Rating and Remunerating the Load Shifting by Consumers Participating in Demand Response Programs

Cátia Silva, Pedro Faria, *Member, IEEE*, and Zita Vale, *Senior Member, IEEE*

***Abstract*—Effective and active consumers providing flexibility through Demand Response (DR) programs have three important aspects: rating each consumer according to previous participation, remuneration of that participation, and determining the rebound effect of consumption after the event. In this article, the authors design a rate to classify and select the proper participants for a DR event considering the context in which the event is triggered. The aggregator estimated the shifting of consumption to periods after the event is modeled, and the respective remuneration is estimated under different scenarios. This shifting can be done in several time frames in the future. The scenarios are developed to test the acceptable time range in which the load should be allocated according to the rebound effect. The results show that a higher time range can avoid huge peak consumption, optimizing the system operation with benefits for consumers, DSO, and the aggregator.**

***Index Terms*—Demand response, load shifting, rebound effect, remuneration, trustworthiness.**

I. Introduction

The present paper follows the work done in [1]. Consumers' role in the power and energy market is empowered with the introduction of the Smart Grids concept [2]. Resorting to bidirectional communication, Aggregators may send signals to the consumers to adapt their load consumption, assisting and contributing to achieving the network balance [3]. Yet the uncertain human behavior and the voluntary option regarding DR events increase the management complexity [4].

Predicting, encouraging, and properly selecting the participants according to the event's context is triggered still needs to be solved in the energy sector [5]. Although the future promises smarter tools, smart buildings, sustainable transport systems, smart appliances, and smart metering, it will take time, education, and good use of the resources for consumers to make profitable market transactions [6]. Nevertheless, the implementation of DR programs has been mainly applied to consumers with higher levels of predictability, such as industrial consumers [7]. However, these consumers are interested in their profits, unlike small players, such as the residential type, that focus on their comfort [8]. It will then be easier to maintain their continuous participation if proper compensation is applied to reward for the discomfort caused [9]. Still, there is a problem that should be discussed when requesting flexibility from small consumers.

A traditional DR approach, such as load shifting, may incur challenges for the community manager thanks to the expected rebound effect [10]. Considering participation in the event periods, the consumers will still need to activate this load, and the shifting to another time frame may amplify the problem intended to be solved with this approach – mitigate the peak loads' effect on the system.

The main motivation and contribution of the authors for this study is to understand how the period range for load shifting affects the community management results. In this way, the authors want to give more interval options in the current paper and understand the economic effect from the aggregator perspective.

Four different scenarios will be compared to evaluate the proper option, namely between three hours after the DR event, fifteen, twenty-four, and forty-eight, and twenty-four and forty-eight after the event.

The paper is organized into six sections. First, an introduction to the topic. After, related work and contributions are in Section II, followed by an explanation of the proposed methodology in Section III. The case study is defined in Section IV. The authors will analyze and discuss the results in Section V. Finally, the conclusions from the study and future works will be exposed in the last section.

II. Related Work and Contributions

The work presented by Hanne Saele and Idar Petersen [11] mentions a critical aspect regarding the use of emerging electric vehicles in the Norway distribution grid. These authors highlight the consequences of introducing new load peaks by applying DR

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The authors are with the Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, Intelligent Systems Associated Laboratory, Polytechnic of Porto, 4200-072 Porto, Portugal (e-mail: cvcds@isep.ipp.pt; pnf@isep.ipp.pt; zav@isep.ipp.pt).

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to these new resources. Several authors have already tried to find strategies to avoid this effect in the literature. Zhenyuan Zhang et al. [12] considered the rebound effect on their work for the load profile reshaping process to avoid additional costs, resorting to a recurring cost minimization algorithm. It was considered that this effect occurred uniformly in the period after DR but never after 11 p.m. With this, the proper business model to consider the power and energy sector's DR should contemplate all these complex and uncertain problems [13].

