A Consumer Trustworthiness Rate for Participation in Demand Response Programs

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Abstract: Local energy communities with information from the real-time market may improve the market operation but also increase the complexity of the management problem thanks to the uncertainty associated with the actual response of these resources. For instance, consumers with price knowledge may change their power consumption to lower-cost periods. The authors present a model to deal with uncertainty from the Aggregator perspective: apply reliability rates to each consumer according to their actual response in events of Demand Response (DR). The consumers with higher rates are chosen to participate in the local flexibility markets. To compute the final rate, three different independent rates are used: Historical rate with past information, Cut-rate from the response in the actual period and the Last Day Rate which is the final reliability rate from the previous day. In the present paper, the influence of each independent rate, through the weight used, is studied.

Keywords: Demand Response, Uncertainty, Aggregator, Smart Grids, Optimization

NOMENCLATURE

Variables

$P_{DG}(p)$	Scheduled power for Distributed Generation unit p
$P_{IDR}(c)$	Scheduled power reduction for Incentive-based Demand Response program for consumer c
$P_{Supa}(sa)$	Scheduled power for additional sa supplier
$P_{Supr}(sr)$	Scheduled power for a regular sr supplier

Parameters

$C_{DG}(p)$	Distributed generation unit p cost
$C_{IDR}(c)$	Incentive-based Demand Response cost for consumer c
C_{NSP}	Non-supplied power cost
$C_{Supa}(sa)$	Regular sa supplier cost
$C_{Supr}(sr)$	Additional sr supplier cost
$P^{Initial}_{Load}(c)$	Initial consumption of the consumers
P^{Max}_{DG}	Maximum power schedule in a Distributed Generation resource
P_{NSP}	Non-supplied power
$P^{add\ Max}_{Sup}(sa)$	Maximum power from an additional supplier
$P^{addTotal}_{Sup}(sa)$	Maximum allowed total power from all the additional suppliers
$P^{reg\ Max}_{Sup}(sr)$	Maximum power from a regular supplier
$P^{reg\ Total}_{Sup}(sr)$	Maximum allowed total power from all the regular suppliers
$P^{TotalMax}_{DG}$	Maximum allowed total power from all the Distributed Generation units

1. INTRODUCTION

Demand Response (DR) is one of the main subjects when applying the concept of Smart Grids in the actual grid. The evolution of the technology introduces intelligence to appliances, enabling bidirectional communication and granting consumers with energy market transaction information (Faria, et al. 2016). With conditions gathered to apply for DR programs, the end-user can react to price or incentive signals. However, as an individual, small resources do not own the capacity to participate directly in the energy market transactions. The main purpose of Aggregator is intermediate operations between active players and the wholesale electricity market (De Paola, et. al, 2017; Khezeli, et al., 2017). An increase on system reliability is expected with the flexibility provided by consumers, fighting the ambiguity involving Distributed Generation (DG) (Wu, Tazvinga and Xia, 2015). To a practical application of this approach, arises the necessity to design models capable of suppressing the eventual losses in a real-time event, selecting the consumers trustworthy of participating in a DR event when requested. The challenges of these models rely on the complexity of selecting the active players willing to participate in DR events – distinct types have different behaviours and goals, so ways to increase the reliability to achieve DR goals be further studied. In the literature, some authors have included DR in their events but the uncertainty on their response is limited (Monfared and Ghasemi, 2019; Jiang *et al.*, 2020)

Previous works from the authors of the present paper were able to optimally manage a local community. The optimization can deal with these small resources, DG and consumers willing to participate in DR events, independent of the size of the dataset or the types of resources included. In contrast, the present paper is innovatively assigning a Trustworthiness Rate (TR) to each consumer, selecting only for scheduling the most reliable ones to reduce at a specific moment according to a reduction goal – DR target. TR is updated according to the actual response overtime considering three different rates. The goal is to study the weight sensibility of these rates in the formulation of DR event final TR, presented in Section 2. Comparison between requested reduction and actual reduction, answers below the requested and higher will also have an impact and are worth studying.

