Aggregation Validation Approach for the Management of Resources in a Smart Grid

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***Abstract*—Power systems evolution to an intelligent energy system – smart grid, encounters several issues when integrating distributed generation and demand response. At the aggregator level, activities such as the energy resource management, capacities aggregation and resources remuneration are needed. The present paper addresses the previous needs of the aggregator by considering an optimization of the resources scheduling, followed by an aggregation of resources, and their remuneration is performed. The considered case study is composed by 20 suppliers, 548 distributed generators and 20310 consumers participating in three distinct demand response programs: load reduction, curtailment and real-time pricing.**

***Index Terms*--Aggregator, Demand Response, Distributed Generation, Smart Grid.**

I. Introduction

The integration of Demand Response (DR) [1] programs remains an issue for European countries, mostly due to the inexistence of the right set of implementation features, technological and commercial [2], [3].

For the operator, system planning and management, becomes several times more difficult and complex because of the unpredictability and fluctuation of some DR programs, and the fluctuating demand value that they cause [4]. This last aspect concerns and affects all energy system operators. Moreover, the unpredictability can also be associated with the integration of Distributed Generation (DG), mainly of renewable sources, that has been raising its share on energy markets in recent times, because of the current strategies and energy policies all over the world [5]. Due to these issues, it is important to have a clear statement of what is going on in the network and present solutions that, within the safe operation conditions, DR and DG can be implemented to reduce operation costs and clear a path for a more sustainable future in power systems.

Some European countries have already started implementing projects that apply the previous concepts, such as, Denmark, Germany, Norway and North America [6], [7]. With more or less success, these projects prove to be realistic and feasible solutions, namely, European countries for DG and North America for DR. Although these projects are ongoing path openers to a better power system, the truth is that several technical and economic barriers are still standing, e.g. small energy amounts negotiation in energy markets, generation shedding, choice of loads to reduce/cut, and remuneration of distributed resources [8]. Considering the barriers mentioned above, the introduction of an aggregator entity, could solve many issues regarding resources, since the management of scheduled resources is part of its activities [9].

In this paper, by performing the aggregation of small energy amounts after their optimal scheduling, the aggregator obtains a considerable summed energy that can be negotiated in the energy market. After this, the aggregator performs the rescheduling of groups in order to reduce its operation costs, and then remunerates the groups based on a group tariff. The current paper is the further development of previous works, namely, [10], [11], namely, the following:

- The mathematical formulation is improved to include an additional demand response program, namely, load curtailment together with the reduction and real-time pricing programs;
- Use of a different clustering algorithm type, partition, by grouping resources with the K-means algorithms;
- Present the rescheduling of resources after aggregation, based on the group remuneration obtained, thus, further minimizing the costs for the operator.

In this way, the authors intend to present the aggregator as an entity that deals with the management of resources, suppliers, distributed generators and active consumers. The possibility of negotiation with the market is addressed by demonstrating the costs that can be avoided with the use of the several distributed energy resources available.

After this introduction section, Section II explains the proposed methodology and the mathematical formulation is detailed in Section III. Section IV details the case study applied, and Section V presents the results obtained from the case study, while conclusions are presented in Section VI.

II. Proposed Methodology

In this section, the details on the proposed methodology are presented. The methodology can be essentially separated into four phases: scheduling, aggregation, rescheduling and remuneration, as shown in Figure 1. Also, this figure shows how the aggregator is included into the network infrastructure, and how he deals with the energy market.

This work has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No 641794 (project DREAM-GO) and from FEDER Funds through COMPETE program and from National Funds through FCT under the project UID/EEA/00760/2013.

In the first phase, by considering the resources characteristics and desired DR programs, it is possible to mathematically formulate an optimization problem to minimize operation costs. For the optimization, TOMLAB toolbox from MATLAB was used, obtaining a mixed-integer quadratic problem. The mathematical formulation used is described forward in section III of the present paper. Also, during the scheduling, several scenarios of operation can be made, modifying for that the availability of DG and DR programs. However, for the present paper, only one scenario is presented and is described further in section V. Taking into consideration that the scheduling is made for one instance in time, the authors assume that uncertainty assumes a very small part in the scheduling, thus not being considered. However, this can easily be overcome by the aggregator by using external suppliers in those situations.

