Aggregation and Remuneration of Electricity Consumers and Producers for the Definition of Demand-Response Programs

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***Abstract*—The use of distributed generation and demand-response (DR) programs is needed for improving business models, namely concerning the remuneration of these resources in the context of smart grids. In this paper, a methodology is proposed in which a virtual power player aggregates several small-sized resources, including consumers participating in DR programs. The global operation costs resulting from the resource scheduling are minimized. After scheduling the resources in several operation scenarios, clustering tools are applied in order to obtain distinct resources' groups. The remuneration structure that better fits the aggregator goals is then determined. Two clustering algorithms are compared: 1) hierarchical; and 2) fuzzy c-means clustering. The remuneration of small resources and consumers that are aggregated is made considering the maximum tariff in each group. The implemented case study considers 2592 operation scenarios based on a real Portuguese distribution network with 548 distributed generators and 20 310 consumers.**

***Index Terms*—Clustering, demand response (DR) programs, distributed generation (DG), smart grids.**

Nomenclature

Variables

$C_{\mathrm{RTP}}^{\mathrm{Increase}}$	Electricity cost increase in the real-time pricing (RTP) program.
OC	Total operation costs.
$P_{\mathrm{Supplier}}^{\mathrm{add}}$	Scheduled power in an additional supplier.
P_{DG}	Scheduled power in a distributed generation (DG) unit.
P_{IDR}	Scheduled power reduction in an incentive-based demand response (IDR).
P_{NSP}	Nonsupplied power.
$P_{\mathrm{RTP}}^{\mathrm{Reduct}}$	Consumption reduction in the RTP program.
$P_{\mathrm{Supplier}}^{\mathrm{reg}}$	Scheduled power in a regular supplier.
J	Fuzzy C-means objective function value.
μ	Membership grade.
x	Centroid of the cluster.
v	Object value.

Parameters

α_{DG}	Maximum allowed DG contribution.
α_{IDR}	Maximum allowed IDR contribution.
α_{RTP}	Minimum aimed RTP contribution.
ε	Price elasticity of demand.
$C_{\mathrm{Supplier}}^{\mathrm{add}}$	Additional supplier cost.
C_{DG}	DG cost.
C_{IDR}	Demand response (DR) cost.
$C_{\mathrm{RTP}}^{\mathrm{Increase\ Max}}$	Maximum cost increase in an RTP resource.
$C_{\mathrm{RTP}}^{\mathrm{Initial}}$	Initial electricity cost for RTP resources.
C_{NSP}	Nonsupplied power cost.
$C_{\mathrm{Supplier}}^{\mathrm{reg}}$	Regular supplier cost.
$P_{\mathrm{Supplier}}^{\mathrm{add\ Max}}$	Maximum power from additional suppliers.
$P_{\mathrm{Supplier}}^{\mathrm{add\ Total}}$	Maximum allowed power for the total of the additional suppliers.
$P_{\mathrm{Load}}^{\mathrm{Initial}}$	Initial consumption in the consumers' resources.
$P_{\mathrm{DG}}^{\mathrm{Max}}$	Maximum power schedule in a DG resource.
$P_{\mathrm{IDR}}^{\mathrm{Max}}$	Maximum power schedule in an IDR resource.
$P_{\mathrm{RTPDR}}^{\mathrm{Max}}$	Maximum allowed total power schedule in a consumer participating in both IDR and RTP.
$P_{\mathrm{DG}}^{\mathrm{Min}}$	Minimum power schedule in a DG resource.
$P_{\mathrm{RTP}}^{\mathrm{Reduct\ Max}}$	Maximum power schedule in a RTP resource.
$P_{\mathrm{Supplier}}^{\mathrm{reg\ Max}}$	Maximum power from a regular supplier.
$P_{\mathrm{Supplier}}^{\mathrm{reg\ Total}}$	Maximum allowed total power from all the regular suppliers.
$P_{\mathrm{DG}}^{\mathrm{Total\ Max}}$	Maximum allowed total power from all DG units.

Indexes

C	Maximum number of consumers c.
D	Distances matrix.
G	Group.
I	Maximum number of objects i.
K	Total number of groups.
m	Weight of fuzziness.
n	Number of levels in the decision tree.
P	Maximum number of producers p.
S	Maximum number of suppliers s.
T	Maximum number of clusters t.

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I. Introduction

THE CONCEPT of DR has been intensively discussed. It can be defined as the modification of electricity consumption patterns by end-use customers, responding to variations in the electricity prices or to any other signals related to technical or market operation issues [1], [2]. Using DR and DG, at the level of distribution networks, is a key element for an efficient smart grid (SG) [3], [4]. Most of the currently implemented DR programs are oriented for large-sized resources [5], [6]. Although these are helpful for large generators, the potential of small-size resources is largely unexplored. Curtailment service providers (CSPs) [7] are currently used to partially overcome this barrier, but more flexible aggregation models are required [2], [6]–[8]. Virtual power players (VPPs), aggregating small-sized DG and DR resources, can enable a wide spread of these resources' participation, making it profitable through market-driven approaches. The present work aims at providing VPPs with tools for resources scheduling and aggregation, bearing in mind the minimization of operation costs and the fair remuneration of the resources. The proposed method considers the actual value of the resources for each specific scenario and the relevant technical constraints.

According to the VPP operation context, some of the managed resources can be scheduled in order to support the participation of the VPP (and its aggregated resources) in the electricity markets. In this way, e.g., in the case of DR programs, the consumption reduction can be used to meet the demand's needs inside the network and also for the participation in the electricity market.

The fact is that, once an aggregator participates in a DR event announced by an independent system operator (ISO) or market operator, the remuneration that has to be made to each aggregated small-sized resource must be determined according to the actual contribution of each one [9]. This is an important issue as a background motivation for the work in this paper. Several remuneration approaches have been proposed in the current literature, namely the proportionality method, the equal percentage method, and the factor *G* method [10], [11]. These methods assume that each resource is remunerated individually and that there is enough available information about each resource objectives and motivations, which is not always possible. This is especially important in the case of DR resources, mostly due to their consumption predictability.

Another issue for the VPP share of revenues, resulting from the participation in a DR event, is the definition of resources' groups. The resources that constitute a group are scheduled and remunerated by the same rules. In this way, the determination of groups of consumers (DR resources) and/or DG resources with similar characteristics can be performed using clustering tools [12], [13]. Several groups (clusters) of resources can be defined using such tools, aiming the capture of common characteristics that better define the resources in a specific context [14], [15]. Decision support regarding the DR and DG remuneration for their participation in DR programs is required [16]. In this context, the proposed methodology has been developed in order to address the remuneration of the aggregated resources (small-sized DG and DR), performed by a VPP. The VPP operates a distribution network and schedules the available DG and DR resources, both for regular operation and for the participation in DR programs announced by the ISO. Resources' scheduling considering DR consumers with onsite generators, load curtailment, load shifting, and energy storage is addressed in [17]. Although the aggregation is not made in practice, the authors consider it of most importance to the success of DR resources' implementation. The remuneration of the consumers is performed considering the revenues of the energy sold in energy markets by a DR aggregator. In [18], the usage of clustering algorithms is directed to the clustering of consumers, namely residential. The paper considers a Belgium case study, and reflects the consumption reduction at residential level considering an expected maximization. This, according to the authors, allows a better clustering due to its ability of easy membership relaxation, smoothing effect, and a uniform distribution of the many resources by the number of groups specified. Also, the paper mentions the technical issues in using different types of clustering algorithms making some comments about the ones used in this paper. In [19], the scheduling is made taking into consideration the use of electrical vehicles and DG, knowing that they are managed by an aggregator. This aggregator provides the interaction of these resources with the system operator and, consequently, the energy markets. In [20], the aggregator is also considered a VPP and it performs the aggregation of consumers considering their load profiles. The focus is given to the formation of a virtual power plant and respective use for market and grid balancing. The final billing is performed individually for each consumer. Reference [21] shows how clustering algorithms (K-means and hierarchical) can be used to model consumers taking into account their load shapes and consumption patterns, showing results for 220.000 residential consumers.

