Economic Impact of Demand Response in the Scheduling of Distributed Energy Resources

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***Abstract*—Demand Response (DR) allows consumers to participate in energy markets, thus assuming an active role. However, the need of an aggregator capable of managing these resources and making decisions accordingly with the objectives of such resources has not been fully addressed. The aggregator activities are complex, and therefore, in the need of intelligent support to accomplish reasonable solutions. This paper proposes a methodology to evaluate the advantages of using DR programs in the resource rescheduling while classification and regression trees are introduced to support the aggregator in terms of scheduling and tariffs definition. Often these techniques are used to help the aggregator decide, as they also learn through training. Focus is given to the use of trees to predict and decide, the consumers' prices and reduction levels to apply, respectively. The case study has 548 distributed generators, 10 external suppliers and 20310 consumers.**

NOMENCLATURE

Variables

$P^{supplier}$	Scheduled power in supplier
P^{DG}	Scheduled power in a DG unit
P_{NSP}	Non supplied power
$\Delta C^{Reduced}{}_{DR}$	Price variation after energy cut
$P^{Reduced}{}_{DR}$	Reduced energy through DR

Parameters

$C^{supplier}$	Supplier cost
C^{DG}	Distributed generation cost
C_{NSP}	Non supplied power cost
$C^{reg}{}_{supplier}$	Regular supplier cost
$P^{Max.supplier}$	Maximum power schedule for suppliers
$P^{Max.DG}$	Maximum power schedule for DG resource
P_{Load}	Total consumption value
$I^{Total}{}_{DR}$	Total incentive to consumers participating in the demand response program
B^{Total}	Bill for all consumers without DR
$B^{Total}{}_{DR}$	Bill for all consumers with DR
$C^{Initial}{}_{DR}$	Initial energy price for all consumers
$P^{Max}{}_{Prod}$	Maximum production value registered

Indexes

N	Maximum number of producers n
K	Maximum number of suppliers k
T	Maximum number of scenarios t

The present work was done and funded in the scope of the following projects: EUREKA - ITEA2 Project SEAS with project number 12004; ELECON Project, REA grant agreement No 318912 (FP7 PIRSES-GA-2012-318912); H2020 DREAM-GO Project (Marie Sklodowska-Curie grant agreement No 641794); and UID/EEA/00760/2013 funded by FEDER Funds through COMPETE program and by National Funds through FCT.

I. INTRODUCTION

Today's power systems are unsustainable due to their high fossil fuel consumption and ambient hazard residues [1], [2]. However, not only production has to be reformulated, but also the consumers need to be sensitized to an efficient use of electricity or even integrated together with alternative sources as ancillary services. Distributed Generation (DG) has been introduced in order to address several actual issues [3], [4]. This type of production, unlike centralized, is characterized by small size generators near consumption centers.

For the consumers, Demand Response (DR) is applied [5]. DR is usually defined as the modification of electricity consumption patters' by consumers, regarding a response to price elasticity signals or monetary incentives. DR consists of two types, depending on which form comes the benefit to the consumer: incentive and price based (elasticity), [6].

DG and DR can be used to reduce energy dependency from fossil fuels, thus reducing transmission costs. In this way, by reducing energy delivery costs, electricity tariffs can be improved from a consumers' perspective, i.e., a top-bottom structure dictates that consumers pay for the inefficiency of power systems. Distributed resources can cause a significant change in power systems operation, dealing with these issues.

978-1-4799-7560-0/15 $31.00 © 2015 IEEE
DOI 10.1109/SSCI.2015.218

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Although distributed resources present several advantages, their integration is complex and not as immediate as one may assume [7]. In this way, an aggregator entity is necessary to fully manage the distributed resources, dealing with technical and commercial issues [8], [9] and [10]. The aggregator, when defining the resources dispatch, can use DR and DG to reduce the amount of power bought to external suppliers, and consequently, reduce the energy price applied to the consumers. The aggregator needs to quickly decide how to perform these activities, taking into consideration the production scheduling.

All the needed operations described above, require a certain level of autonomy and intelligence that is not accomplished by conventional applications. Artificial intelligence applications have become the most adequate techniques to deal with such problems (economic dispatch, scheduling, etc.). Classification and regression trees have become a widely used tool for decision support, since they use simple rules to trace a path to the outcome making it more understandable. In [11], the authors proceed to the economic and environmental evaluation of DR integration in the scheduling. In [12], a discussion is made for economic potential of DR integration in power systems.