Considering related works and comparing with the present study, the authors from [14] defined a model to assist the distribution system planer, considering both uncertainties from photovoltaic-based generation as well as from demand response. There was a previous assumption that a predefined mutual agreement was done between the DSO and the end-users to make available a percentage of manageable demand for the community manager to comply with technical constraints under normal and emergency conditions.

Clear communication and an effective remuneration system can be a step forward to successfully implementing DR in the real market. In the study from [15], the authors introduced the possibility of using blockchain technology for resource aggregation – both load and generation. Customer Baseline Load (CBL) was widely referred to and defined as a typical consumer's consumption profile [16]. With this, the community manager will be able to evaluate if changes occur in response to a DR program. The case study from [15] considered only an hourly perspective for a consumer where the availability profile was composed of difficulty and compliance. In the present study, the DR participant's performance, evaluated with a rate, also considers the environment in which the DR event is triggered, adding the contextual approach – event period and weather. Different types of consumers have different price sensitivity and strategies for participating in DR events, as the authors from [17] remember by implementing an incentive-compatible bidding mechanism for the DR integration.

The proposed solution intends to complement the literature works by aggregating all these different problems: selecting the active consumer considering the DR event context, remunerating with a fair tariff, and providing a solution to deal with the rebound effect for all the time frames. In this way, the following features listed are considered as the innovative aspects of the proposed methodology when considering the previous works [18], [19] and the related literature:

- Deal with the rebound effect when using DR programs, such as load shifting.
- Sensitivity test regarding the period range where the load should be shifted.
- Select the proper participants for a DR event considering a Trustworthy Rate (TR), dividing the consumers into different levels [17].
- TR provides contextual information to the community manager to increase its performance by using the most trustworthy consumers.
- Use contextual features to predict the participation through TR, resorting to the period and the weather.
- Remuneration according to three different schedules to encourage participation.
- Use DR events to achieve DR targets for the active community.
- Collaboration between community members regarding local balance highlights the importance of the active consumer, and the prosumer and the influence of prioritizing the local generation to suppress the demand.
- Agreement between both community manager and participants. Contrary to [14], contextual aspects are referred to considering the consumers' availability. The contract might consider that all the days of the week are the same but can have high discrepancies.
- Comparison between the expected and the actual consumption to evaluate the performance of each DR participant. Confronting with [15], [16], in this case, was used to attribute a rate further and remunerate accordingly.
- Instead of considering the CBL as an average and typical consumption profile like [15], here, only information from similar contexts is gathered and averaged to provide data closer to the actual.

This paper's main contribution is understanding how the period range for load shifting affects the community management results under four scenarios. In this way, the authors explore more interval options and understand the economic effect from the aggregator perspective.

III. Proposed DR Trustworthy Rate Methodology

To successfully implement the Smart Grids concept in the real market, and since the small consumers will play a crucial role, the business models must consider their uncertain behavior and ways to mitigate the impact on the system. Like the Aggregators, the entities controlling active communities will need the right tools for DR events to deal with the new and uninformed players regarding the market transactions. However, can the aggregator define an acceptable period range to shift the load from the local community without causing major discomfort? So, as an innovation from the previous works, the authors want to evaluate different time ranges for the load shifting and how the actual economic impact throughout the week.

The small consumer's behavior changes according to the context in which the DR event is triggered, so guaranteeing the response from the whole community is very difficult.

A. Trustworthy Rate

The authors designed a Trustworthy Rate (TR) to understand which active consumers, in the event context, are more willing to participate, according to their performance in previous events. Two different perspectives are considered: preliminary when the rate is used to select the participants, and then updated when the current event must be taken into consideration current event's performance must be considered. Fig. 2 represents the dependencies between the independent and dependent rates – Preliminary Trustworthy Rate (PTR) and Updated Trustworthy Rate (UTR).