The methodology in this paper provides results concerning several number of energy resource clusters according to the defined scenarios, giving support to the VPP in the decision of the most advantageous number of groups, according to the limitations that a VPP can have on the number of DR programs to be implemented (each resource cluster corresponds to a DR program). In this way, several tariff groups (each group has a price for the energy provided by its resources) are defined according to the actual energy scheduled for each resource in each operation scenario. Several tariff groups can be defined, as well as the respective remuneration tariff, in distinct operation scenarios.

After Section I, Section II explains the proposed methodology, including a detailed explanation of its contributions. Then, Section III presents the resource scheduling formulation. The case study is in Section IV and Section V includes the obtained results. Finally, Section VI presents the main conclusion of the work.

II. Proposed Programs' Definition Methodology

The methodology proposed in this paper was developed in order to support the decisions of a VPP in what concerns the use of DG and DR resources and the remuneration of each aggregated resource by this VPP. The diagram presented in Fig. 1 illustrates how the proposed methodology is schematized. As it can be seen, the VPP manages the available resources, namely

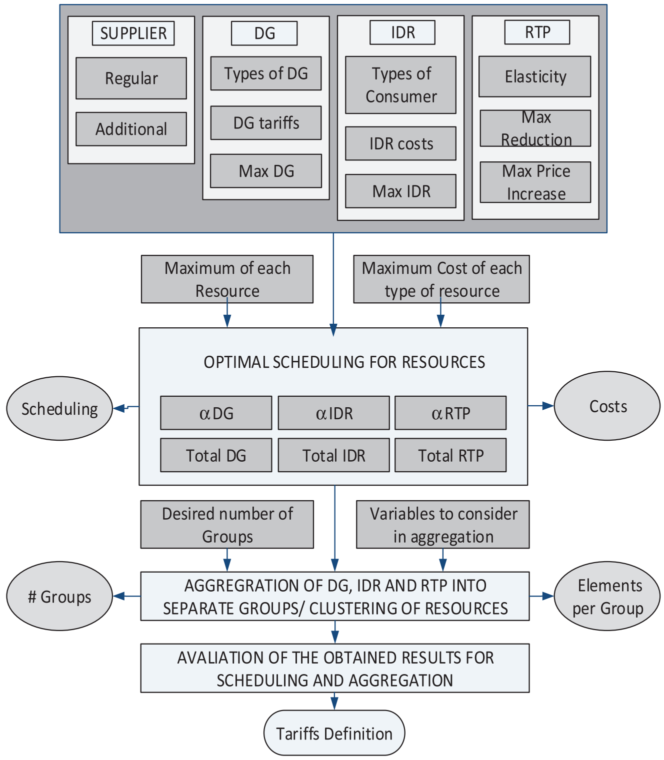

Fig. 1. Diagram of the proposed methodology.

DG units, DR consumers, and the Suppliers (to which the VPP is able to buy electricity outside of the network). In the case of DR programs, one can usually have two types: 1) incentive-based; and 2) price-based DR programs.

In the proposed methodology, we have an IDR, in which the consumers are remunerated at a fixed price per provided kW of consumption reduction. We also have a price-based program (RTP), in which the consumers change their load according to the actual price signals while they are modeled by the price elasticity of demand [22], [24]. Given the VPP operation context and the available resources, it is possible to define three phases of implementation for the proposed methodology, accordingly with Fig. 1. In the first phase, the optimal scheduling of the resources is performed taking into account their prices and operation constraints, and also the operational constraints imposed by the VPP in order to reach its goals. In other words, the input data are used in the scheduling algorithm so that constraints and resources' characteristics are taken into account. In this context, the VPP defines three α parameters, concerning DG, IDR, and RTP. This parameter limits the contribution of the associated resources type to the resulting resource scheduling, allowing the VPP to choose the percentage of total energy delivered obtained from each type of resource. The detailed explanation of the energy resource scheduling, which aims at minimizing the VPP operation costs, is presented in Section III. In this first phase, it is also defined several operation scenarios that are intended to cover the resources' availability possibilities in order to support the VPP decisions in these scenarios. In the second phase, according to the number of tariff groups (DR and DG units programs) specified by the VPP, several consumers and DG units clusters are computed. Only the resources scheduled in the optimization with nonzero power are considered. Each type of distributed resource (DG, IDR, and RTP) is associated with a certain cluster concerning its characteristics and the attributes of the other resources in the cluster.

The definition of the attributes of each resource to be considered by the clustering algorithm is therefore of most importance. The attributes considered are the regular and additional supplier cost, DG cost, regular and additional supplier, and DG maximum capacity, initial load, all α parameters and finally, maximum reduction for IDR. For IDR and RTP consumers, the attributes considered are the IDR cost, maximum cost increase for RTP consumers, initial energy price for consumer, initial load, all α parameters, and maximum reduction for IDR and RTP.

The resource characteristics to be given as input attribute to the algorithm must be chosen having in mind that some characteristics lead directly to the usual grouping according to the resource type [photovoltaics (PV), wind, or hydro generation, and domestic, commercial, or industrial consumer, including the respective elasticity]. This should be avoided since the proposed methodology aims at defining the remuneration for each resource and, in fact, resources of the same type can put different value in the aggregation to a VPP.

The clusters computation is based on two methods: one using a hierarchical algorithm and the other a partition algorithm similar to K-means, the fuzzy C-means method. The hierarchical clustering is made by using the *cluster* function of MATLAB. First, the Euclidean distance between pairs of objects (resources in this case) and variables (each attribute of the resources characterization, as the case of prices, resource capacity in each scenario, etc.) is computed. Then, the linkage of the obtained data is performed, obtaining a matrix that encodes a tree of hierarchical clusters

$$D(C,\, C') \;=\; \min_{x\in C,\; y\in C'} d(x,y). \tag{1}$$

Lastly, by applying the cluster function, which basically applies (1) [13], several clusters are obtained from the agglomerative hierarchical cluster tree, as generated by the linkage function. Using the cluster function, it is possible to specify a minimum and maximum number of clusters to be computed. The results include, in this case, the resources in each cluster, in each case of number of defined clusters. The fuzzy C-means algorithm was also implemented using a MATLAB function, namely *fcm* (fuzzy C-means clustering).