After this introductory section, the proposed methodology is explained in Section II and the mathematical formulation in Section III. Further, Section IV details the case study applied in this paper, Section V the results obtained from the case study, and the conclusions are presented in Section VI.

II. Proposed Methodology

The implemented methodology is fully explained in this section, as shown in Figure 1. The purpose of the current paper is to provide the resources aggregator with techniques that enable it to perform the resources scheduling, reconfigure it, and introduce consumers' with active contribution to a cost and tariff reduction. Four phases are used: data input and treatment, resources scheduling, DR introduction, and finally, new consumer tariff definition.

In the first phase, the suppliers and distributed generators characteristics are defined. Different levels of total consumption are computed in order to form several operational scenarios for the scheduling. In phase two, the resources scheduling is performed without considering DR. The optimization criteria and restraints are implemented in TOMLAB [13]. The consumption variation referred above, is obtained using *randi* function of MATLAB [14], that gives random values between two limits: maximum load of the consumers, and a minimum load of 10 MW. Phase three initiates and thus the demand response integration.

The next step is to compute the initial global tariff applied to the consumers through the calculation of the weighted average of the producers' energy prices. DG was considered by type, while external supplier are separate individuals. In each of the three reduction levels (implemented in each scenario), the new price is computed in the same way as before. With these reductions, the new electricity price will be lower and the reduced energy will be balanced by the contribution of DR participants, reducing the aggregator production costs. Only one type of DR program is considered –an incentive based program – compensating the contributions of the consumers, with monetary amounts. These incentives are obtained by splitting the energy price variation in two. In this way, half of the reduced cost is subtracted to the original price and applied to all of the consumers in the network, while the other half is paid as incentive to the consumers participating in the DR program. DR economic impact in the total cost of the scenarios and global tariff reduction corresponds to the fourth phase. This phase is a decision stage, where the aggregator must evaluate the different outcomes that the three levels create and choose from them to obtain the desired energy tariff (to be applied to the consumers). In the tariff definition, the aggregator can work together with a consumers association so that the choice may tend to benefit both sides.

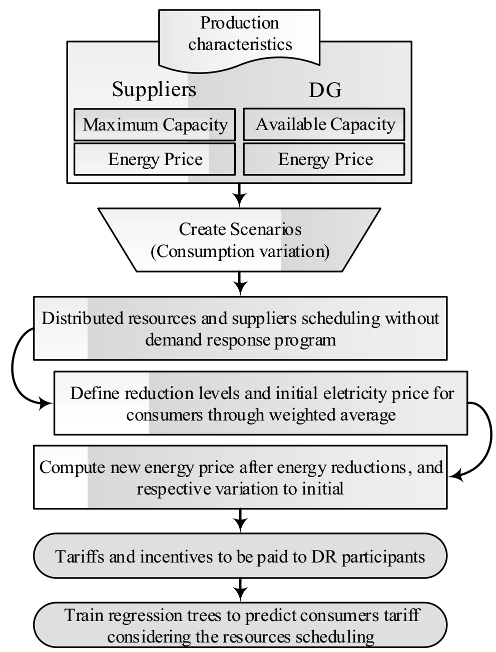

Figure 1. Methodology characterization.

In this paper, for the decision support it was implemented decision trees capable of aiding the user with a relative intuitive method (Figure 2). Classification and regression trees are variations of decision trees, where, through several iterations, the data is divided into smaller groups or areas. These groups contain some observations relative to the variables or predictors, given as input.

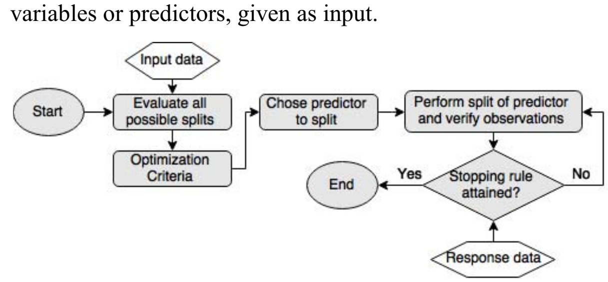

Figure 2. Decision trees process.

Considering regression trees, before dividing any of the predictors it is analyzed, using an optimization criteria, each one of the predictors (variables) possible binary splits. The predictor chosen to be divided, is the one with the best optimization criteria value, since this is performed in each iteration. This criteria is given, for the present paper, by the Mean Squared Error (MSE). The stopping criteria for splitting the predictor is also defined by the MSE, however, there are other ways to perform this evaluation, as shown in [15]. The term "pure set" is often used to address the stopping criteria, since this is obtained considering that the MSE drops below a certain defined value. The predictions made by the tree, are then compared with the actual response for best adjustment of the rules formed during each iteration.