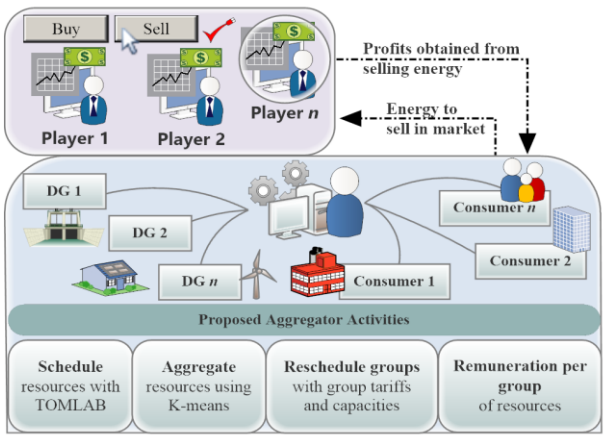

Figure 1. Proposed methodology.

Following the scheduling, aggregation of resources is performed in order to provide the aggregator with a considerable amount of energy for negotiation in the energy market. The aggregation is achieved using the K-means clustering algorithm [12], a partition type – equation (1) and (2) show the mathematical basis of the k-means algorithm. Partition algorithms tend to obtain more balanced groups than other clustering algorithms, such as, hierarchical. Taking this into consideration, in energy systems, in order to not benefit any type of resource, the mixture of DG and DR guarantees a fair distribution of contributions. The clustering algorithm considered, takes upon the following steps:

- **Step 1:** Random assignment of resources into the groups wanted. Compute the centroid of each group (C_k), considering the number of resources (N_k) composed by (x) – Equation (1);

$$C_k = \frac{1}{N_k} \cdot \sum_{x \in C_k} x \tag{1}$$

- **Step 2:** Compute the distances between all resources and the group's centres. – Equation (2);

$$x \in C_k \rightarrow if\ \left|x - C_k\right| < \left|x - C_j\right|,\ j \neq k \tag{2}$$

- **Step 3:** Recalculate the group's centre;
- **Step 4:** Repeat the points 2 and 3, until the elements of each group don't alter.

After performing the aggregation, a rescheduling of the groups is applied using new tariffs. The new tariffs are made by applying the weighted average of all resources prices in a group, i.e. there will be a group tariff for each cluster formed, where all resources inside the cluster, are remunerated at the same energy price. In this way, the aggregator can reduce even further its operation costs, by taking advantage of the full energy potential present in each of the groups formed. In Figure 2, the aggregation concept is presented.

The clustering has inputs to serve as the basis to find the patterns between resources, namely, observations of different features allow to better assemble the resources into groups, reflecting the same principles. In the presented case study, the aggregation is made based on the scheduled energy by the aggregator in the first stage. In this way, the groups will be made independently of the type of consumer or generator, according only to the scheduled energy.

Regarding the clustering components, one considers all resources scheduled by the aggregator, i.e. every resource that contributes for the scheduling is also in the aggregation process. The resources non-scheduled will also not be considered in the aggregation. Still in aggregation, the authors have defined three scenarios, by changing the number of groups wanted by the aggregator (4, 5, and 6), thus providing an analysis on how resources and costs are affected by these options.

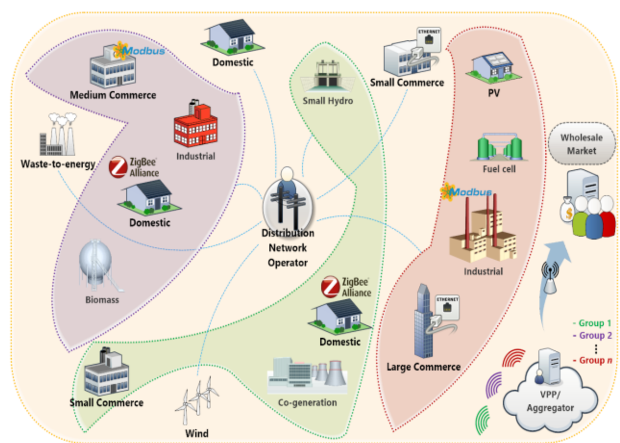

Figure 2. Aggregation concept and structure for a virtual power player (VPP) or aggregator of distributed energy resources.