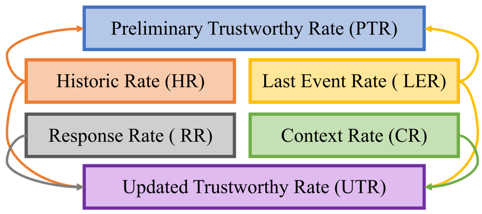

Fig. 1. DR trustworthy rate: Independent rates used for formulation.

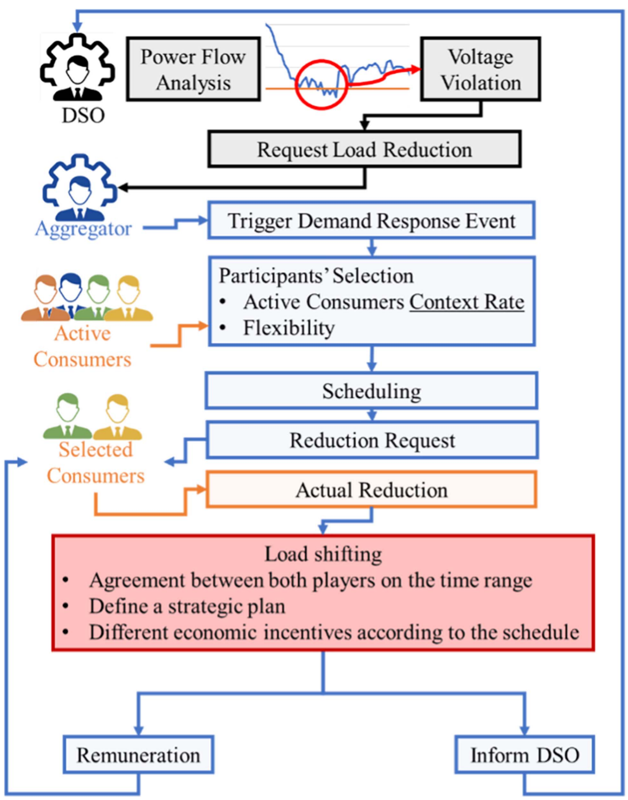

Fig. 2. The proposed DR trustworthy rate methodology is adapted from [1] but focuses on the load shifting step.

The main goal of the proposed approach is to create a suitable solution to select trustworthy participants by studying the behavior of the community members, by attributing them a level of trust, from the Aggregator perspective. With this, the confidence levels of achieving the reduction goal will increase. The Aggregator must not consider the active consumers as rational and economic players since it can lead to inaccuracies. In the authors' opinion, understanding their previous behaviors and ways to motivate their participation will be crucial for the success of this approach in the real market, avoiding reliability and security problems in the grid.

In this way, the formulation of TR depends on several independent rates: Context Rate (CR), Historic Rate (HR), Last Event Rate (LER), and Response Rate (RR). In this approach, the lowest rate is assigned when the consumer does not have any previous information, and their trust must be earned. The same assumption is applied to all independent rates in the same condition. With this, PTR, used for selecting the participants, is formulated according to (1).

$$PTR = \omega_{HR}.HR + \omega_{LER}.LER + \omega_{CR}.CR \quad (1)$$

PTR is then formulated by the sum of the product between the independent rates and the respective weights, namely HR, LER, and CR. Depending on the purpose, CR depends on the active consumer's availability and willingness to participate, considering the weather recorded (CRW) and the period (CRP) when the event moment is triggered. (2) shows the formulation from CR.

$$\mathrm{CR} = \omega\mathrm{CRP}\ \mathrm{CRP} + \omega\mathrm{CRW}\ \mathrm{CRW} \quad (2)$$

The authors consider this a crucial factor. Both features have a major influence on consumer response. For instance, the authors believe that distinguishing working days from weekends or days with extreme temperatures affects each active consumer's behavior and response.