The present paper is structured into five different sections. Section 1 served as an introduction to the topic addressed and a brief explanation of the proposed work. Section 2 presents a more detailed description of the proposed method. Section 3 describes the assumptions for the case study as well as the local community selected from the dataset to prove the feasibility of the methodology. In Section 4 the discussion of the results is done. Section 5 presents the outcomes of the presented studies.

2. PROPOSED METHODOLOGY

Section 2 presents the proposed methodology in detail. The present paper focuses on the Aggregator and the interaction with active consumers. In this way, the authors proposed a method to deal with the consumers' actual response to DR programs, i.e., the request for a reduction. According to the response, to each consumer is assigned a Trustworthiness Rate (TR). The proposed methodology has four main stages: Identification of Trustworthy consumers, Scheduling of resources, Rate Update and Remuneration.

Figure 1 expose that depending on the stage of the model, TR calculation is different and relies on several independent rates, which can derive from prior knowledge or implementation results from the proposed methodology. The Historical Rate (HR) is assigned according to consumer existing data on DR events. So, or the Aggregator has previous information, or the value starts in 0 and can decrease and increase according to the response. The Last Day Rate (LDR), is the rate given to the consumer for the same period in the previous event day using the proposed model. Finally, Cut-Rate (CR) is defined by the actual response of the consumer for the present period and fluctuates if the value is higher, equal or lower than the requested reduction. So, TR depends on these considered as independent factors – a change noticed on them can sort effects on the final TR rate, considered as a dependent variable. Equation 1 represents the formulation of the final TR from the DR event. The ω represents the weight attributed to each independent rate.

$$FINALTR = HR \times \omega_{HR} + LDR \times \omega_{LDR} + CR \times \omega_{CR} \quad (1)$$

Considering the first time that TR is applied, Fig. 1 initial rate depends only on the prior data from the DR programs actual response of each consumer, i.e., HR. A linear optimization was implemented for resources scheduling in the local community. In the first stage of Scheduling phase, only consumers with higher reliability rates than the selected minimum are chosen to participate. Since a DR target is applied, if the selected consumers were not able to achieve this goal, all the remaining consumers are called to participate in later scheduling, the Re-scheduling stage.

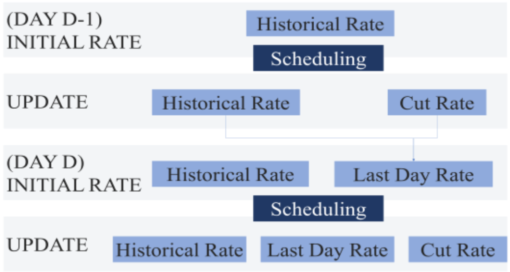

Fig. 1. Definition of the Final Rate for Day (D)

Being used already in previous works from the authors, for example (Silva, et al. 2019a) and (Silva, et al. 2019b), the idea is to minimize the operation costs and increase the profits for the Aggregator by balancing the small resources, such as consumers participating in DR programs (P_{DR}) and DG units (P_{DG}). This model also can be applied to prosumers and is capable to manage a larger number of resources or only one type of resource. Although this optimization can be functional to micrograms in island mode – when the operation is done isolated from the national or local electricity distribution network, for the cases where this concept isn't applied, external suppliers were added, and two types can be found: regular (P_{SUPR}) and additional (P_{SUPA}). Equation 2 presents the objective function attributing a cost to each parameter and all the constraints are shown from Equation 3 to Equation 13.

$$MinOF = \sum_{p=1}^{P} P_{DG}(p)C_{DG}(p) + \sum_{sr=1}^{Sr} P_{SUPR}(sr)C_{SUPR}(sr) + \sum_{sa=1}^{Sa} P_{SUPA}(sa)C_{SUPA}(sa) + \sum_{c=1}^{C} P_{DR}(c)C_{DR}(c) + P_{NSP}C_{NSP} \quad (2)$$

$$\sum_{c=1}^{C} [P_{Load}^{Initial}(c) - P_{DR}(c)] = \sum_{p=1}^{P} P_{DG}(p) + \sum_{sr=1}^{Sr} P_{SUPR}(sr) + \sum_{sa=1}^{Sa} P_{SUPA}(sa) + P_{NSP} \quad (3)$$