Remuneration of resources, third phase, is needed for encouragement of distributed resources collaboration with the aggregator in the network operations, and for payment of each resource contribution to the final scheduling. The final remuneration is achieved by the tariffs obtained before. Although the remuneration computations are made, from the point of view of the aggregator, the present paper does not address the view from the market, i.e. the energy bought from an aggregator considering the power groups made.

As one can see, the aggregator manages the resources, aggregating a certain number of them in order to obtain a considerable amount of energy to be negotiated in the energy market, along with the other players.

III. MATHEMATICAL FORMULATION

In this section, the mathematical formulation for the optimal scheduling of resources is presented. The optimization intends to minimize the operation costs of the aggregator and can be expressed as in (3). The problem as mentioned before is a mixed-integer quadratic problem. The problem requires quadratic programming due to the product of two variables that occurs with $P_{DR(c)}^{RTP}$ and $C_{DR(c)}^{RTP}$. Mixed-integer is obtained because of the binary variables associated with the use of suppliers and consumers participating in a DR curtailment program. In this formulation, P refers to energy amounts and C to energy costs.

$$Min\ OC = \sum_{s=1}^{S} P_{Sup(s)} \times C_{Sup(s)} + \sum_{p=1}^{P} P_{DG(p)} \times C_{DG(p)} + \sum_{c=1}^{C} \begin{bmatrix} P_{DR(c)}^{Reduce} \times C_{DR(c)}^{Reduce} + P_{DR(c)}^{Cut} \times C_{DR(c)}^{Cut} \\ -(P_{Load(c)}^{Initial} - P_{DR(c)}^{RTP}) \times (C_{Load(c)}^{Initial} + C_{DR(c)}^{RTP}) \end{bmatrix} \quad (3)$$

In equation (4), the balance of the network is guaranteed by making production equal to consumption, when applying DR programs and distributed generation with the normal use of external suppliers, outside the aggregators' management.

$$\sum_{c=1}^{C} \left[P_{Load(c)}^{Initial} + P_{DR(c)}^{Reduce} + P_{DR(c)}^{Cut} + P_{DR(c)}^{RTP} \right] = \sum_{s=1}^{S} P_{Sup(s)} + \sum_{p=1}^{P} P_{DG(p)} \quad (4)$$

For DG, only (5) is considered, representing the maximum value of generation available for each of these units.

$$P_{DG(p)} \le P_{DG(p)}^{Máx} \quad , \forall\ p \in P \quad (5)$$

Equations (6), (7) and (8) are relative to the external suppliers' interaction with the aggregator of distributed energy resources. The supplier only participates if at least a certain amount of energy is bought - in (8). After the minimum amount is bought, from there on the aggregator can buy what he needs taking into account the suppliers' maximum capacity. This is demonstrated by in (6) and (7). The binary variable $\lambda_{Sup(s)}^{var}$ decides if the supplier provides energy between his minimum and maximum amount, while $\lambda_{Sup(s)}^{fix}$ defines that, if supplier s is used, then a minimum capacity is to be bought by the aggregator. This is especially important, since some units have operation costs that only become viable when a certain amount of energy is produced.

$$P_{Sup(s)} \le P_{Sup(s)}^{Máx} \times \lambda_{Sup(s)}^{var} \quad , \forall\ s \in S \quad (6)$$

$$P_{Sup(s)} \ge P_{Sup(s)}^{Min} \times \lambda_{Sup(s)}^{var} \quad , \forall\ s \in S \quad (7)$$

$$P_{Sup(s)} = P_{Sup(s)}^{Min} \times \lambda_{Sup(s)}^{fix} \quad , \forall\ s \in S \quad (8)$$

Equation (9) presents the DR curtailment program that is only applied to some consumers, through the use of $\lambda_{DR(c)}^{Cut}$.

$$P_{DR(c)}^{Cut} = P_{Step(c)}^{Cut} \times \lambda_{DR(c)}^{Cut} \quad , \forall\ c \in C \quad (9)$$

Equation (10) shows the limits of the consumers participating in the reduction demand response program, where the aggregator reduces loads to a certain amount.

$$P_{DR(c)}^{Reduce} \le P_{DR(c)}^{Reduce\ Máx} \quad , \forall\ c \in C \quad (10)$$

Equations (11) and (12), present the maximum acceptable values for the consumer's reduction in RTP demand response program and the respective price increase that can be performed in order to incentive the consumer to reduce.