In the HR case, the Aggregator must gather historical information from the active consumer in previous events at similar contexts and perform the average. The number of participants depends on the amount of data available.

$$HR = average\ previous\ performances \quad (3)$$

After, the HR value can be obtained by performing an average from previous performances, excluding the last one since this is already considered in LER, according to (4). Always within the same context – weekday, period, and temperature.

$$LER = UTR\ last\ event\ in\ the\ same\ context \quad (4)$$

Regarding the weights used, the authors already published a work where a sensitivity study was done to understand the impact of each independent rate in both PTR and UTR, and the conclusions withdrawn were used in the present paper [20].

As soon as each response from the DR event is obtained, the community manager will be able to update the info from each player and obtain the UTR according to (5).

$$UTR = \omega_{HR}.HR + \omega_{LER}.LER + \omega_{CR}.CR + \omega_{RR}.RR \quad (5)$$

The final independent rate, RR, represents the performance according to the actual response of the consumer in the current event. In other words, if selected consumer responded as requested, the performance rate attributed is the highest. The opposite will also apply, and the active consumer will be punished reducing the overall UTR. With this, the availability of each consumer to participate in the DR event is predicted according to the previous events since the UTR will be the LER for the next event triggered at the same context. Should be highlighted that DR participation is voluntary. The created rate only identifies the most probable response from each consumer considering previous experiences at the same context - does not guarantee the actual response.

B. Proposed Methodology Steps

With this, the authors in the present paper compare different period ranges for the load-shifting approach using the same methodology proposed in [1], as seen in Fig. 2. Considering the scenario where the Distribution System Operator (DSO), after a power flow analysis, requests a load reduction to all the Aggregators managing the communities nearby the bus where a voltage violation was found.

Here, the authors focused on understanding how the period range for load shifting affects the community management results. The results from the power flow applied are only used to identify the periods where the DR program must be triggered. Nonetheless, the periods where the loads are shifted to are normally far from having grid constraint issues. Still, after running the optimization, if the DSO finds that the obtained solution is not feasible, corrective actions should be considered. A DR event is then triggered, and to achieve the reduction goal, the proper participants must be selected and called using the previously presented method.

In the previous work [1], the authors defined a TR minimum for the selection. For instance, in a range between 1 and 5, only the participants above the rate 3 are selected in the first iteration. Only in the case where the reduction from these consumers is not enough to suppress the remaining members will be called to participate. So, after the proper participants are selected, they can be included in the Scheduling phase.

The implemented optimization is classified as linear, where the variables are set to optimally manage the community. The objective function minimizes operational costs from the Aggregator perspective, as seen in (6), subjected to several constraints later presented in (7) to (13). The aggregator may also aggregate other resources, such as electric vehicles or energy storage means, which are not in the scope of the present paper.

The initial consumption (Pinitial) is assumed as input. It can be obtained using several methods, most commonly using CBL, which is the consumption expected in the absence of a DR event. To achieve a network power balance between consumption and generation, (7) is defined. By adding the requested reduction to the initial consumer load (Pinitial), the value should be equal to the total generation.

$$
\begin{aligned}
Min.OF = &\sum_{p=1}^{P}\left[P_{DG(p,t)}C_{DG(p,t)}\right] + \sum_{c=1}^{C}\left[P_{DR(c,t)}C_{DR(c,t)}\right] \\
&+ \sum_{s=1}^{S}\left[P_{Supplier(s,t)}C_{Supplier(s,t)}\right] \\
&+ P_{NSP(t)}C_{NSP(t)} \\
&c,t,p,s \in \mathbb{Z} \ : \ c,t,p,s > 0
\end{aligned} \tag{6}
$$

$$
\begin{aligned}
&\sum_{c=1}^{C}\left[P_{(c,t)}^{initial} - P_{DR(c,t)}\right] \\
&= \sum_{g=1}^{G}\left[P_{DG(g,t)}\right] + \sum_{s=1}^{S}\left[P_{Supplier(s,t)}\right] \\
&+ P_{NSP(t)} \ c,t,g,s \in \mathbb{Z} : c,t,g,s > 0
\end{aligned} \tag{7}
$$