This algorithm is much simpler than the previous one since it only needs an input data matrix and the desired number of groups. This method assigns different membership values to each one of the resources according to their relationship with the needed groups. The higher the membership grade is, the most likely is the resource to be assigned to the specified group. The function returns the values of the centroid of each group and the membership matrix containing each resource similarity with all of the groups. The fuzzy C-means objective function is defined by the following expression:

$$J = \sum_{t=1}^{T}\sum_{i=1}^{I} \mu_{it}^{m} d_{it}^{2}, \quad d_{it}^{2} = \|x_t - v_i\|^2. \tag{2}$$

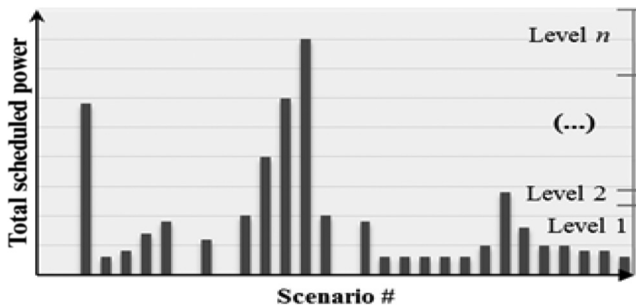

Fig. 2. Power levels using the *classregtree* function.

In the third phase of the proposed methodology, the evaluation of the economic impact of the resources' remuneration is performed based on the computed resource clusters and on the type of resource, for each cluster's scenarios. For each cluster's scenario, the remuneration of each resource is calculated. All the resources belonging to a certain cluster are remunerated at the higher price that has been established for any resource of that cluster, as determined in the second phase. In this way, the VPP is able to improve the resources' remuneration effectiveness inducing its participation in DR programs and in the resource scheduling, including DG.

This third phase also considers the establishment of decision trees. In this way, in the presence of a certain operation scenario, the VPP is able to determine the resources' levels to be scheduled without the need of having the computational tools required for performing the resource's scheduling. These decision trees have been implemented using the classregtree function of MATLAB. The function, in this context, intends to provide the VPP with the definition of power levels that can be used to quickly identify the assigned group for new resources. The following Fig. 2 exemplifies, in a generic way, the possibilities of this tool in the resources' aggregation.

Having a set of operation scenarios, e.g., for DG, the total amount of scheduled power is computed. Several scenario characteristics—average regular supplier cost; DG cost (CDG); total initial demand in the scenario; maximum available IDR; maximum available RTP; α DG; α IDR; α RTP—are also inputs to the trees' computation. According to the maximum scheduled power in a scenario, the VPP defines the number of levels to be implemented in the decision tree and the respective label. As an example, in the case study of this paper, the labels (0, 15 000, 18 000, 22 000, 25 000) have been defined as the average total power in each level.

The proposed methodology is therefore able to provide the VPP with adequate tools for the decision support, in what concerns the establishment of DG and DR programs' tariffs. This methodology is innovative, considering the work presented in [23], as follows.

1) Definition of the remuneration of distributed DR and DG resources by a VPP that operates the resources aiming the participation in DR programs, namely in what concerns the share of profits obtained in the participation in a DR program announced by an ISO.
2) Implementation of an energy resource scheduling optimization model that considers the resources' characteristics and the modeling of VPP operational constraints. Several constraints have been added to work in [23] for a better modeling of the VPP activity.
3) Definition of DG and DR resources' groups (which are usually defined according to the types of consumers and types of DG), considering other resources' characteristics, using two clustering algorithms. In [23], only one algorithm was considered.
4) Definition of different remuneration tariff groups according to the desired number of tariffs/programs to be implemented, considering a large set of operating scenarios. The larger dimension of the case study and the higher number of variables in the optimization problem lead to a largely increased number of scenarios than in [23].
5) Establishment of decision rules (decision trees) concerning the use of each type of resource in an operation scenario distinct from the previously studied ones, without the need of performing a new resource scheduling; this feature is not included in [23], so this is a main improvement contribution.

III. DG and DR Resources' Scheduling

The optimal scheduling of the energy resources is one of the main contributions of the paper, as well as an important part of the proposed methodology. This section presents the mathematical formulation of the optimization problem that solves the energy resources' scheduling.

The objective function of the optimization problem is as presented in (3). It models the minimization of the operation costs from the point of view of the VPP, by scheduling the cheaper resources in each operation context, taking into account the optimization constraints modeled by the (4)–(19).

In the proposed methodology, the VPP is able to manage all the available resources, as the case of the DG, the suppliers (available to supply power from the main network, considering regular and additional quantities contracted at distinct prices) and the consumers (participating in both IDR and RTP programs). It is important to note that the RTP part of the objective function considers the multiplication of two variables. In this way, the optimization problem becomes a nonlinear one. In the optimization problem, according to objective function (3), the DG, the suppliers, and the IDR resources are remunerated (paid by the VPP) according to the actual scheduled power. In the case of RTP, the consumers pay the actual (initial plus the price increase) price for the resulting (initial minus the reduction resulting from the response to the price signal) consumption

$$\begin{aligned}\text{Min OC} = &\sum_{p=1}^{P} P_{\text{DG}(p)} \times C_{\text{DG}(p)} + P_{\text{NSP}} \times C_{\text{NSP}} \\ &+ \sum_{s=1}^{S} \begin{bmatrix} P^{\text{reg}}_{\text{Supplier}(s)} \times C^{\text{reg}}_{\text{Supplier}(s)} \\ +P^{\text{add}}_{\text{Supplier}(s)} \times C^{\text{add}}_{\text{Supplier}(s)} \end{bmatrix} \\ &+ \sum_{c=1}^{C} \begin{bmatrix} P_{\text{IDR}(c)} \times C_{\text{IDR}(c)} \\ -(P^{\text{Initial}}_{\text{Load}(c)} - P^{\text{Reduct}}_{\text{RTP}(c)}) \times (C^{\text{Initial}}_{\text{RTP}(c)} + C^{\text{Increase}}_{\text{RTP}(c)}) \end{bmatrix}.\end{aligned} \quad (3)$$

The first constraint is the balance equation (4). The initial consumption minus the scheduled IDR and RTP consumption reductions must meet the scheduled power for all the DG units and suppliers. If it is not possible to supply the demand, it will result a certain amount of nonsupplied power. In what concerns the capacity of each resource, it has been modeled the maximum energy bought from each of the regular and additional supplier (5) and (7), respectively, and the total energy bought from all the regular and the additional suppliers (6) and (8), respectively,

$$\sum_{c=1}^{C}\left[P_{\text{Load}(c)}^{\text{Initial}} - P_{\text{IDR}(c)} - P_{\text{RTP}(c)}^{\text{Reduct}}\right] = \sum_{p=1}^{P} P_{\text{DG}(p)} + \sum_{s=1}^{S}\left[P_{\text{Supplier}(s)}^{\text{reg}} + P_{\text{Supplier}(s)}^{\text{add}}\right] + P_{\text{NSP}} \tag{4}$$

$$P_{\text{Supplier}(s)}^{\text{reg}} \leq P_{\text{Supplier}(s)}^{\text{reg Max}} \tag{5}$$

$$\sum_{s=1}^{S} P_{\text{Supplier}(s)}^{\text{reg}} \leq P_{\text{Supplier}}^{\text{reg Total}} \tag{6}$$

$$P_{\text{Supplier}(s)}^{\text{add}} \leq P_{\text{Supplier}(s)}^{\text{add Max}} \tag{7}$$

$$\sum_{s=1}^{S} P_{\text{Supplier}(s)}^{\text{add}} \leq P_{\text{Supplier}}^{\text{add Total}}. \tag{8}$$