$$P_{DR(c)}^{RTP} \le P_{DR(c)}^{RTP\ Máx} \quad , \forall\ c \in C \quad (11)$$

$$C_{DR(c)}^{RTP} \le C_{DR(c)}^{RTP\ Máx} \quad , \forall\ c \in C \quad (12)$$

The elasticity of a consumer defines his ability to react and changes its load, in response to a price signal sent by the aggregator or another entity that is responsible by presenting, in real-time, the energy price to the consumer. The elasticity can therefore be expressed as in (13).

$$\varepsilon_{(c)} = \frac{P_{DR(c)}^{RTP} \times C_{Load(c)}^{Initial}}{C_{DR(c)}^{RTP} \times P_{Load(c)}^{Initial}} \quad , \forall\ c \in C \quad (13)$$

The following control parameters allow the aggregator to define the final percentage, in relation with the consumption, for the distributed energy resources, i.e. the distributed resources share in the final energy mix. These are represented for DG – (14), and for all DR programs – (15), (16) and (17). The scheduling mentioned before, concerning the resources groups, after the aggregation, is also made considering the minimization of operation costs for the aggregator, as expressed in (18).

$$\alpha_{DG} \ge \frac{\sum_{p=1}^{P} P_{DG(p)}}{\sum_{s=1}^{S} P_{Sup(s)} + \sum_{p=1}^{P} P_{DG(p)} + \sum_{c=1}^{C} \begin{bmatrix} P_{DR(c)}^{Reduce} + \\ P_{DR(c)}^{Cut} + P_{DR(c)}^{RTP} \end{bmatrix}} \quad (14)$$

$$\alpha_{RTP} \le \frac{\sum_{c=1}^{C} P_{DR(c)}^{RTP}}{\sum_{s=1}^{S} P_{Sup(s)} + \sum_{p=1}^{P} P_{DG(p)} + \sum_{c=1}^{C} \begin{bmatrix} P_{DR(c)}^{Reduce} + \\ P_{DR(c)}^{Cut} + P_{DR(c)}^{RTP} \end{bmatrix}} \quad (15)$$

$$\alpha_{Cut} \geq \frac{\sum_{c=1}^{C} P_{DR(c)}^{Cut}}{\sum_{s=1}^{S} P_{Sup(s)} + \sum_{p=1}^{P} P_{DG(p)} + \sum_{c=1}^{C} \left[\begin{array}{l} P_{DR(c)}^{Reduce} + \\ P_{DR(c)}^{Cut} + P_{DR(c)}^{RTP} \end{array} \right]} \quad (16)$$

$$\alpha_{Reduce} \geq \frac{\sum_{c=1}^{C} P_{DR(c)}^{Reduce}}{\sum_{s=1}^{S} P_{Sup(s)} + \sum_{p=1}^{P} P_{DG(p)} + \sum_{c=1}^{C} \left[\begin{array}{l} P_{DR(c)}^{Reduce} + \\ P_{DR(c)}^{Cut} + P_{DR(c)}^{RTP} \end{array} \right]} \quad (17)$$

Equation (19) refers to the same point as (4), seen before in this section. In (18), the parameter $C_{Group(k)}$ refers to the weighted average cost (being K the total number of groups), obtained through the resources present in each group, also, RTP participants are considered without cost for the aggregator. This means that their reduction capacity is considered for the scheduling, but not for the calculation of the group price.

$$Min\ OC_{Groups} = \sum_{k=1}^{K} E_{Group(k)} \times C_{Group(k)} \quad (18)$$

$$\sum_{k=1}^{K} E_{Group(k)} = \sum_{c=1}^{C} P_{Load(c)}^{Initial} \quad (19)$$

IV. Case Study

The case study where the methodology has been applied is a real Portuguese distribution network, composed by 548 distributed generators and 20310 consumers, described in Table I and Table II, respectively. Also, 20 suppliers, outside of the network, are considered in case of the aggregator cannot act in isolated mode with the available resources. The respective case study concerns a 30 kV distribution network, with a unique high voltage substation (60/30kV) with a maximum capacity of 90 MVA. A total of 937 buses accommodates the resources mentioned before [13].