In classification trees, the stopping rule is in a way simpler, since the pure sets are obtained when, splitting the predictors one obtains observations of the same classification value. For the optimization criteria, exists several measures that can be implemented (the Gini's diversity index is usually used).

The regression and classification trees are created using the MATLAB functions, *fitrtree* and *fitctree*, respectively. The inputs of the tree, in training, are matrix X and a vector Y (further detailed). The proposed methodology intends to create market opportunities for the aggregator to introduce DR programs, while reducing its operational costs. The aggregator can chose between different reduction levels in order to obtain better energy prices for the consumers. This paper intends to present the following features.

- Scheduling of production, without DR resources;
- Consideration of several reduction levels, accordingly with the DR capacity;
- Incentives determination method for compensation of consumers contributions;
- Appliance of regression and classification trees as decision support techniques for the aggregator.

III. MATHEMATICAL FORMULATION

The mathematical formulation for the optimization and economic evaluation is presented in this section. The objective function considers the minimization of DG and suppliers cost, without the participation of DR reductions. Only two types of resources are considered: DG and suppliers, and the "non-supplied energy" generator. The objective function was implemented as shown in Equation (1), representing the minimization of operation costs.

$$Min\ Costs = \sum_{n=1}^{N} P_{(n)}^{DG} \times C_{(n)}^{DG} + \\ + \sum_{k=1}^{K} P_{(k)}^{Supplier} \times C_{(k)}^{Supplier} + P_{NSP} \times C_{NSP} \quad (1)$$

The variable identified by NSP, corresponds to a fictitious generator that will compensate in case of the rest of the producers aren't able to provide enough energy for the demand level. Following Equation (1), comes the first restriction which maintains the network in correct operation (production must equal the consumption at every moment). The balance of the network is guaranteed by Equation (2).

$$P_{Load} = \sum_{n=1}^{N} P_{(n)}^{DG} + \sum_{k=1}^{K} P_{(k)}^{Supplier} + P_{NSP} \quad (2)$$

As said before, now is necessary the definition of capacity limits to every type of resource. These restrictions are represented for DG, Equation (3), and Suppliers, Equation (4).

$$P_{(n)}^{DG} \le P_{(n)}^{Máx.DG},\ \forall n \in \{1, \dots, 548\} \quad (3)$$

$$P_{(k)}^{Supplier} \le P_{(k)}^{Máx.Supplier},\ \forall k \in \{1, \dots, 10\} \quad (4)$$

After the scheduling, the replacement of producers' generation by consumers' reductions is performed. For the consumers' contribution, an amount of monetary incentives have to be computed using Equation (5). As said before, the consumers that don't actually participate in the DR program, also benefit from others reduction. These consumers bill is calculated as shown in Equation (6), while the consumers that indeed participate in the DR program have a bill demonstrated by Equation (7).

$$I_{DR}^{Total} = \frac{\Delta C_{DR}^{Reduced}}{2} \times P_{DR}^{Reduced} \quad (5)$$

$$B^{Total} = \left(C_{DR}^{Initial} - \frac{\Delta C_{DR}^{Reduced}}{2} \right) \times \left(P_{Load} - P_{DR}^{Reduced} \right) \quad (6)$$

$$B_{DR}^{Total} = \left[\begin{array}{c} \left(C_{DR}^{Initial} - \frac{\Delta C_{DR}^{Reduced}}{2} \right) \\ \times \left(P_{Load} - P_{DR}^{Reduced} \right) \end{array} \right] - I_{DR}^{Total} \quad (7)$$

The predictions made, using regression trees, were evaluated using the Mean Absolute Percentage Error (MAPE) and the Root Mean Square Error (RMSE), defined by Equation (8) and (9), respectively.

$$MAPE = \frac{1}{T} \times \sum_{t=1}^{T} \left| \frac{actual_t - forecast_t}{actual_t} \right| \quad (8)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T} \left| actual_t - forecast_t \right|^2}{T}} \quad (9)$$

IV. CASE STUDY

The case study used in this paper, consists of 548 distributed generators, ten external suppliers and 20310 consumers in a 30kV distribution network with 937 buses, and supplied by one high voltage substation (60/30kV) [16].

Consumption has a maximum value of 62.63 MWh. As explained before this is accomplished using a random number function, *randi function*, from MATLAB.