In the case of DG units, the maximum capacity of each DG unit—in (9), the minimum capacity of each DG unit—in (10), and the maximum capacity from all the DG units—in (11) have been modeled

$$P_{\text{DG}(p)} \leq P_{\text{DG}(p)}^{\text{Max}} \tag{9}$$

$$P_{\text{DG}(p)}^{\text{Min}} \leq P_{\text{DG}(p)} \tag{10}$$

$$\sum_{p=1}^{P} P_{\text{DG}(p)} \leq P_{\text{DG}}^{\text{TotalMax}}. \tag{11}$$

Focusing on the consumers' participation in DR programs, the modeled constraints consider, for each consumer: the maximum consumption reduction capacity in the IDR program—(12); the maximum consumption reduction capacity in both the IDR and the RTP programs—(13); the maximum electricity cost increase in the RTP program—(14); and the maximum consumption reduction capacity in the RTP program—(15). The price elasticity of the consumption, important in the RTP program, is modeled as in (16) [24]

$$P_{\text{IDR}(c)} \leq P_{\text{IDR}(c)}^{\text{Max}} \tag{12}$$

$$P_{\text{IDR}(c)} + P_{\text{RTP}(c)}^{\text{Reduct}} \leq P_{\text{RTPDR}(c)}^{\text{Max}} \tag{13}$$

$$C_{\text{RTP}(c)}^{\text{Increase}} \leq C_{\text{RTP}(c)}^{\text{Increase Max}} \tag{14}$$

$$P_{\text{RTP}(c)}^{\text{Reduct}} \leq P_{\text{RTP}(c)}^{\text{Reduct Max}} \tag{15}$$

$$\varepsilon_{(c)} = \frac{P_{\text{RTP}(c)}^{\text{Reduct}} \times C_{\text{RTP}(c)}^{\text{Initial}}}{P_{\text{Load}(c)}^{\text{Initial}} \times C_{\text{RTP}(c)}^{\text{Increase}}}. \tag{16}$$

As considered by the proposed methodology, the VPP is able to define several α parameters in order to limit the participation of the resources in each operation context. In fact, the VPP may have, for any reason, the need to limit the contribution of a certain group or program. These parameters are modeled as presented in (17)–(19), respectively, for DG, IDR, and RTP. In this way, these three α parameters are limited; the sum of α can be greater than 1, since the motivation of these parameters is not to define a share of the resource scheduling

$$\frac{\sum_{p=1}^{P} P_{\text{DG}(p)}}{\sum_{s=1}^{S}\begin{bmatrix} P_{\text{Supplier}(s)}^{\text{reg}} \\ +P_{\text{Supplier}(s)}^{\text{add}} \end{bmatrix} + \sum_{p=1}^{P} P_{\text{DG}(p)} + \sum_{c=1}^{C}\begin{bmatrix} P_{\text{IDR}(c)} \\ +P_{\text{RTP}(c)}^{\text{Reduct}} \end{bmatrix} + P_{\text{NSP}}} \leq \alpha_{\text{DG}} \tag{17}$$

$$\frac{\sum_{c=1}^{C} P_{\text{IDR}(c)}}{\sum_{s=1}^{S}\begin{bmatrix} P_{\text{Supplier}(s)}^{\text{reg}} \\ +P_{\text{Supplier}(s)}^{\text{add}} \end{bmatrix} + \sum_{p=1}^{P} P_{\text{DG}(p)} + \sum_{c=1}^{C}\begin{bmatrix} P_{\text{IDR}(c)} \\ +P_{\text{RTP}(c)}^{\text{Reduct}} \end{bmatrix} + P_{\text{NSP}}} \leq \alpha_{\text{IDR}} \tag{18}$$

$$\frac{\sum_{c=1}^{C} P_{\text{RTP}(c)}^{\text{Reduct}}}{\sum_{s=1}^{S}\begin{bmatrix} P_{\text{Supplier}(s)}^{\text{reg}} \\ +P_{\text{Supplier}(s)}^{\text{add}} \end{bmatrix} + \sum_{p=1}^{P} P_{\text{DG}(p)} + \sum_{c=1}^{C}\begin{bmatrix} P_{\text{IDR}(c)} \\ +P_{\text{RTP}(c)}^{\text{Reduct}} \end{bmatrix} + P_{\text{NSP}}} \geq \alpha_{\text{RTP}}. \tag{19}$$

IV. Case Study

The proposed methodology has been applied to a case study concerning a real 30-kV distribution network, supplied by one high voltage substation (60/30 kV) with 90 MVA. A total of 937 buses accommodates 20 310 consumers of several types and DG (548 DG units) according to [25].

The peak power demand is 62 630 kW. Due to space limitations, in this paper, only the minimum network resources' data needed to apply the proposed methodology are presented; further details can be found in [25].

The 20 310 consumers connected to this network are classified into five consumer types: 1) domestic (DM); 2) small commerce (SC); 3) medium commerce (MC); 4) large commerce (LC); and 5) industrial (ID). Table I presents the information of the consumers of each consumer type, concerning the participation in the two implemented DR programs (IDR and RTP). It can be seen that large commerce and industrial consumers are not able to participate in the IDR program. Domestic and small commerce consumers are denied to participate in the RTP program. The medium commerce can participate in both the IDR and the RTP programs. Regarding the participation of the consumers in each one of the proposed DR programs, a determined maximum power reduction and the respective remuneration price were initially established for each consumer type. Table I presents the values of demand reduction costs in the IDR program and the parameters concerning the RTP program.

Concerning the power sources' characterization, we have DG units of several types, with a total capacity of 25 388 kW, and energy suppliers that are connected to the network through the main substation. Table II presents the values of prices (unitary

TABLE I
CONSUMERS AND DR PROGRAMS

Type of consumer	# Consumer	IDR		RTP		
		Capacity (kW)	Price (m.u./kWh)	Max. load reduction (kW)	Elasticity	Initial price (m.u./kWh)
DM	10 168	4684.7	0.20	0	0.27	0.21
SC	9828	3991.7	0.16	0	0.33	0.18
MC	82	5627.4	0.19	10 129.3	0.37	0.20
LC	85	0	0.18	9792.4	0.41	0.19
ID	147	0	0.14	20 828.2	0.53	0.15
Total	20310	14 303.7	–	40 749.9	–	–

TABLE II
SOURCES CHARACTERIZATION

Resource	Price (m.u./kWh)	Capacity (kW)	No. of units	Resource	Price (m.u./kWh)	Capacity (kW)
PV	0.150	7061.2	208	Supplier3	0.25(0.33)	3000(1500)
Wind	0.071	5866.0	254	Supplier4	0.23(0.29)	3000(1500)
CHP	0.001	6910.1	16	Supplier5	0.24(0.31)	3000(1500)
Biomass	0.086	2826.5	25	Supplier6	0.22(0.32)	3000(1500)
MSW	0.056	53.1	7	Supplier7	0.26(0.30)	3000(1500)
Hydro	0.042	214.0	25	Supplier8	0.23(0.30)	3000(1500)
Fuel cell	0.028	2457.6	13	Supplier9	0.21(0.32)	10000(1500)
Supplier1	0.23(0.28)	3000(1500)	–	Sup. 10	0.21(0.32)	10000(1500)
Supplier2	0.21(0.30)	3000(1500)	–	Total DG	25388.5 kW	

TABLE III
SCENARIOS SPECIFICATION

Parameter	Parameter variation			# scenarios
	Min	Step	Max	
Regular supplier cost	0.8	0.2	1.2	3
DG cost (CDG)	1	0.2	1.2	2
Total initial load	1.2	−0.2	0.8	3
IDR maximum reduction	1	0.2	1.2	2
RTP maximum reduction	1	0.2	1.2	2
α DG	0	0.3	0.6	3
α IDR	0	0.15	0.3	3
α RTP	0	0.05	0.15	4
Total number of scenarios	2592			

operation costs), the total available capacity, and the number of units for each type of DG technology. The respective values for the 10 considered suppliers are also presented. The values in brackets concern the additional supplier capacity (power and price) considered in the proposed methodology.