Equation 3 represents the balance between demand and generation. As can be seen, in the left side, from the initial load is reduced the requested curtailment and on the right side, the sum of all the DG units and external suppliers. If well managed, the production side is enough to suppress all the consumption but for extreme situations, the variable Non-Supplied Power (P_{NSP}) was added. The goal is to maintain this value always null. The constraint associated with DR programs is presented in Equation 4, Equation 5 and Equation 6. The first one threshold reduction value, according to state in the contract with the consumers.

$$P_{DR(c)} \leq P_{DR(c)}^{Max}, \quad \forall c \in \{1, \ldots, C\} \quad (3)$$

Equation 5 and Equation 6 control DR Target. This value was introduced as innovation from previous works and is a crucial factor in the study, as aforementioned. If the second stage is needed, Re-scheduling, all the consumers could increase their rate by participating in the DR event. Values of reduction lower than the expected may prejudice the consumer's performance rate.

$$\sum_{c=1}^{C} P_{DR(c)} \le DR\text{Target}_{\max} \tag{5}$$

$$\sum_{c=1}^{C} P_{DR(c)} \ge DR\text{Target}_{\min} \tag{6}$$

Equation 7 to Equation 13 present the generation resources' constraints are. Equation 7 to Equation 9 represent upper and lower bounds for DG units and restrict the total amount of generation used from these technologies.

$$P_{DG(p)} \le P_{DG(p)}^{Max}, \ \forall p \in \{1, \dots, P\} \tag{7}$$

$$P_{DG(p)} \ge P_{DG(p)}^{Min}, \ \forall p \in \{1, \dots, P\} \tag{8}$$

$$\sum_{p=1}^{P} P_{DG(p)} \le P_{DG}^{TotalMax} \tag{9}$$

The remaining equations refer to Regular and Additional Suppliers. Equation 10 and Equation 12 create the upper bound. Equation 11 and Equation 13 limit the quantity available from each type of external suppliers in the network. The Aggregator, with this approach, has more power in the scheduling.

$$P_{Supplier(sr)}^{reg} \le P_{Supplier(sr)}^{regMAX}, \forall \in \{1,\dots,Sr\} \tag{10}$$

$$\sum_{sr=1}^{Sr} P_{Supplier(sr)}^{reg} \le P_{Supplier(sr)}^{regTOTAL} \tag{11}$$

$$P_{Supplier(sa)}^{add} \le P_{Supplier(sa)}^{addMAX}, \forall \in \{1,\dots,Sa\} \tag{12}$$

$$\sum_{sa=1}^{Sa} P_{Supplier(sa)}^{add} \le P_{Supplier(sa)}^{addTOTAL} \tag{13}$$

Returning to Fig. 1, updated TR is accomplished considering the results from scheduling. Now, the CR is introduced and with HR, the final rate for Day (D-1) is determined and used to the next DR event in the same period. Moving to the Day (D), HR and LDR are considered to the initial rate. The proposed methodology loop starts all over again and another Scheduling is performed. This time, the three rates will be considered for the final rate for this period. The model is repeated according to Day (D). For the study on the present paper, some questions arise and must be answered: should the HR have more impact on the final TR rate of the given period? It is more important what has been done in the past? The Aggregator should still trust in this consumer although in this period didn't respond according to the expectations? Or should the CR be higher and punish/exonerate for the answer in this period where the Aggregator needed the most? What about the LDR? Is important? The idea is to perform a sensitivity analysis, which is defined as the study of the influence of a certain independent variable in a particular dependent one under a given set of assumptions (Liu, 2008). The approach used is the local sensitivity analysis being a One-at-a-time (OAT) technique – this method analyzes the effect of a parameter keeping the other fixed.