Moving to consumer participation constraints in DR events, (8) represents the maximum contribution from each active consumer according to the DR contract done between the player and the Aggregator. Both agree on the quantity, but participation is always voluntary.

$$P_{DR(c,t)} \leq P_{DR\ (c,t)}^{Max} \quad c,t, \in \mathbb{Z} : \ c,t > 0 \tag{8}$$

Equations (9) to (11) aid the Aggregator on controlling the upper and lower bounds as well as the total value of generation provided from each different technology.

$$P_{DG(g,t)} \leq P_{DG\ (g,t)}^{Max} \quad g,t, \in \mathbb{Z} : \ g,t > 0 \tag{9}$$

$$P_{DG(g,t)} > P_{DG\ (g,t)}^{Min} \quad g,t, \in \mathbb{Z} : \ g,t > 0 \tag{10}$$

$$\sum_{g\,=\,1}^{G}\left[P_{DG(g,t)}\right] \leq P_{DG\ (g,t)}^{Total} \quad g,t, \in \mathbb{Z} : \ g,t > 0 \tag{11}$$

Finally, (12) and (13) represent the external supplier related constraints. These equations restrict the maximum capacity and the total amount of generation provided from this source to suppress the demand side needs.

$$P_{Supplier(s,t)} \leq P_{Supplier\ (s,t)}^{Max} \qquad s,t, \in \mathbb{Z} : \ s,t > 0 \tag{12}$$

$$\sum_{s\,=\,1}^{S}\left[P_{Supplier(s,t)}\right] \leq P_{Supplier\ (s,t)}^{Total} \quad s,t, \in \mathbb{Z} : \ s,t > 0 \tag{13}$$

As soon as Scheduling phase is completed, the reduction request is sent to the active consumers. This approach shifts the load to another period according to the consumers' preferences. A comparison between the reduction request and the actual reduction is performed to update the TR resorting to RR. After the TR revision, the Aggregator compensates the actual participants and informs the DSO of the load reduction obtained. The authors also believe that proper remuneration will increase participation and the trustworthiness level, So higher TR rates receive higher rewards to keep the motivation and continuous contribution.

The remuneration for each DR participant is assumed to be a rebate in the monthly bill. Higher participation frequency results in higher rebates. Another benefit from the consumer perspective is associated with load shifting since their consumption can be moved to a period with lower prices.

IV. Case Study

In the present section, a case study is defined to prove the viability of the proposed methodology. As a comparison between the two works, as in [1], the dataset was the same and had a total of 96 consumers; only 62 have DR contracts with the Aggregator. The initial load (sum of each consumer baseline) and considering the maximum DR flexibility for the week in the study can be seen in Fig. 3.

The days are divided into 15 minutes, and a whole week is considered, starting on Monday. In this way, a day has 96 periods and a week 652. In this scenario, the DR events are trigged upon lower voltage bound limit violation detection. During the week of the study, a total of thirteen lower bound limit violations were identified, which can be seen in Fig. 4. The four periods studied in [1] were also used in the present study, but the remaining were also included.

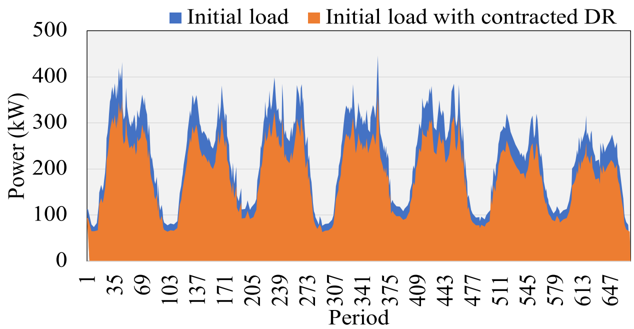

Fig. 3. Prediction of the load consumption before the DR event.