DG resources are divided into seven distinct types: Wind, Biomass, Photovoltaic (PV), Waste-to-Energy (WtE), Cogeneration (CHP), Small Hydro and Fuel Cell (FC). In Table I the characterization of these resources is presented. The last column is referred to the capacity of each type of resource (same for Table 2), considering the total amount delivered by production. As shown in Table I, the external suppliers are the main source of energy in terms of installed capacity, reaching almost 41 MW.

TABLE I. DG RESOURCES CHARACTERIZATION.

Type	# Resources	Capacity (kWh)	Average Price (€/kWh)	Total Percentage (%)
Wind	254	5866,09	0,07	8,84
Biomass	25	2826,58	0,08	4,26
CHP	16	6910,10	0,00	10,41
Small hydro	25	214,05	0,04	0,32
WtE	7	53,10	0,05	0,08
Fuel cell	13	2457,60	0,09	3,70
PV	208	7061,28	0,14	10,64
Ext. Supplier	10	40974,00	0,26	61,74

The external suppliers were considered as separate individuals, thus Table II is presented to specify these resources characteristics. Considering the consumers' characteristics, these are divided by five types: Domestic (DM), Small Commerce (SC), Medium Commerce (MC), Large Commerce (LC) and Industrial (ID).

For the definition of reduction levels, it is important to evaluate the capacity of demand response program participants, in order to guarantee the capability of replacement by consumers. The present case study has a capacity of forty percent (25.75 MWh) of the maximum total load. In this paper, it was considered three reduction levels that correspond to ten, twenty and thirty percent energy reduction (level one, two and three, respectively). Each of these levels causes an energy reduction that the consumers participating in the DR program will have to compensate. In this way, the most expensive producers are replaced allowing a cut in operational costs.

TABLE II. SUPPLIERS CHARACTERIZATION.

Type	Capacity (kWh)	Price (€/kWh)	Total Percentage (%)
Supplier 1	4802	0,247	11,72
Supplier 2	4894	0,286	11,94
Supplier 3	4213	0,219	10,28
Supplier 4	4740	0,225	11,57
Supplier 5	3742	0,262	9,13
Supplier 6	3029	0,296	7,39
Supplier 7	3983	0,287	9,72
Supplier 8	3305	0,281	8,07
Supplier 9	4913	0,257	11,99
Supplier 10	3353	0,258	8,18

The known characteristics of these resources allows us to determine our output data matrix. The number of lines is equal to the sum of all of our resources, so 561 lines (DG – 548, Suppliers – 10, NSP – 1, objective function value and result message). The number of columns is equal to the wanted scenarios that in this case will be fifteen. In each scenario, the three reduction levels are applied and the new electricity prices are computed. After this, the prices applied, to in and out DR program consumers, are calculated according with the variation compared to the initial price and the incentives are obtained.

V. RESULTS

In this section, a discussion is made to the obtained values for the second, third and fourth phase. The presented results, in exception for the classification and regression trees, were obtained considering always the same fifteen scenarios.

In Figure 3, the resources scheduling before reduction is presented. The resources are organized by unitary energy price in ascent order, i.e., the least expensive resource is placed at the bottom, while the most expensive is on top, for each of the considered scenarios. One can see by Figure 3 and Table I, that CHP is the cheapest resource and external supplier 6 the most expensive. The total load value will determine which resources are necessary to be used, therefore, some aren't needed in the scenarios considered.

Small Hydro and WtE, are very low in terms of delivered energy causing a difficult visualization of their values in the graph, between CHP and Wind. Figure 4, in similarity with Figure 3, presents the same scenarios costs per type of resource, i.e., the cost corresponding to the amount of energy bought from each resource. It is possible to see that in several occasions, an equal amount of energy is more expensive for some resources than for others. After the scheduling, one must define which reduction level is to be used in order to obtain a better electricity price for the consumers. In order to present the methodology, all of the reduction levels are presented, but for not all scenarios due to space limitations.

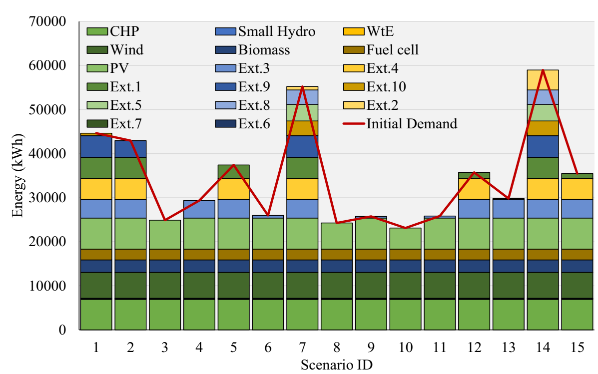

Figure 3. Total production scheduling.