3. CASE STUDY

In the present case study, a dataset from a real Portuguese distribution network with five types of consumers willing to participate in DR programs and seven types of DG units is used. Table 1 present the detailed characterization of the small resources in 10 random local communities. The studied dataset is divided into periods of 15 minutes. The DR target selected was 100 kW. To attribute an initial rate to each consumer, the information for a whole year was processed resulting in an HR: for each consumer, 5 samples from previous weeks: in the same day of the week and the same period of the day.

Table 1. Small Resources Characterization

CONSUMERS			
Type	#	Capacity (kWh)	Initial Price (m.u./kWh)
Residential	10,168	21,354.36	0.12
Small Commerce	9,828		0.18
Medium Commerce	82		0.20
Large Commerce	85		0.19
Industrial	147		0.15
Total	20,310		
DG UNITS			
Type	#	Capacity (kWh)	Tariff (m.u./kWh)
Small Hydro	25	25 388.79	0.0961
Waste-to-energy	7		0.0900
Wind	254		0.0988
Photovoltaic	208		0.2889
Biomass	25		0.1206
Fuel Cell	13		0.0945
Co-generation	16		0.0975
Total	548		

Highlighting that this study was done in two consecutive DR event days at the same period (for example when a peak load occurs), the selected days of the week were Tuesday (Day (D-1)) and Wednesday (Day (D)) for the same period – 3 pm and has a duration of 1 hour. The rates are between 1 and 5 being 3 the minimum required to participate in Scheduling. To study the sensibility was assumed the weights in Table 2 which vary to produce several combinations and examine the influence of each independent rate in the result. An assumption regarding CR was considered: the weight attributed to this rate may never be null since the actual response and reduction from the consumer it is an essential element to this study. Through several steps of the study, the performance is tested and the considered better option (lower number of unacceptable situations) was chosen instead of showing all the resulting combinations from Table 2 in the Result Section. Table 3, represents the number of elements per rate, considering the initial rate of Day (D-1).

Table 2. Weight Rate Combinations

Day	Test	HR (%)	LDR (%)	CR (%)
D-1	0	100	0	0
	1	0-50 (step 10)	0	50-0 (step 10)
D	2	50-0 (step 10)	0-50 (step 10)	0
	3	0-100 (step 33)	0-100 (step 33)	100-0 (step 33)

Table 3. Consumers per rate in the selected community

Group	1	2	3	4	5
Elements (#)	215	68	66	43	14

4. RESULTS

The organization of this section follows the steps from Fig. 1 and considers the one possible way to follow the weight combinations from Table 2. In this way, Scheduling Results are presented but the focus of the study is the sensibility from independent rate weights in the final TR. Thus, throughout the section and from the two Event days in study, the comparison between the initial number of consumers in a group and the updated number after the scheduling phase; also, how many of them were selected; the amount of requested and actual reduction, and which ones responded lower or higher than the requested. The Remuneration from each stage is also presented to provide an economic analysis.
Starting with the initial TR from Day (D-1), this one relies only on HR from each consumer. Hence, the Scheduling Results for Day (D-1) are the base for the following studies and are presented in Table 4.

Table 4. Scheduling Results from Day (D-1)

TR	1	2	3	4	5
# Initial Elements	215	68	66	43	14
# Selected	0	0	36	19	7
Requested (kW)	0	0	64.61	24.05	11.33
Actual (kW)	0	0	68.61	23.64	11.21
Total Reduction (kW)	103.46				

Considering the weight from CR and HR – the two independent rates that constitute the final TR for Day (D-1), the resulting number of elements for each test is presented in Fig. 2 according to the several combinations obtained. The effect in TR1 and TR2 was small since the actual reduction was null – only elements from higher groups descend to these lower levels. TR3 started with a low number of elements in the first tests – CR had higher influence and according to their performance, the climbing to higher levels is distinct. As the HR increase its weight, TR5 sees their elements move to under levels. As an outcome from this stage, the levelling speed depends on the percentage that is assigned to the CR: higher CR, the easier the group climbing. However, this may not be desirable as the past information may prove otherwise (dissimilar behaviours) and although these consumers have responded accordingly, it is expected that levels above the designated minimum will do so. Therefore, consumers in this limit should be treated differently and the levelling speed, to higher or lower groups, should be more controlled.