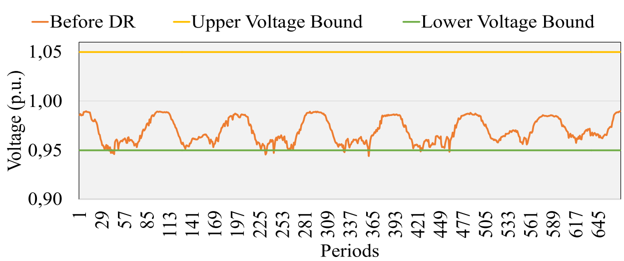

Fig. 4. Limit violation detection throughout the week.

TABLE I
DR Programs Definition

Program	Load Allocation
DR1	+03h to +15h after event
DR2	+03h to +24h after event
DR3	+03h to +48h after event
DR4	+24h to +48h after event

TABLE II
Remuneration Scheduling

Schedule	Peak	Off-valley	Valley
00:00AM – 08:00AM			x
08:00AM – 10:30AM		x	
10:30AM – 01:00PM	x		
01:00PM – 07:30PM		x	
07:30PM – 09:00PM	x		
09:00PM – 10:00PM		x	
10:00PM – 00:00AM			x

The software for resource scheduling has been adapted from [1]: using R language and resorting to the lpsolve package for linear approaches. The authors created four scenarios for this case study, as seen in Table I.

As already mentioned, the selected DR program is load shifting and can be identified as DRX throughout the text, where X represents each one.

The active consumers and the aggregator have these different options; however, the incentive is different according to a schedule defined in Table II. Three distinct zones were created throughout the day and are applied all week: peak, valley, and off-valley. The zones have different remuneration values, according to Table III. The aggregator's goal is to avoid peak hours, so the compensation value is lower in this schedule. If the active consumer has the flexibility to move the load to valley zones will have the highest compensation.

TABLE III
Incentive Tariffs

	Peak	Off-valley	Valley
Incentive (m.u./kW)	0.1124	0.1515	0.2468

V. Results

The current section presents a discussion and analysis of the proposed methodology's results, comparing the four different DR programs with different time ranges. Fig. 4 compares the Scheduling results and respective load allocation from each DR program. With this, the authors try to fill research gaps with three different goals:

- *First goal:* Increase community trustworthiness by selecting only the ones with higher performance levels for the context in which the DR event is triggered.
- *Second goal:* Deal with the rebound effect by doing a sensitivity to allocate the load shifted.
- *Third goal:* Improve the incentives for DR participation with additional remuneration according to the time of the day.

To achieve the first goal, the authors will compare the actual and the requested reduction, comparing the initial and after DR load diagram in Fig. 5. The second goal is implicit throughout this section since each figure and table compare the four different DR programs created according to Table I.

After, Fig. 6 and Table II compare the results regarding the remuneration per period, fulfilling the third goal. The identification speed of the DR participants depends on the amount of previous data gathered from each participant and the number of previous contexts. For the present study, the optimal scheduling was the step that took more time, and the overall running was below the 30s, which is compatible with a low latency real-time scenario.

It must be highlighted that Scheduling results regarding the requested and the actual participation from the active consumers are the same for all the scenarios. Their availability at the time of the DR event must be preserved. The range in which the load is allocated differs for each scenario. This will impact the final load curve, including the actual reduction and load allocation values. The actual reduction curve – represented with an orange color, shows how active consumers can have volatile behavior. The TR was applied, aggrouping the community members according to their participation chances, considering their historic performance on DR events in the same context.