Taking the previous information (present in Tables I and II) into account, several operation scenarios have been implemented. Those scenarios result from the variations applied to some selected input parameters, like the more relevant and volatile ones. The input parameters are the regular supplier and distributed generators cost (CDG), the maximum reduction allowed for IDR and RTP consumers programs, the total initial load and, finally, α parameters described before (as shown in Table III). For each parameter, a minimum, a maximum, and a step on the actual scenario change have been defined. In the case of the first five parameters, the presented values are the percentage change.

In the case of α parameters, the actual parameter values in each scenario are presented. The total number of the resulting scenarios is 2592. The present case study's characteristics lead to a large number of results from the optimization of the energy resources' scheduling. Considering the variables of the optimization problem, concerning suppliers, DG, IDR, RTP (both price and consumption variations), and the nonsupplied power, each scenario' results are composed by 61 499 values. Considering the created scenarios, and the size of each scenario itself, one can conclude that the results of the resource scheduling phase are structured in a 61 499∗2592 matrix.

Considerable computational means are required in order to handle such amount of data both in the scheduling phase and in the aggregation phase, in order to provide VPP with the required decision support tools.

V. RESULTS

The application of the proposed methodology in its distinct phases to the case study presented in Section IV brings a large set of results. The energy resource scheduling optimization has been implemented in TOMLAB. For a more detailed description of the obtained results, an example scenario, referred as "selected scenario" has been selected. This scenario is characterized by the following parameters: regular supplier cost—1; CDG—1.2; total initial load—0.8; IDR maximum reduction—1.2; RTP maximum reduction—1; α DG—0.3; α IDR—0.15; α RTP—0.05. The objective function value obtained is 1056.8 m.u. Section V includes details on the selected scenario results in Sections V-A and V-B, and the results concerning all the scenarios in Sections V-C and V-D.

A. Selected Scenario—Resource Schedule

The proposed methodology includes performing an energy resource scheduling for each implemented scenario, considering its constraints. Here, the scheduling results for the selected scenario are presented. The results presented in Fig. 3 concern the resource scheduling by the type of resource.

The first column shows the contribution of suppliers, DG, IDR, and RTP; the second column shows, from the DG resources, the power scheduled in each DG unit type; finally, the third column focuses on the DR contribution by consumer's type. This information includes the total amounts per groups due to space constraints. However, it is important to note that each resource (DG unit or consumer) is scheduled individually. For better exemplification of the individual resource schedule, Fig. 4 shows the results concerning the consumers' participation in the RTP program.

For a better visualization, Fig. 4 only includes the MC consumers. Since all the consumers in this figure have the same elasticity and the same initial electricity cost, for the same consumption reduction, one will have a distinct price increase level, taking into account the distinct initial consumption for each one, according to (16).

It can be seen in Fig. 4 that for all the consumers, the same consumption reduction has been scheduled. Due to the distinct initial consumption by each consumer, and as the elasticity is

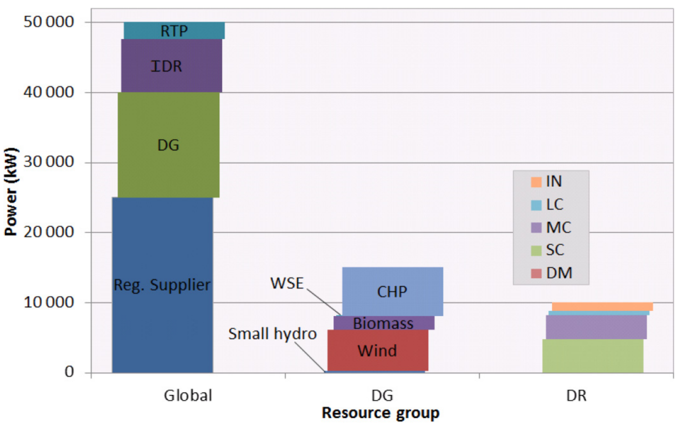

Fig. 3. Energy resources' schedule in the selected scenario.

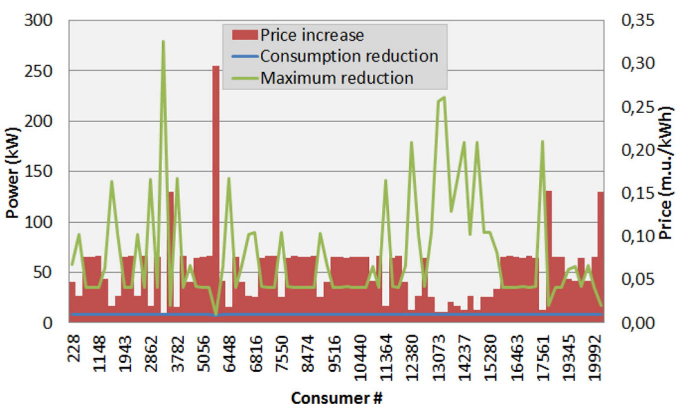

Fig. 4. Schedule results for medium commerce consumers in RTP.

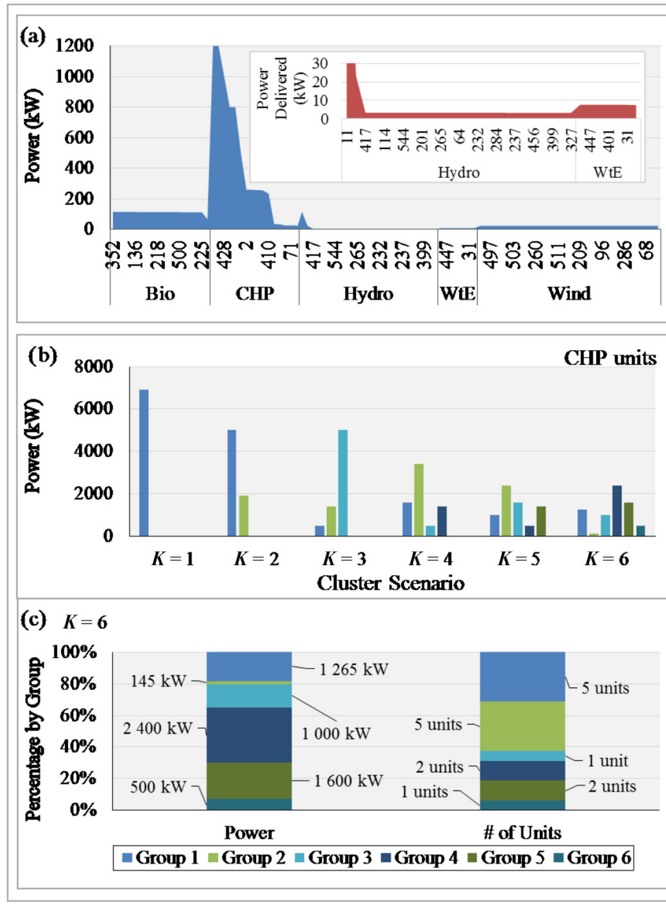

Fig. 5. CHP units in each cluster and respective scheduling. (a) Scheduled power for each DG unit. (b) Clustering results for CHP units for different clustering scenarios. (c) Distribution of CHP units among the groups.

the same for all consumers, a distinct price increase is applied. The maximum possible power reduction is also presented.