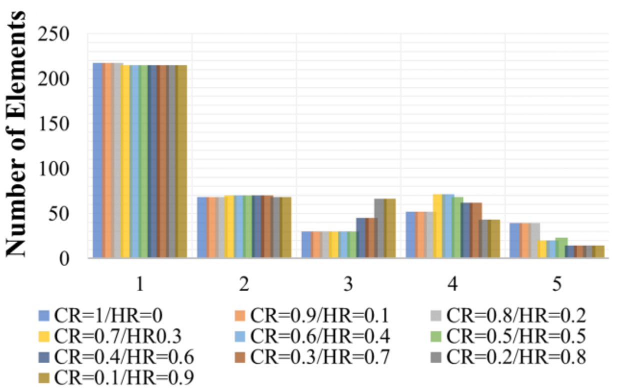

Fig. 2. Test 1 – Weight Variation Influence (step 0.10)

The noticeable turning point happens when the weight assigned to each rate is the same. Yet, the authors decide to study further -10% and +10% to compare and understand the behaviours. Yet the remaining combinations were performed although not presented. Hence, three different paths for Test 2 are possible and the resulting number of elements per group are presented in Fig. 3.

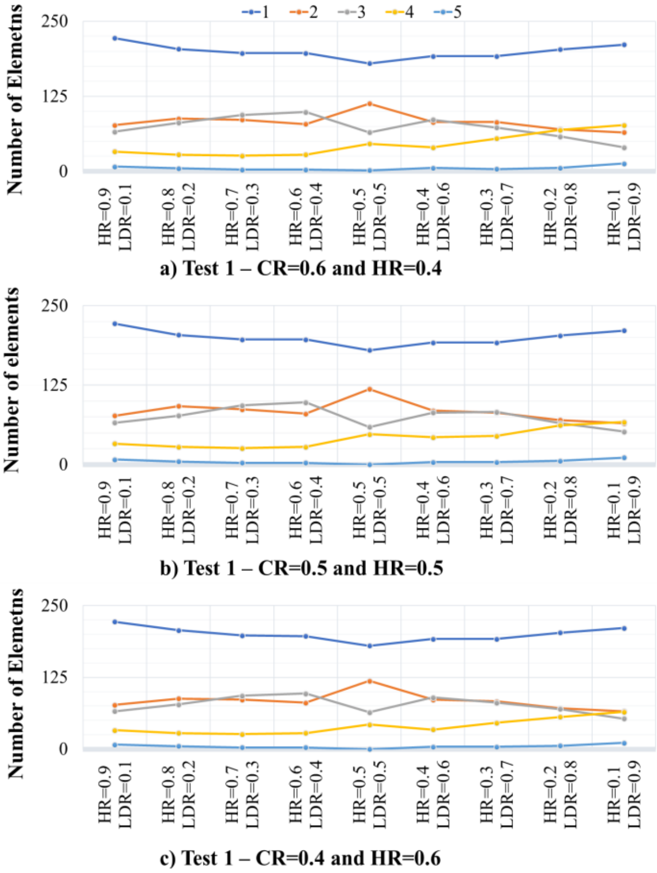

Fig. 3. Test 2 – Weight Variation Influence (step 0.10)