TABLE I. DG Characteristics

DG Resource	Price (m.u./kWh)	Capacity (kWh)	# Units
Wind	0.071	5 866.09	254
Co-generation	0.00106	6 910.10	16
Waste-to-energy	0.056	53.10	7
Photovoltaic	0.150	7 061.28	208
Biomass	0.086	2 826.58	25
Fuel cell	0.098	2 457.60	13
Small hydro	0.042	214.05	25
Total DG	25 388.79 kWh		548

For the demand side management, three types of DR programs were considered and applied to different types of consumers, as shown in Table II. The values in brackets in the last column of Table II, refers to the price of execution of a certain DR program on a specific type of consumer. In the case of ID consumers, the value in brackets represents the elasticity of the consumer type. The peak power demand for this case study is 62.63 MW, making impossible the operation in isolated mode, i.e. the aggregator cannot manage the network with only distributed resources. The curtailment program can achieve up to five percent of the initial load of a consumer, while reduction programs can reach fifty percent of the initial load. For the RTP program, unlike the other programs, the consumer chooses or not to participate according with its elasticity and reduction capacity. In RTP, the aggregator raises the electricity price in order to indirectly increase the odds of voluntary reduction by consumers.

TABLE II. Consumers in DR Programs

DR Resource	Reduce	Cut	RTP	Initial Price (m.u./kWh)
Domestic (DM)	•			0.12 (0.20)
Small commerce (SM)	•			0.18 (0.16)
Medium commerce (MC)		•		0.2 (0.20)
Large commerce (LC)		•		0.19 (0.20)
Industrial (ID)			•	0.15 (0.53)
Total # DR	19 996	167	147	20 310
Total Capacity DR	8 676	1 106	11 571	21 354.36

V. Results

In the next section, the results for a given scenario are presented and analyzed. In this section, only one scenario is analyzed, where α_{DG}, α_{Cut} and α_{Reduce} are equal to one, not imposing any limits in generation for these types of resources. The same is applied to RTP, however, since the inequality sign is the contrary of the above said, α_{RTP} is equal to zero.

In Figure 3, one can see the scheduling results for all resources, considering different energy sectors as DG and DR. In distributed generation, the main sources of energy are wind, photovoltaic (PV) and co-generation (CHP), due to their high installed capacity.

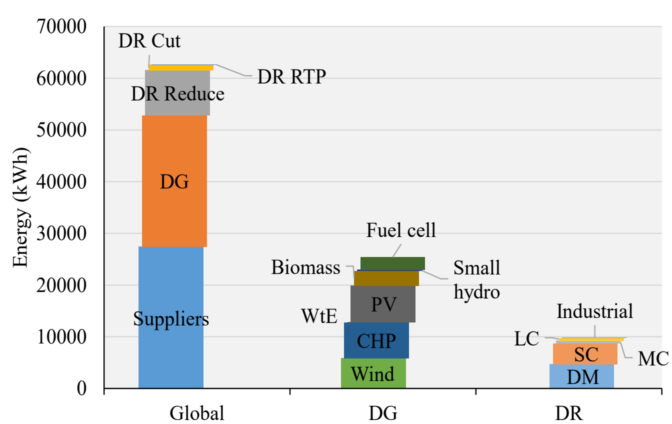

Figure 3. Scheduling results for all resources.

Also, looking at the global overall, distributed generation has approximately supplied the same energy as the external suppliers, having demand response programs guaranteed the remaining energy needed. The consumers with higher contributions are from type Domestic and Small commerce, mostly due to their large number of elements, as one can see by Table II. RTP program was the lower contributor for the network of all resources, although it can be forced to be higher, if applied α_{RTP}.

The change of scheduling control parameters has to be made having attention to the capacity of each type of resource, especially in the case of RTP programs. This program, when defined a percentage superior to its capacity, will cause the optimization to not find a feasible solution for the scheduling. Three scenarios were considered for the aggregation: K equal to five, six and seven groups. The aggregation is demonstrated by Figure 4. This figure shows the amount of energy present in each group for all aggregation scenarios. As one can see, the energy amounts obtained are considerably higher, and thus are more likely to be negotiated by the aggregator in the energy market.

