented previously with the Consumers database. Together, the Fig. 23 e a Table 5 present the results from the aggregation of the elements from the database with 100 producers.

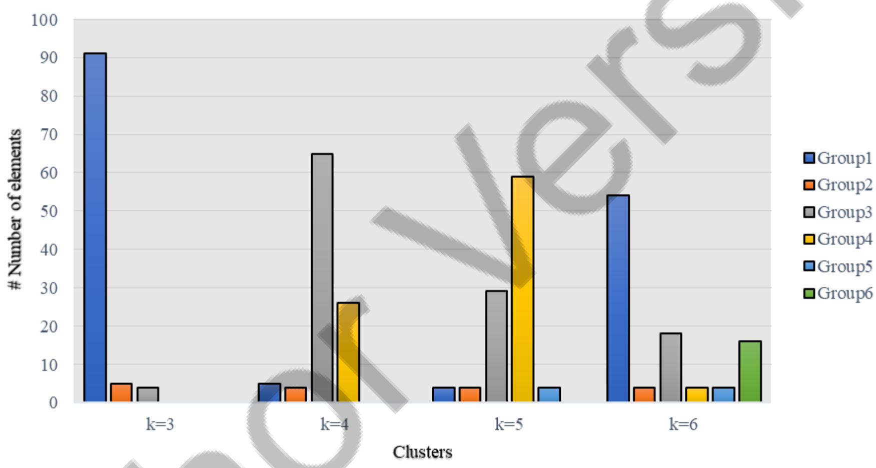

Fig. 23: Producers – Results from clustering method kmeans for different k clusters.

Table 5: Producers – Detailed results from clustering method kmeans for different k clusters.

	k=3	k=4	k=5	k=6
Group1	91	5	4	54
Group2	5	4	4	4
Group3	4	65	29	18
Group4	0	26	59	4
Group5	0	0	4	4
Group6	0	0	0	16

The information in Fig. 23 and Table 5, shows that for k = 3, this method chose to join most of the Producers, 91 elements in 100, in a group. Although in k = 4, these same elements form groups 3 and 4. Moving to k = 5, 3 of the 5 groups are formed by 4 elements. Finally, for k = 6, Group 3 and Group 6 are formed mostly by elements formerly belonging to Group 3 in k = 5.

Moving on to the analysis of the prosumers, this new player was formed through the junction of the Producers and consumers previously studied. Again, following the aforementioned logic, we tested the kmeans clustering method for different k clusters. Like the figures and tables presented above, the Fig. 1 e a Table 6 show the results obtained for the aggregation carried out.

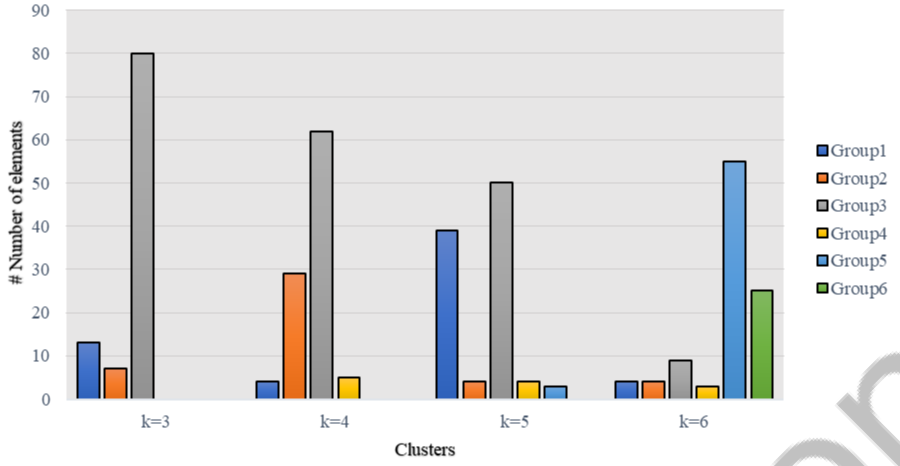

Fig. 24: Prosumers – Results from clustering method kmeans for different k clusters.

Table 6: Prosumers – Detailed results from clustering method kmeans for different k clusters.

	k=3	k=4	k=5	k=6
Group1	13	4	39	4
Group2	7	29	4	4
Group3	80	62	50	9
Group4	0	5	4	3
Group5	0	0	3	55
Group6	0	0	0	25

After examining and comparing with the previous results we can verify that, as in the case of the Consumers in k = 3, the group consisting of the majority of the elements has about 80. This groups are rather similar since 66 of the 80 elements are the same that belong to Group 1 of the Consumers. In k = 4, we can see similarities in the case of Producers. It should be noted that two of the groups have the same elements: Group 1 corresponds to Group 2 of Producers and Group 4 corresponds to Group 1 of Producers. At k = 5 and k = 6, the similarity continues between this Prosumers test and the Producers test.

It was also decided to test another method of clustering. In this paper, the selected method was CLARA, an extension of PAM, and it was compared for a k cluster - in this case we chose k = 6, with the method used before, kmeans. Considering the two methods belonging to Partitioning Clustering, the authors found this final comparison interesting.

Table 7: Comparison between two clustering methods.

	Consumer		Producer		Prosumer	
	CLARA	**kmeans**	**CLARA**	**kmeans**	**CLARA**	**kmeans**
Group1	43	45	32	54	25	4
Group2	22	2	55	4	39	4
Group3	10	18	5	18	1	9
Group4	18	1	1	4	28	3
Group5	6	13	3	4	3	55
Group6	1	21	4	16	4	25

According to the results presented in the Table 7, for Consumers the groups are similar, differing only in a very small number of elements. Concerning Producers and Prosumers, the differences are more noticeable.

5. Conclusions

The concept of smart grids revolutionized the electrical system and with the introduction of new concepts the level of complication of the management became higher. The possibility of distributed resources to actively participate allows the creation of the concept of prosumers – consumers with the possibility of producing and even selling their own energy. The authors suggest a methodology to manage these new players more efficiently - through aggregation methods. By associating them optimally, it will be easier to enter the market and then, according to the model proposed, remunerate the resources in accordance with their cooperation to better manage the operation of the network. This paper focuses on the aggregation phase, comparing different clusters and two different methods.

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