B. Selected Scenario—Aggregation and Remuneration

It is important to focus on the aggregation and remuneration of each resource, for the selected scenario, according to the proposed methodology. In Fig. 5(a), one can see the scheduled power for each DG unit. The specific case of some CHP units, with a much higher scheduled power value, must be noted as it influences the clustering process.

In Fig. 5(b), the clustering results for CHP units for different clustering scenarios (total number of $K = 2$ to $K = 6$ groups) are presented. One can see that for $K = 6$, the CHP units' distribution between the groups allows several groups to maintain a certain minimum amount of power due mostly to the large capacity of CHP units. Fig. 5(c) demonstrates, in terms of power and number of resources, the distribution of CHP units among the groups. It is interesting to observe the way that CHP units are mixed with units of other types in the clustering process. As referred before, due to space constraints, only the main important and illustrative details are presented. Similar to the results presented in Fig. 5, one also obtains the results concerning the IDR and the RTP resources' aggregation. After determining the DG units, the IDR resources, and the RTP resources' clusters, one can define the remuneration to be given to the resource in each specific cluster, and determine the number of tariff groups to be implemented, taking into account several implementation constraints.

In the present scenario and case study, the bounds of one and five clusters to be defined have also been considered for DG, IDR, and RTP resources' groups.

In Fig. 6, the consumers' bill is presented for three different types of the selected scenario, considering only the variation in the parameter αIDR: without IDR ($\alpha\text{IDR} = 0$) and with IDR ($\alpha\text{IDR} = 15\%$ and 30%). As shown in Fig. 6, without the use of IDR programs, the consumer's bill is positive. One can also see that for αIDR equal to 15% and 30%, only some of the consumers can reduce their bill and even obtain profit from the participation in DR events, as for DM and SC consumers. Also, for αIDR equal to 15%, the medium commerce was used in a certain amount, being the consumer bill less than in the other two examples, but still positive.

The results presented in Table IV concerns the DG and DR programs defined clusters, showing the total remuneration in each cluster, in monetary units (m.u.), for each case of number of clusters and for the type of resources' grouping case. In the case of DG, since the remuneration price is not the same for all the clusters in each number of clusters case, the total remuneration in each case (including the type of resource grouping case) is distinct.

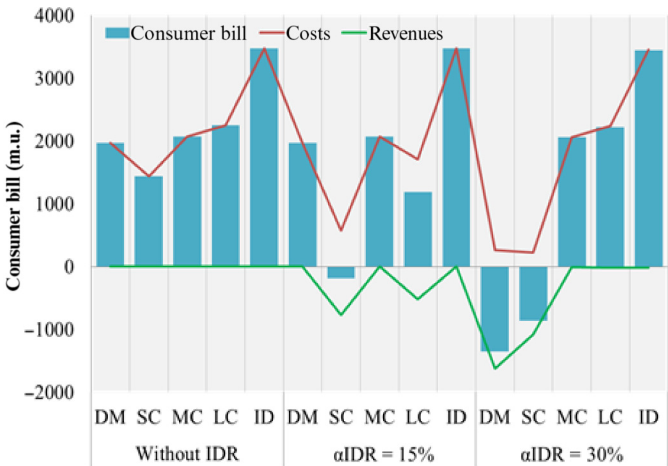

Fig. 6. Consumers' bill obtained from the scheduling.

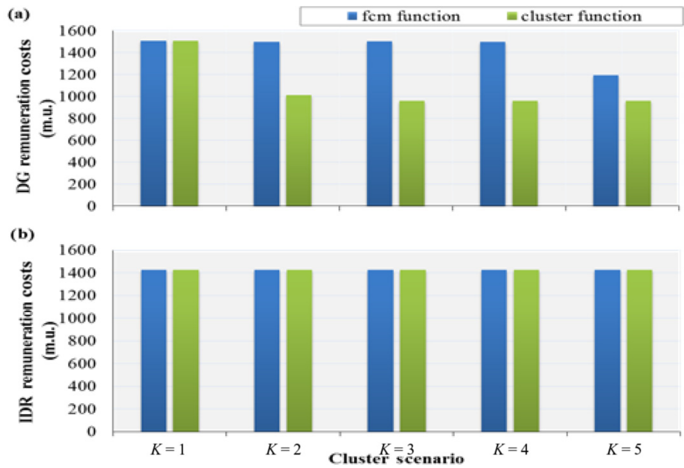

Fig. 7. Total remuneration for DG (a) and IDR (b) units.

TABLE IV
TOTAL REMUNERATION IN EACH CLUSTER

Res. cluster		Number of clusters 1	2	3	4	5	Type	
DG	1	1508	6.20	0.60	1.92	1.24	Wind	480
	2	–	1006	956	4.22	2.95	CHP	8.41
	3	–	–	6.20	0.60	1.92	MSW	3.41
	4	–	–	–	956	0.60	Hydro	10.2
	5	–	–	–	–	956	Bio	196
	Total	1508	1012	963.2	963.1	963.0	–	699
IDR	1	1427	25.2	40.12	65.08	77.76	DM	–
	2	–	1402	1362	1297	1219	SC	766
	3	–	–	25.23	40.12	65.08	MC	517
	4	–	–	–	25.23	40.12	LC	–
	5	–	–	–	–	25.23	IN	–
	Total	1427	1427	1427	1427	1427	–	1284

One can also see that by increasing the number of clusters, the value of the total remuneration paid by the aggregator (VPP) becomes lower. In the case of IDR, since in the present case-study selected scenario, only small commerce and medium commerce consumers were scheduled, and due to the large number of consumers in each type, it happened that each cluster always have at least one medium commerce consumer (that has higher remuneration price). In this way, the total remuneration paid by the VPP is the same for any number of clusters case.

As one can see in Table IV, the total remuneration is less expensive for the VPP when considering the remuneration by the type of resource. This is acceptable if it does not represent a high increase in the VPP costs and enables to achieve the goal of the proposed method (i.e., to reflect in the remuneration the importance of the resources in each scenario while not remunerating any resource at a lower tariff than expected when only the resource type is considered). According to this, the tariff for each resulting cluster is never lower than the one that the members of each cluster would profit from if the original resource-type-based tariff was applied. Ultimately, the use of the proposed method causes a slight increase in the resource remuneration costs supported by the VPP (in this case, 1427 m.u. versus 1284 m.u., i.e., an increase of 11%) but enables fairer remuneration of the resources.