According to the charts in Fig. 5, there is a variation between the requested reduction (blue) and their actual reduction (orange) or, in other words, their CBL and the actual consumption – community perspective (DR1 with green, DR2 with blue, DR3 with purple and DR4 with yellow). As mentioned earlier, the players have a DR contract to provide flexibility, and a fault can result in penalties. However, participation is still voluntary. Furthermore, another assumption that should be emphasized is that aggregator has information regarding the voltage-bound

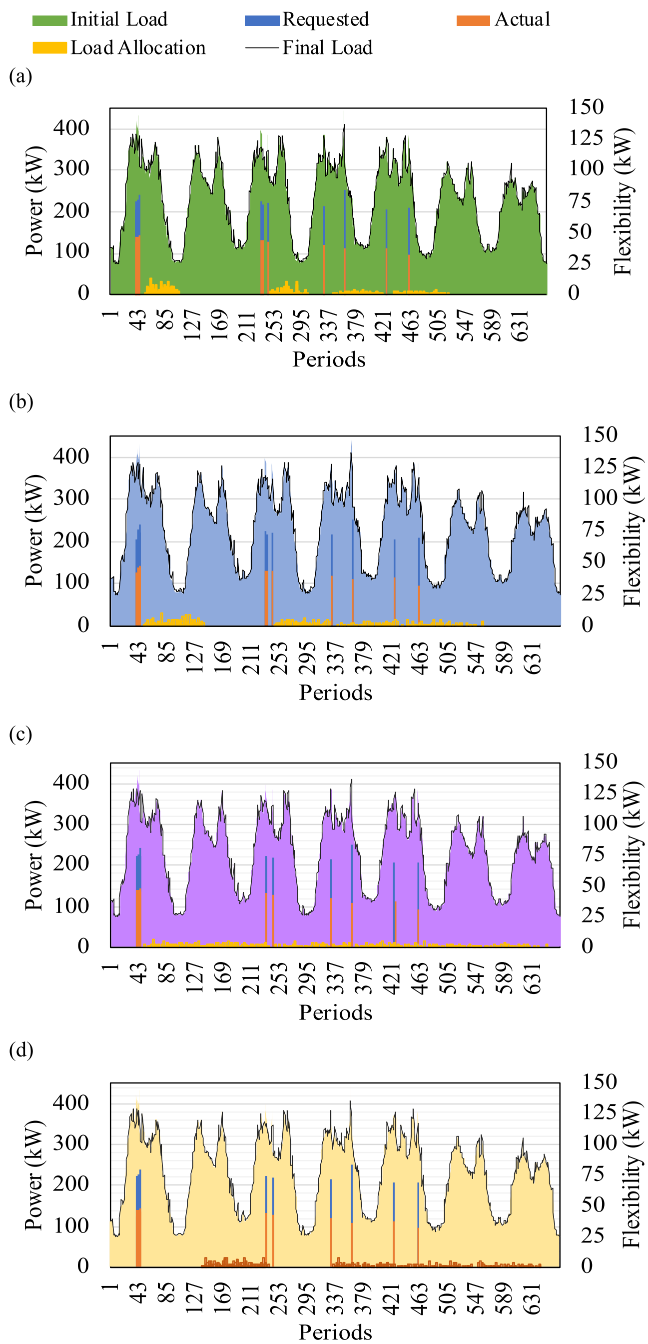

Fig. 5. Scheduling results and load allocation from (a) DR1, (b) DR2, (c) DR3, and (d) DR4 perspective.