This scheduling, as an optimization problem, is obtained using TOMLAB. The cut order or level will determine the variation between final and initial price that also depends from the scenario consumption. When considering the calculation of all reduction levels in each scenario, the number of outputs grows to 45 lines, since one has three results per scenario.

Also, six columns can be extracted as output from the data treatment after the scheduling phase.

The six columns represent the chosen parameters to output the algorithm: reduction level number, initial energy price, the identification of the last resource to be reduced, the amount and percentage of energy reduced, and finally, the global energy price after reduction. After the reduction results, one can compute the global tariff after reduction and the price variation between before and after the reduction. The price variation is then divided in half, guaranteeing the benefit for both types of consumers, i.e., the ones who participate in DR programs and those who don't.

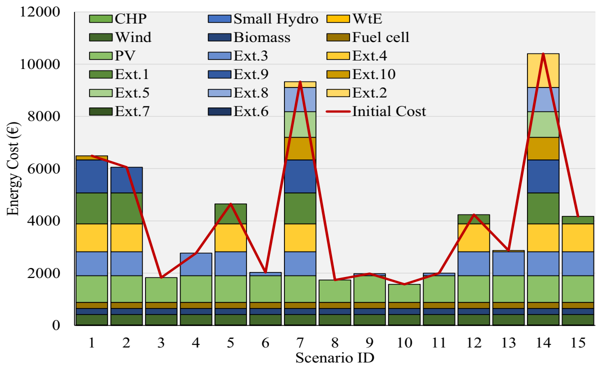

Figure 4. Total scheduling cost.

The consumers without contribution in the DR program, benefit from a reduction in their energy price using half of the price variation to subtract to the initial price – Equation (6). Consumers that do participate in the DR program, have obviously more advantages. As consumers that don't contribute for demand decrease, DR participants have a decrease in the initial price, but additionally, receive incentives – Equation (5). DR consumers have a bill as showed in Equation (7). Table III describes the prices operations to obtain the final price applied to all consumers. Only two scenarios are considered.

TABLE III. FIRST TWO SCENARIO RESULTS – PRICES

Scenario	Level	Initial Price (€/kWh)	Final Price (€/kWh)	Price Variation (€/kWh)	Tariff(€/kWh)
1	1	0,1454	0,1329	0,0124	0,1391
	2	0,1454	0,1184	0,0269	0,1319
	3	0,1454	0,1022	0,0431	0,1238
2	1	0,1410	0,1282	0,0128	0,1346
	2	0,1410	0,1134	0,0276	0,1272
	3	0,1410	0,0974	0,0436	0,1192

The initial tariff, price variation and the final tariff applied to consumers, are presented in Figure 5. For each scenario, the three reduction levels were implemented, obtaining therefore three times the number of scenarios for the results.

Figure 5, is easily attained when considering the calculations demonstrated in Table III, being the price variation in the secondary y-axis.

Obviously, by applying the highest reduction level (third level), one will obtain the best tariff reduction and the biggest price variation, however, the aggregator must consider some rules of reduction in order to overcome this issue. Per example, when the energy reduction effects the distributed generation, it is best to not apply a level superior to 10%, since some of these resources may have priority in terms of use. Per example, if the aggregator defined that the electricity price had to be at maximum 0.16 €/kWh, in some scenarios is necessary the use of the reduction levels. For this example, scenarios 7 and 14 have to be applied the reductions levels two or three, in order to obtain a price equal or inferior to the desired by the aggregator.

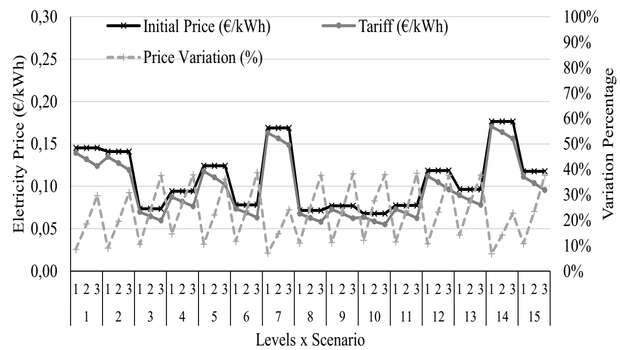

Figure 5. Total production scheduling.