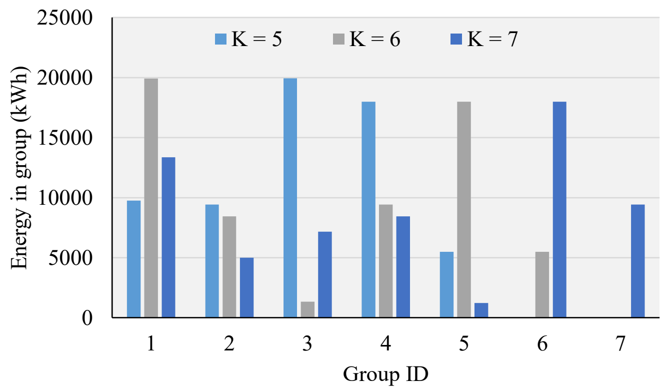

Figure 4. Energy per group.

In this context, the aggregation scenario with a total number of groups equal to five, corresponds to the better solution, since the groups in this scenario are more balanced, i.e. the energy per group are more alike with each other than in the other scenarios. After this aggregation, the weighted average is calculated considering each price of the resources inside each group, with exception of RTP participants that don't have any cost for the aggregator. This new tariff will be used to run the optimal scheduling of the groups obtained, considering the capacities of each resource. This will allow to use less groups and reduce even further the operation costs for the aggregator.

In Table III, the results are presented before and after the rescheduling of groups. It is possible to see that, the aggregation scenario mentioned above as the better solution in terms of energy balance, has become the worst with the application of new tariffs. The better solution, in terms of energy balance, is K equal to seven, in the new scheduling. Although the operation costs are inferior, is important to notice that the energy distribution on the groups is worse than before the rescheduling, making more difficult the participation of these groups in the energy market.

TABLE III. ENERGY PER GROUP

K	Group ID	Before	After	# Resources	Max. Capacity
5	1	9750,6	21295,3	20332	21295,3
	2	9431,9	10000,0	1	10000,0
	3	19947,9	19947,9	520	19947,9
	4	18000,0	5887,3	6	18000,0
	5	5500,0	5500,0	6	5500,0
6	1	19926,9	19926,9	519	19926,9
	2	8437,4	19982,0	20040	19982,0
	3	1334,2	1334,2	293	1334,2
	4	9431,9	10000,0	1	10000,0
	5	18000,0	5887,3	6	18000,0
	6	5500,0	5500,0	6	5500,0
7	1	13373,4	13373,4	481	13373,4
	2	5000,0	5000,0	5	5000,0
	3	7163,9	7163,9	45	7163,9
	4	8437,4	19982,0	20040	19982,0
	5	1223,8	1223,8	287	1223,8
	6	18000,0	5887,3	6	18000,0
	7	9431,9	10000,0	1	10000,0
Total	-	62 630.4	62 630.4	20865	74 743,1

In this way, the aggregator may not be able to sell these amounts, however, if the aggregator is managing a micro grid with these resources in it, he can always use them to supply load. In case the energy is insufficient for supplying all load, as in the example scenario, the aggregator obtains from external suppliers the needed amount of energy. The clustering algorithm K-means, as one can see in Figure 4, achieves a good resources distribution in terms of energy. This is due to the data given to the clustering algorithm. Only the resources scheduling was given, therefore, only energy amounts are taken into consideration by the algorithm. This can be easily seen, since the number of resources is largely diversified in each of the groups, as demonstrated in Table III. After seeing the results for aggregation, considering energy balance, it is now presented the results in terms of operation costs, detailed in Figure 5.

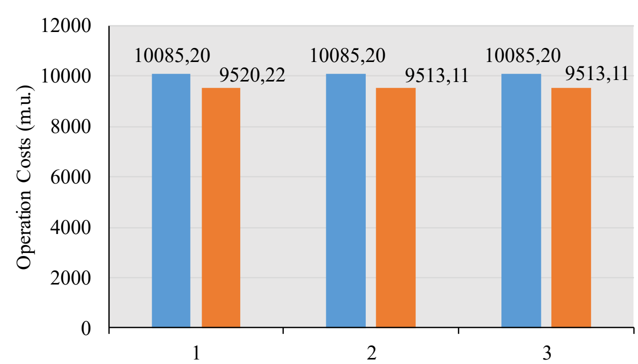

Figure 5. Operation costs, before and after rescheduling.