Analyzing Fig. 3 by groups, TR1 tendency is very similar in all tests. Regarding the curve that represents TR2, in the first experiments, the trend follows the curve for TR3, increasing in the number of elements. However, the curves reverse directions between step 0.8 and 0.7 (TR3 with a higher number of elements) and between 0.6 and 0.5 from HR (TR2 with a higher number of elements), reaching the highest element disparity when HR=0.5 and LDR=0.5 (Fig. 3b). When the last day actual reduction of the consumer has less influence, the curves from TR2 and TR3 reach their minimum difference, almost overlapping. About TR4, the higher the percentage of LDR, the number of elements in this group increased: when the weight of the consumer's history is lower, the ease of switching groups is higher and depends, of course, on the response of the consumer during the same period of the previous day. In this case study, elements from TR3 had better performance than the remaining requested groups since TR4 and TR5 results were lower than expected. In this way, and according to the percentage attributed to CR, these elements increased their level of trustworthiness. Since the disparity of elements is higher when HR=0.5 and LDR=0.5, the authors opted for following this combination in

Test 3. The resulting combinations of Test 3 had a step of 0.33 – three different rates were used to perform the final TR of the consumer, as presented in Table 4.

Table 5. Test 3 – Weights per Rate

Test	3.0	3.1.1	3.1.2	3.2.1	3.2.2	3.3.1
HR	0	0	0	0.33	0.33	0.67
CR	1	0.33	0.67	0.33	0.67	0.33
LDR	0	0.67	0.33	0.33	0	0

The first scheduling was enough to achieve the DR target and, giving this, possible responses from the groups above the minimum will be considered to also understand the influence in these elements. Individual cases will be studied in the following subsection. Table 6 shows the initial number of elements per group and the scheduling results for Test 2.1.
The number of elements selected to participate in DR event came from Group 3 to Group 5 (60 consumers). Although, without request, elements from Group 2 reduced 32.80 kW, resulting in a total reduction of 166.48 kW. In this situation, the actual reduction per group is higher than the requested. Figure 4 shows the number of elements per group for each Test 3 performed updated according to their actual response: if Selected and answered lower than requested; Selected and answered higher than requested and Not Selected.

Table 6. Test 2.1 – Scheduling Results

Group	1	2	3	4	5
# Initial Elements	180	113	65	46	2
# Selected (Test 2.1)	0	0	38	21	1
Requested (kW)	0	0	70.73	28.50	0.77
Actual (kW)	0	32.80	92.56	39.52	1.61
Total Reduction (kW)	166.48				

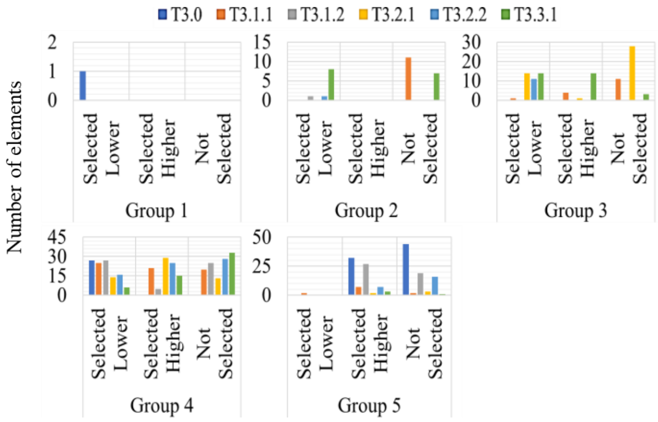

Figure 4. Test 3 – Number of elements per group (Test 2.1)

To evaluate each of these final tests, a set of assumptions was established regarding the actual response, generating some alerts if there were elements in these conditions. For instance, when a selected consumer reduced lower than the expected and the final TR is higher than the previous: 13 consumers are in this situation for T3.1.1 (null weight for HR). Test 3 with the lower number of warnings was T3.2.1, where the LDR had no influence. For the following test, Table 6 presents initial and selected elements and the reduction results per group. Highlighting the fact that Group 5 don't have elements in this test.

Table 7. Test 2.2 – Scheduling Results

Group	1	2	3	4	5
# Initial Elements	180	119	59	48	0
# Selected (Test 2.2)	0	0	36	24	0
Requested (kW)	0	0	68.82	31.18	0
Actual (kW)	0	37.00	73.57	39.18	0
Total Reduction (kW)	149.75				

To achieve the 100kW for the DR target, 36 elements from Group 3 and 24 from Group 4 were selected, reducing a higher value than the expected as a group. Also, Group 2 elements reduced without being selected.
Figure 5 shows the updated TR for the consumers who participate in the DR event, selected and not selected.