Figure 6 allows us to verify what was been mentioned before: the higher the price variation, greater will be the incentives to be paid to the DR participants. Thus, it is also dependable of the generation prices because they define the weighted tariff.

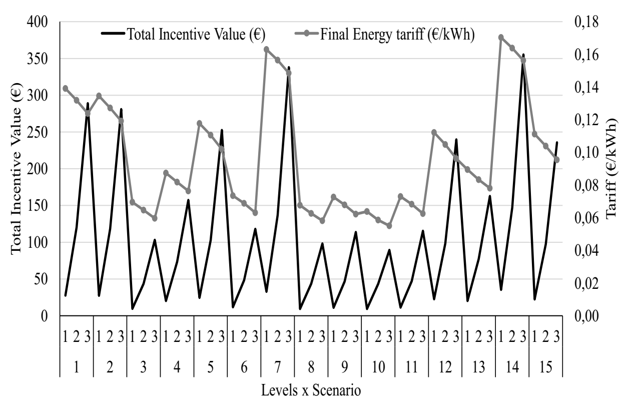

Figure 6. Total production scheduling.

The incentive value for DR participants is computed considering the energy reduced in each level, with half of the price variation. In this way, one obtains a monetary incentive, as showed in Equation (5). Table IV shows the results obtained for the total costs before and after the reduction levels are applied. Also, the total incentive value is presented in the last column, in the respective monetary unit. This incentive value corresponds to the total amount that will be distributed by the DR participants.

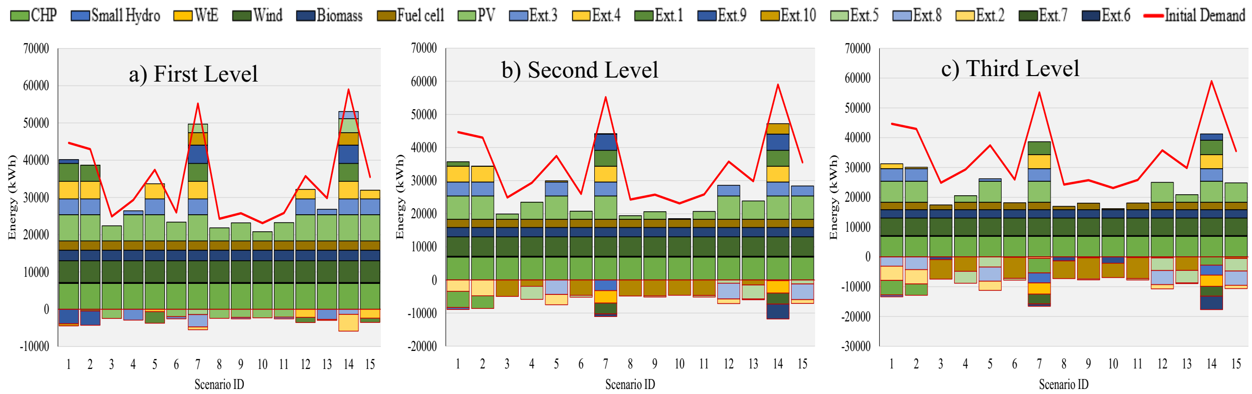

Figure 7. Reduced energy levels.

TABLE IV. FIRST TWO SCENARIO RESULTS – TOTAL COSTS

Scenario	Level	Initial Cost (€)	Final Cost (€)	Total Cost Variation (%)	Total Incentive Value (€)
1	1	6490,1	5591,3	13,9	27,8
	2		4711	27,4	120,3
	3		3868,9	40,4	288,9
2	1	6055,5	5203	14,1	27,4
	2		4370,7	27,8	118,4
	3		3583,7	40,8	280,8

In Figure 7, the influences of the different levels implementation is showed (a, b, and c), namely, the energy reduction verified on each of the scenarios. By these subplots, one concludes that the cost reduction percentage is clearly superior to the energy reduction percentage, due to expensive producers being withdrawn and replaced by DR reductions.

Per example, in the first level (Figure 7 – a), only 10% of the total load is decreased, however the costs reduced are superior to 10% since the cut is applied by descent order, i.e., the most expensive resources are the first to be reduced. The red line defines the initial consumption. In all plots of Figure 7, reduced energy is shown as negative. The energy reduced by the producers, is replaced by the reduction of consumption by the consumers participating in the DR program. Depending on total consumption, different resources will be used, i.e., in some occasions the distributed generators delivered energy will be sufficient to satisfy demand.