As one can see, the total operation costs obtained from after the rescheduling are about 5.7% inferior, relative with the obtained before rescheduling. Also, in Figure 5, one can see that the total number of groups influences the groups' remuneration after the rescheduling. The results demonstrate that for a total number of groups equal to six the costs are lower than in the other two scenarios of aggregation, for this case study. The proposed approach for the rescheduling of the groups can also be performed to guarantee a certain energy level between the groups, i.e. if the aggregator has knowledge that he needs at least a specific amount of energy from each group to take them to the market, the rescheduling can be made to sort resources between groups in order to achieve the energy amount required per group.

In Figure 6, one can see the energy present in each cluster group, after the rescheduling, similar of how it is considered in Figure 4. When looking at scenario K=5, in a first analysis it is easily seen that the groups 1, and 3, are the most used in the rescheduling, since they have the lowest prices, as shown by Table IV, namely, 0.1811 and 0.1005 m.u./kWh, respectively. Although, the group tariff for the cluster 5 is lower than for groups 1, and 3, the maximum capacity is low and thus its contribution is inferior – as in Table III and Figure 7.

TABLE IV. ENERGY PRICE PER GROUP, AFTER AGGREGATION

	Group ID						
	1	2	3	4	5	6	7
K=5	0,1811	0,2300	0,1005	0,2300	0,0011	0,0	0,0
K=6	0,1004	0,1804	0,1853	0,2300	0,2300	0,0011	0,0
K=7	0,1146	0,0011	0,0685	0,1804	0,1839	0,2300	0,2300

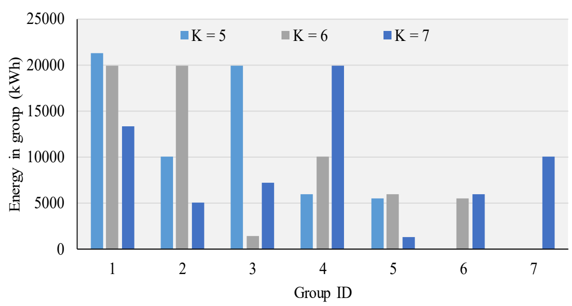

Figure 6. Energy per group after rescheduling.

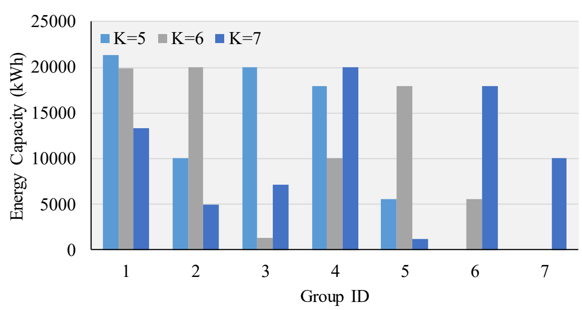

Figure 7. Maximum capacity per group after rescheduling.

For scenario K=6, one can see that the amounts of energy are maintained almost the same amonsgt the groups, however, there are slight changes on which groups have the lowest prices, also dependent on how the resources are put into the different groups considering the distinct clustering scenarios. In scenario K=7, the energy distribution becomes less singular than in the other scenarios, being more distributed amongst all groups, however, one can still see the group with the biggest contribution, number four.

The reschedule causes the aggregator to reassess the scheduling made, namely, concerning the resources used and taking into account the groups made. Also, has Figure 5 proves, the rescheduling allowed the aggregator to reduce the operation costs in about 5.7%.

VI. CONCLUSIONS

In the present paper, a methodology is proposed to support energy resources aggregators in their activities. A model is presented to solve the resources optimal scheduling, followed by the proposition of a clustering algorithm to deal with the clusters formation, taking into consideration the previous scheduling. After the aggregation, a group tariff is computed in order to model the groups as an aggregate. This group tariff is the basis for the groups rescheduling, with the intention of reducing further the operation costs of the aggregator.

The final remuneration is made by group and is performed considering the same group tariffs as described above. Results show that the rescheduling of groups after aggregation, benefits the aggregator by reducing its operation costs by approximately 5.7%, for the case study presented. Also, the scheduling of resources shows the possible integration of distributed energy resources, in this case distributed generation and demand response, as a viable solution for the energy systems operation. By introducing control parameters, it is possible to obtain several distinct scenarios that can be evaluated by the aggregator.

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