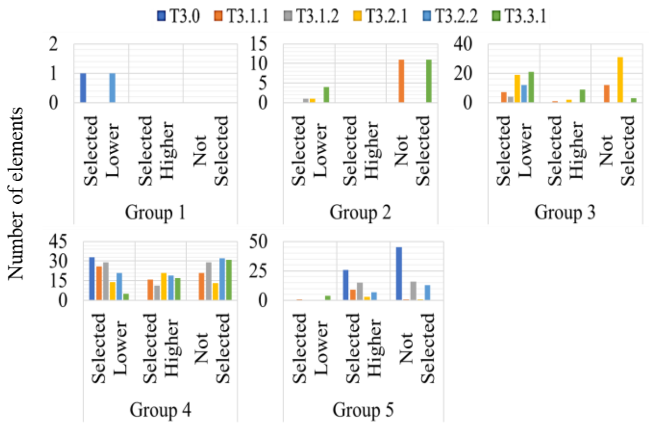

Figure 5. Test 3 – Number of elements per group (Test 2.2)

The test that generates more warnings was T3.1.1 and the one with better performance regarding this matter was T3.2.1. Finally, the scheduling results from Test 2.3 are presented in Table 7 and the updated number per group according to the actual response in Figure 6. It can be concluded that when weights are equal, better performance was achieved. Also, in cases where the LDR could not be included, the CR should be higher than HR.

Table 8. Test 2.3 – Scheduling Results

Group	1	2	3	4	5
# Initial Elements	180	119	64	43	0
# Selected (Test 2.3)	0	0	41	19	0
Requested (kW)	0	0	75.89	24.11	0
Actual (kW)	0	36.49	79.37	34.00	0
Total Reduction (kW)	149.87				

To further study the result combination in this case study, the following parameters are now selected: the final TR from Day (D-1) has 60% of influence from the CR and 40% from HR (Test 1); the initial rate to Day (D) is composed by 50% of LDR and 50% of HR (Test 2); the final TR for Day (D) used 33% of each independent rate. Looking at the elements that were not selected to participate, Group 2 was the one with higher reduction. Highlighting the fact that consumers with this characteristic, were not selected and yet reduced, had a CR = 5.

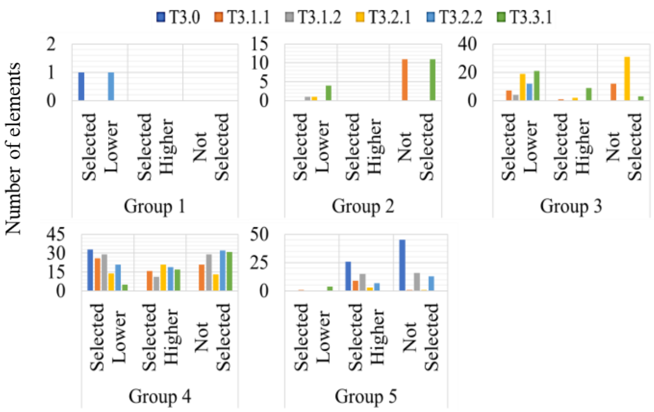

Figure 6. Test 3 – Number of elements per group (Test 2.1)

All the 25 elements from initial Group 2, through this combination of weights for independent rates, were able to move up to Group 3. The elements not selected from initial Group 3, six of them were able to increase their rate. Regarding Group 4, only two ascents to a higher group since their HR was 4 and the LDR was 5. The consumers selected which had a lower response than the expected stayed in the initial group. Regarding the elements from Group 3 which were selected and reduced higher than expected, only one stayed in the same group, the remaining saw their updated rate increase one level. The final Group 5 is constituted by two elements: one who managed to ascend from Group 4 and another who, by answering the higher than requested, managed to keep up. From the perspective of the entity manager, the method must be economically viable, so, the comparison between DR and non-DR approach considering the Day (D) is presented in Table 9.