In this case, one assumes that this can be done since no priority is given to the energy delivered from renewable sources. In the opposite way, a larger amount of consumption will result in a higher amount of energy bought from external suppliers, since the DG won't have enough capacity. In this way, reductions to external suppliers are most welcome, since the aggregator wants to reduce its network energy dependency and exterior activities.

In sum, the use of a DR program to reduce operational costs in the aggregator network, can support several benefits for the aggregator itself and for the consumers. The aggregator can reduce its expenditure with production and reduce the related issues, as energy losses, transmission and distribution, and improve the network reliability, etc. For the consumer, it can help reduce the energy prices, through the same features mentioned before.

After obtaining the prices wanted, one must now consider the use of regression and classification tree so that posterior scenarios can be evaluated in an easier and quicker way. Regression trees allow the data prediction considering a training phase, where the tree is given a certain dataset with the solution. In this way, the tree is able to learn rules from this data and solve future problems based on the same learning.

For the regression tree, in this paper it was considered a separation of processes, i.e., the reduction levels were computed into individual trees. As said before the tree needs a training set to learn, composed of two elements, input data (question) and target (solution). In this paper, the purpose of such trees is to determine the tariff for all consumers, to be applied to each of the reduction levels considering the input data given. In this context, our targets in training are three column vectors containing the prices obtained from the three reduction levels (as in Table III) separately. The input data considered for the training of each tree differs. For all of the level reduction trees, one considers the following common variables: the energy scheduling before reduction for each of the producers (Table I and II), scenario consumption, and finally, the total scenario cost. In addition to these variables, accordingly with the reduction level, the following were considered: initial energy cost, last reduced resource identification, the amount of energy reduced and finally, the energy price after energy cut.

For the trees training, a larger set of scenarios was considered in order to improve the results of the prediction made, since less training scenarios implicates a poorer training and learning.

With only 15 scenarios, the error obtained from validation was clearly higher and the trees decision rules are not as interesting.

The trees shown in Figure 8, were trained on the basis of four different training sets for predictions – 50, 200, 500 and 1000 scenarios. After the training, the trees were used to predict the consumers applied tariffs for the scenarios presented in Figure 2 to 6. The following Table V, presents two performance indicators for the regression predictions (MAPE and RSME).

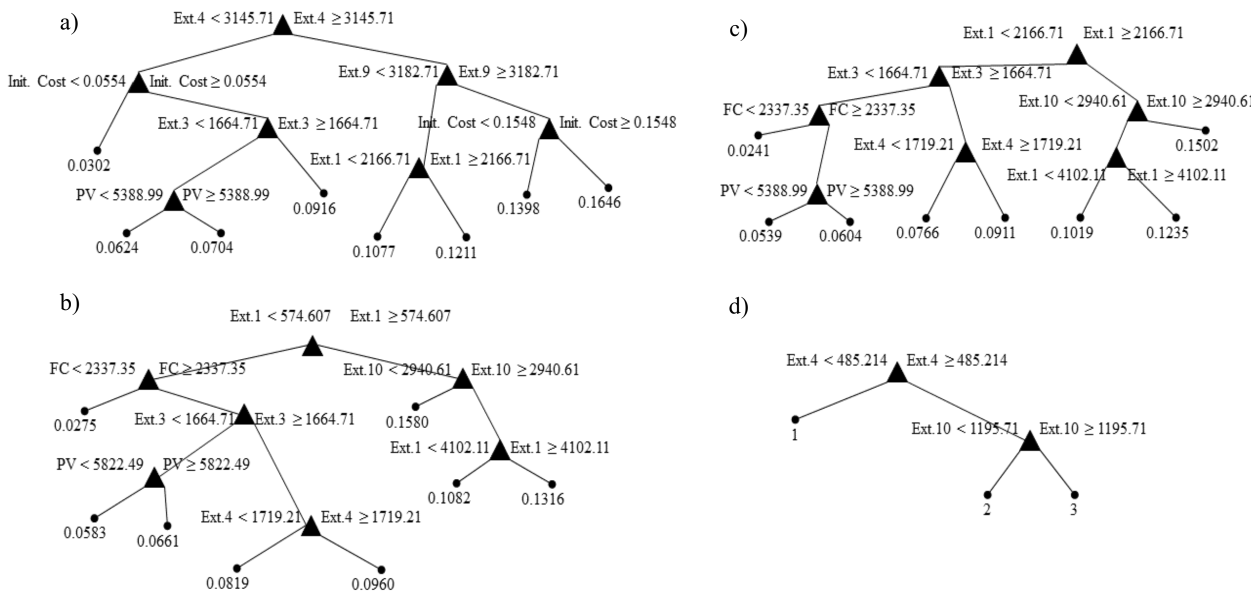

Figure 8. First, second, third level regression tree (a, b and c) and classification tree (d).