One can see that for a higher number of groups, the total remuneration by group tends to decrease. The VPP is then able to discuss on the number of groups to implement according to the remuneration and the number of DR programs that is technically possible to implement.

In the case of RTP clusters, it cannot be analyzed in a similar way, since the consumers with RTP are not remunerated by the reduction. They are compensated by the way they manage the consumption according to the electricity actual price. The implemented case study considers the use of fcm and cluster functions for the aggregation of the resources. Due to space limitations, this paper focuses on the operation costs obtained from each one of the clustering algorithms. The results presented in Fig. 7 allow the comparison of remuneration results between the cluster and fcm functions used in this paper. In what concerns the number of resources in each group, it has been verified that the fcm function makes a more uniform division of resources.

This means that, while the cluster function schedules the highest resource in a separate group, the fcm function deals better with integrating more resources in that group. Obviously, this has an impact on the operation costs, since all the resources in a certain group are remunerated at the highest price. In this context, the resources that are scheduled in the same group (fcm function results) will all have the same remuneration. This is more visible in the case of DG, as can be seen in Fig. 7.

In the case of DR, since we have much more resources, such operation costs' difference is not visible. In what concerns the VPP standpoint, focusing on the DG, the fcm function use implies a higher remuneration of the resources, which is less advantageous economically. Moreover, the resources are more accurately separated in groups with the cluster function.

C. All Scenarios—Resource Schedule

Focusing now on the resources scheduling in all the scenarios, it is relevant to compare results concerning the objective function value. Fig. 8 presents representative objective function values; each one corresponds to a specific operation scenario).

While Fig. 8(a)–(d) considers the CDG parameter according to Table III equal to 1, this parameter is equal to 1.2 in

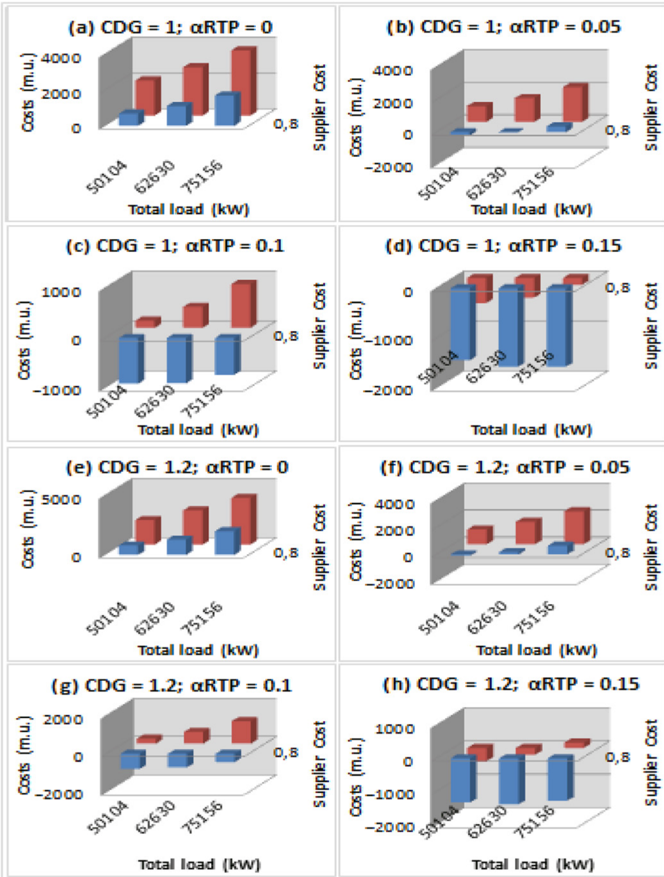

Fig. 8. Objective function results.

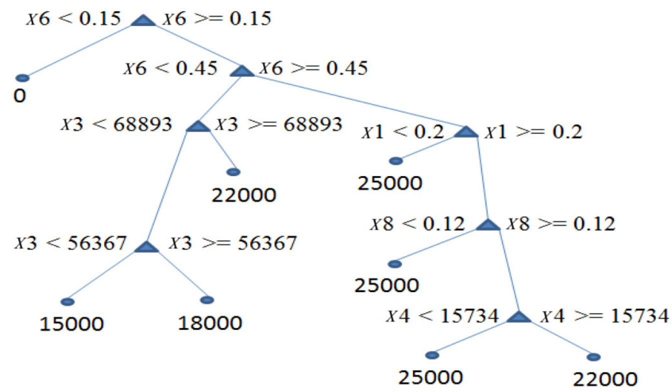

Fig. 9. Decision tree for the use of DG.

Decision rules for the use of DG & IDR & RTP.

1: if x6<0.15 then **n2** elseif x6>=0.15 then **n3** else 13754
3: if x7<0.075 then **n4** elseif x7>=0.075 then **n5** else 20713
5: if x3<68893 then **n6** elseif x3>=68893 then **n7** else 31259
6: if x6<0.45 then **n8** elseif x6>=0.45 then **n9** else 28500
7: if x8<0.025 then **n10** elseif x8>=0.025 then **n11** else 35097
8: if x8<0.125 then **n12** elseif x8>=0.125 then **n13** else 23625
9: if x8<0.025 then **n14** elseif x8>=0.025 then **n15** else 33375
10: if x1<0.207 then **n16** elseif x1>=0.207 then **n17** else 28347
11: if x1<0.207 then **n18** elseif x1>=0.207 then **n19** else 37347
13: if x3<56367 then **n20** elseif x3>=56367 then **n21** else 28500
14: if x4<15734 then **n22** elseif x4>=15734 then **n23** else 28500
16: if x4<15734 then **n24** elseif x4>=15734 then **n25** else 25250
17: if x4<15734 then **n26** elseif x4>=15734 then **n27** else 35428
18: if x8<0.125 then **n28** elseif x8>=0.125 then **n29** else 36000
19: if x8<0.075 then **n30** elseif x8>=0.075 then **n31** else 40428
25: if x6<0.45 then **n32** elseif x6>=0.45 then **n33** else 28500
29: if x6<0.45 then **n34** elseif x6>=0.45 then **n35** else 38000
30: if x7<0.225 then **n36** elseif x7>=0.225 then **n37** else 39285
2: 0; **4**: 0; **12**: 22000; **15**: 35000; **20**: 22000; **21**: 35000; **22**: 22000; **23**: 35000; **24**: 22000; **26**: 35000; **27**: 36000; **28**: 35000; **31**: 41000; **32**: 22000; **33**: 35000; **34**: 35000; **35**: 41000; **36**: 37571; **37**: 41000.

Fig. 8(e)–(h). Also α RTP, the supplier cost, and the total load in the scenario are parameters that characterize the shown scenarios. The red bars regard supplier's cost parameter equal to 1, whereas in the blue ones, this parameter is equal to 0.8. It can be seen that the increase in the total demand always increases the total operation costs. The large influence of the supplier cost on the operation costs can be seen.

In the present case study, it has been developed four decision trees: one for DG, one for IDR, one for RTP, and a last one for the simultaneous use of DG & IDR & RTP, as demonstrated in Section V-D.