Table 9. Economic analysis

Approach	Remuneration Value (m.u.)	Losses (m.u.)	Final Operation Costs (m.u.)
Non-DR	0.00	0.00	176.44
DR	22.18	0.00	166.88

The final operation cost considers all the expenses to balance the consumption and generation in the community, including already the remuneration value from DR. In this way, the entity manager can benefit from this approach.

6. CONCLUSIONS

To achieve a DR target and deal with the uncertainty from small resources, the authors present a solution to manage local communities. According to the actual response to requested reductions, each consumer has independent rate associated: historical information (HR), information from the reduction of the previous day (LDR) and the reduction from the current period (CR). According to the stage of the model, these independent rates will be used to formulate the final TR for each period. The goal in this study was to understand the influence of each independent rate in the result, in the several stages of the model. When there is no information regarding the previous day, CR should have more influence. The speed change from trustworthiness group depends on this factor and thus, the higher its weight, the higher the rate update of a given consumer. However, HR must also be considered to control abrupt variations. In the case where the three independent rates were used, the assignment of equal weights obtained the best performance. As future works, independent rates should be analysed; the same study for different days focusing on one consumer, i.e., how the long-term variation weight of CR influence in an individual consumer. Another assumption that can be interesting is the limitation of the actual amount of reduction: if the total reduction is higher than the DR target, the Aggregator will have no advantage in reducing the value above offered by the consumer but that information can be used to improve the TR of the nominated consumer.

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REFERENCES

Faria, P., Spinola, J. and Vale, Z. (2016) 'Aggregation and Remuneration of Electricity Consumers and Producers for the Definition of Demand Response Programs', IEEE Transactions on Industrial Informatics, PP(99), pp. 952–961. DOI: 10.1109/TII.2016.2541542.

Jiang, Y. et al. (2020) 'A Hybrid Stochastic-Interval Operation Strategy for Multi-Energy Microgrids', IEEE Transactions on Smart Grid, 11(1), pp. 440–456. DOI: 10.1109/TSG.2019.2923984.

Khezeli, K., Lin, W. and Bitar, E. (2017) 'Learning to Buy (and Sell) Demand Response', IFAC-Papers Online, 50(1),pp.6761–6767.DOI: 0.1016/j.ifacol.2017.08.1193.

Liu, S. (2008) Global Sensitivity Analysis: The Primer by Andrea Saltelli, Marco Ratto, Terry Andres, Francesca Campolongo, Jessica Cariboni, Debora Gatelli, Michaela Saisana, Stefano Tarantola, International Statistical Review. doi: 10.1111/j.1751-5823.2008.00062_17.x.

Monfared, H. J. and Ghasemi, A. (2019) 'Retail electricity pricing based on the value of electricity for consumers', Sustainable Energy, Grids and Networks, 18, p. 100205. DOI: 10.1016/j.segan.2019.100205.

Paola, A., Angeli, D. and Strbac, G. (2017) 'A Semi-Decentralized Scheme for Integration of Price-Responsive Appliances in the Electricity Market', IFAC-PapersOnLine, 50(1), pp. 6729–6736. DOI: 10.1016/j.ifacol.2017.08.1171.

Silva, C., Faria, P. and Vale, Z. (2019a) 'Demand response and distributed generation remuneration approach considering planning and operation stages', Energies, 12(14). DOI: 10.3390/en12142722.

Silva, C., Faria, P. and Vale, Z. (2019b) 'Multi-Period Observation Clustering for Tariff Definition in a Weekly Basis Remuneration of Demand Response', Energies, 12(7), p. 1248. doi: 10.3390/en12071248.

Wu, Z., Tazvinga, H. and Xia, X. (2015) 'Demand side management of photovoltaic-battery hybrid system', Applied Energy, pp. 294–304. doi: 10.1016/j.apenergy.2015.03.109.