TABLE V. INDICATOR VALUES IN TRAINING

Indicator	Training Set	50	100	200	500	1000
MAPE	1º Level	0,0733	0,0423	0,0340	0,0084	0,0029
	2º Level	0,0731	0,0352	0,0382	0,0085	0,0047
	3º Level	0,1134	0,0343	0,0222	0,0073	0,0047
RMSE	1º Level	0,0074	0,0042	0,0035	0,0009	0,0004
	2º Level	0,0070	0,0037	0,0037	0,0008	0,0005
	3º Level	0,0110	0,0033	0,0022	0,0007	0,0004

As said in Section II, the trees need two inputs in order to make the regression/classification, X and Y. Matrix X is composed by the power schedule, global initial tariff and initial consumption (number of scenarios as lines and nineteen columns – seven types of DG plus ten suppliers (17), 2 columns for initial tariff and initial consumption). Vector Y, is the final price applied to all the consumers without incentives.

When testing each one of the trees, it was considered again fifteen scenarios, changing between 10 MWh and the total load of the network, 62.63 MWh. The predictions were performed using the *predict* function from MATLAB, usually used together with the tree functions mentioned in the proposed methodology – Section II.

Regarding the classification tree, it is implemented in order to support the decision on which of the reduction levels is to be used according to the initial resources scheduling, the demand value and total scenario cost (X, as in regression). The choice between each of the reduction levels was made considering the total production scheduled. The following rules in Equation (10) assign to each scenario, a reduction level. One of the main advantages of decision trees, is their easy interpretability or understanding, i.e., one can easily comprehend the information demonstrated.

$$\begin{cases} Level\ 1, & for\ other\ situation \\ Level\ 2, & \dfrac{P_{Prod}^{Max}}{2} < Total\ Production \le \dfrac{3P_{Prod}^{Max}}{4} \\ Level\ 3, & \dfrac{3P_{Prod}^{Max}}{4} < Total\ Production \le P_{Prod}^{Max} \end{cases} \tag{10}$$

In Figure 8.a to 8.c, the regression trees obtained are made considering a training set of 50 scenarios, although in order to predict the prices and classify scenarios they were trained with several sets, as referred before. Each leaf of the tree minimizes the mean square error in order to correspond with the solution given (Y matrix) through iterative operations, creating a regression model. When a pure set is found, the leaf corresponds to a value, whereas if not, another variable is chosen in order to find a pure set.

Considering these rules, one obtains the response vector (Y, as in regression) to create the classification tree. The obtained classification tree is demonstrated in Figure 8.d.

In Figure 8.d, the tree tells us that if external supplier number four has a scheduling inferior to 0.485 MWh, the reduction level to be applied is the first. Else, we have to consider another variable – the scheduled energy from external supplier number 10. If supplier 10 has a scheduled power inferior to 1.2 MWh, then one shall apply the second reduction level, else, apply third reduction level. The logic applied to the classification tree is the same for regression reduction level trees. This classification tree is very simple mostly because, our variation throughout the scenarios is only made at consumption level, and consequently, the resources scheduling. In this way, one can see the options made by the tree to determine which variables are responsible for the classification of reduction levels, considering each scenario.

VI. CONCLUSIONS

In this paper, a reconfiguration of dispatch considering the use of an incentive-based demand response program is presented. The proposed methodology presents an economic reduction, by replacing the most expensive producers with energy reductions of DR consumers, guaranteeing the benefit of both aggregator and consumer. For this, three reduction levels are considered, accounting for the DR capacity. In this way, the aggregator reduces its operational costs, while consumers obtain lower tariffs and monetary incentives for their contribution to the DR program.

Also, classification and regression trees were implemented in order to obtain consumers price predictions, using the performed scheduling and its initial tariffs. The trees were performed individually for each of the three reduction levels, therefore, obtaining a total of three prices per scenario. In this way, each tree can aid the aggregator to define the most advantage situation for consumers and cost minimization for production. The implemented classification tree intends to provide the aggregator with an easy decision in what concerns which reduction level is more adequate to use in each scenario/situation.

In sum, this paper presents a simple methodology for the economic evaluation of a possible integration of DR programs in power systems and in the scheduling problem.

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