D. All Scenarios—Decision Trees

The decision support tools considered in the proposed methodology also include the use of decision trees, in Fig. 9 for DG. Using this tool, along all the implemented scenarios, some representative scenario parameters are given as input:

$x1$—average regular supplier cost;
$x2$—CDG;
$x3$—total initial demand in the scenario;
$x4$—maximum available IDR;
$x5$—maximum available RTP;
$x6$— α DG; $x7$-α IDR; $x8$-α RTP.

Each one of these trees has as output the total amount of the scheduled power in the respective resource type, concerning all the implemented scenarios. Given the actual value for each input variable, it is possible to know the due scheduled power (presented in the branch terminations) concerning DG units. The rules presented concern the decision tree using DG & IDR & RTP. This tree makes possible to provide the VPP simple representations of the results when the interest is to easily determine the amount to be bought to the suppliers, which will not be covered by the rest of resources.

VI. Conclusion

The work presented here makes possible to define several groups of DG, IDR, and RTP resources, different from the traditional definition of type of resource, with advantages for the remuneration of each DG unit owner and consumer participating in DR.

The proposed methodology provides tools for a VPP to attend to technical constrains that limit the number of tariff groups to be implemented in a specific SG. Currently, the most used method corresponds to the division of consumers and distributed generators according to their types.

A clustering approach is used in this paper to define a fairer tariff group organization that takes into account not only the resource type but also the importance of each individual resource participation in the context of a specific scenario. For this purpose, the method departs from tariffs fixed for each resource type and uses clustering to catch the individual resource importance for the envisaged scenario.

The proposed methodology also uses decision trees to allow the VPP to have a set of rules that, facing an operation scenario, easily provides a result for the total amount of a resource-type scheduled in that scenario, avoiding the need of performing a complex resource scheduling.

References

[1] Z. Yang, M. Chow, G. Hu, and Y. Zhang, "Guest editorial new trends of demand response in smart grids," *IEEE Trans. Ind. Informat.*, vol. 11, no. 6, pp. 1505–1508, Dec. 2015.

[2] E. Karangelos and F. Bouffard, "Towards full integration of demand-side resources in joint forward energy/reserve electricity markets," *IEEE Trans. Power Syst.*, vol. 27, no. 1, pp. 280–289, Feb. 2012.

[3] IEA, Technology Roadmap Smart Grids, International Energy Agency (IEA), France, Tech. Rep, 2011, [Online]. Available: http://www.iea.org

[4] "Association for demand response & smart grid," Washington, DC, USA. [Online]. Available: www.demandresponsesmartgrid.org

[5] O. Kilkki, A. Alahaivala, and I. Seilonen, "Optimized control of price-based demand response with electric storage space heating," *IEEE Trans. Ind. Informat.*, vol. 11, no. 1, pp. 281–288, Feb. 2015.

[6] P. Faria, T. Soares, Z. Vale, and H. Morais, Distributed generation and demand response dispatch for a virtual power player energy and reserve provision, *Renew. Energy*, vol. 66, pp 686–695, Jun. 2014.

[7] Grayson, C., Heffner, C. A. Goldman, and M. M. Moezzi, "Innovative approaches to verifying demand response of water heater load control," *IEEE Trans. Power Del.*, vol. 21, no. 1, pp. 388–397, Jan. 2006.

[8] P. Vrba *et al.*, "A review of agent and service-oriented concepts applied to intelligent energy systems," *IEEE Trans. Ind. Informat.*, vol. 10, no. 3, pp. 1890–1903, Aug. 2014.

[9] J.L. Mathieu, D.S. Callaway, and S. Kiliccote, "Examining uncertainty in demand response baseline models and variability in automated responses to dynamic pricing" in *Proc. 50th IEEE Conf. Dec. Control (CDC-ECC'11)*, Dec. 12–15, 2011, pp. 4332–4339.

[10] H. Morais, T. Pinto, Z. Vale, and I. Praça, "Multilevel negotiation in smart grids for VPP management of distributed resources", *IEEE Intell. Syst., SI "Sustain. Energy Distrib. AI"*, vol. 27, no. 6, pp. 8–16, Nov. 2012.

[11] "Handbook of renewable energy technology," in *Renewable-Based Generation Integration in Electricity Markets With VPPs*, A. F. Zobaa and R. C. Bansal, Eds. Singapore: World Scientific Publishing Co, Jan. 2011, pp. 637–670.

[12] Z. Vale, H. Morais, S. Ramos, J. Soares, and P. Faria, "Using data mining techniques to support DR programs definition in smart grids", in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 24–29, 2011, pp. 1–8.

[13] G. Gan, C. Ma, and J. Wu, Data clustering: Theory, algorithms, and applications, in *ASA-SIAM Series on Statistics and Applied Probability*. Philadelphia, PA, USA: SIAM, 2007.

[14] L. Kaufman and P. Roussesseeuw, *Finding Groups in Data: An Introduction to Cluster Analysis*. Hoboken, NJ, USA: Wiley, 1990.

[15] V. Figueiredo, F. Rodrigues, Z. Vale, and J. B. Gouveia, "An electric energy consumer characterization framework based on data mining techniques" *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 596–602, May 2005.

[16] G. Chicco, R. Napoli, P. Postulache, M. Scutariu, and C. Toader, "Customer characterization options for improving the tariff offer", *IEEE Trans. Power Syst.*, vol. 18, no. 1, pp. 381–387, Feb. 2003.

[17] M. Parvania, M. Fotuhi-Firuzabad, and M. Shahidehpour, "Optimal demand response aggregation in wholesale electricity markets," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 1957–1965, Dec. 2013.

[18] W. Labeeuw, J. Stragier, and G. Deconinck, "Potential of active demand reduction with residential wet appliances: A case study for belgium", *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 315–323, Jan. 2015.

[19] M. A. Ortega-Vazquez, F. Bouffard, and V. Silva, "Electric vehicle aggregator/system operator coordination for charging scheduling and services procurement", *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1806–1815, May 2013.

[20] A. Mnatsakanyan and S. W. Kennedy, "A novel demand response model with an application for a virtual power plant", *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 230–237, Jan. 2015.

[21] J. Kwac, J. Flora, and R. Rajagopal, "Household energy consumption segmentation using hourly data", *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 420–430, Jan. 2014.

[22] K. Wang, Z. Ouyang, R. Krishnan, L. Shu, and L. He, "A game theory-based energy management system using price elasticity for smart grids", *IEEE Trans. Ind. Informat.*, vol. 11, no. 6, pp. 1607–1616, Dec. 2015.

[23] P. Faria and Z. Vale, "Remuneration structure definition for distributed generation units and demand response participants aggregation", in *Proc. IEEE PES Gen. Meeting Conf. Expo.*, Washington, DC, USA, Jul. 27–31, 2014.

[24] R. A. Arnold, *Economics*, 9th ed. Mason, USA: South-Western College Pub, 2008.

[25] P. Faria, J. Soares, Z. Vale, H. Morais, and T. Sousa, "Modified particle swarm optimization applied to integrated demand response and dg resources scheduling," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 606–616, Mar. 2013.

Pedro Faria, (M'15–S'10) photograph and biography not available at the time of publication.

João Spínola, photograph and biography not available at the time of publication.

Zita Vale, (SM'10–M'93–S'86) photograph and biography not available at the time of publication.