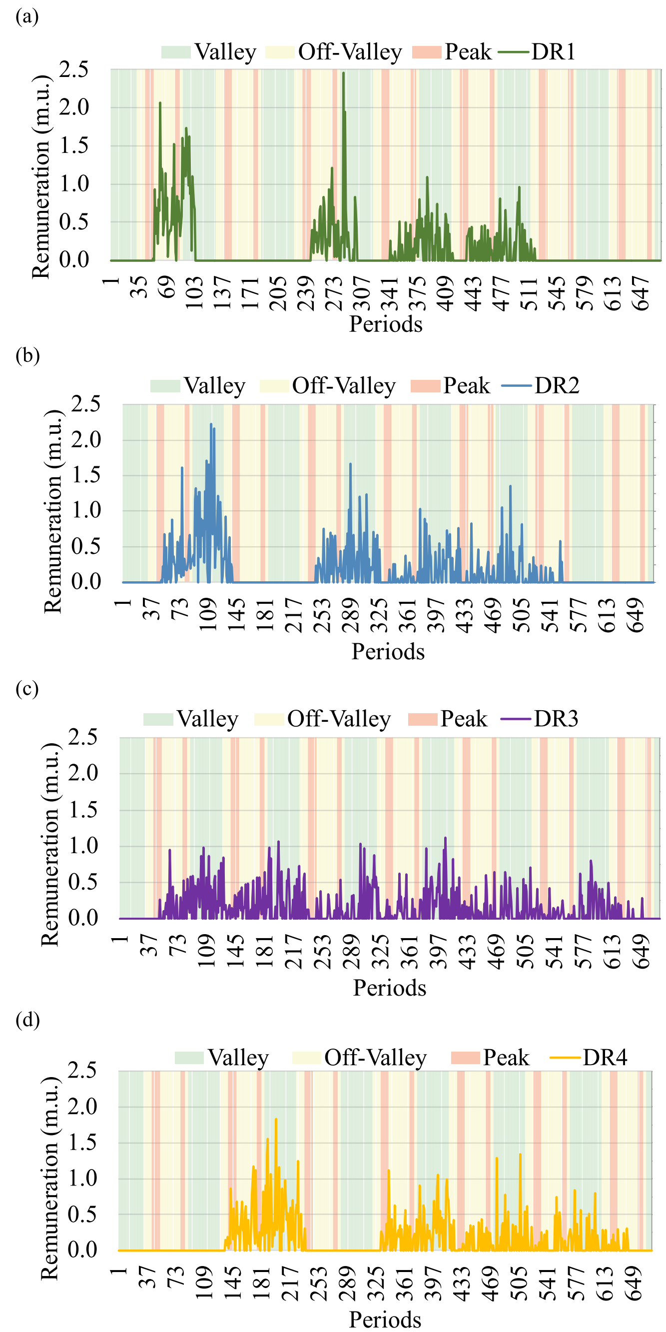

Fig. 6. Remuneration per period for (a) DR1, (b) DR2, (c) DR3, and (d) DR4 perspective.

limit violation throughout the week. So, no load is allocated in the known periods. Still, new violations may be detected, but it is not the focus of the current study and will be considered as future works.

Analyzing Fig. 5(a), the results from the DR1 program. According to consumer availability, this scenario gives the aggregator the opportunity to make a load allocation between 3 hours and 15 hours after the DR event. Giving a more detailed perspective, a total of 888.89 kW was requested for DR participants throughout the week. From the thirteen DR events triggered, only 503.63 kW was reduced. Since no goal reduction value was considered, it can be enough to trigger another voltage-bound limit violation if the load is allocated in a small range of time.

Moving on to Fig. 5(b), the results from DR2 are represented. The wider range allowed a decrease in the load attributed to each period. In this case, the highest value attributed to a period after the DR event was 10.68 kW, and in DR1 was 13.62 kW which still are high values.

When comparing the results from DR3 (Fig. 5(c)) with the first one, the difference in this scenario can easily be seen with the highest period range – between 3h and 48h after the event.

TABLE IV
REMUNERATION FOR EACH SCHEDULE

	Remuneration (m.u.)
DR1	90,77
DR2	98,72
DR3	96,29
DR4	92,37

The load was allocated over time, reducing even more than DR2, the value attributed to each period. It must be emphasized that the highest load value shifted to a period was 6.27 kW – less than half of the quantity achieved in DR1.

Still, the authors are aware of the discomfort that can be caused in this scenario since it can be too high from the active consumer perspective – mainly for small consumers, such as the domestic type. For them delaying, for instance, a washing machine or the dishwasher for 48h may not be ideal or even practical, decreasing their trust in fulfilling the agreement.

Nevertheless, there are plenty of options to be applied in this range. Giving the option to community members, those with this type of availability may consider different schedules and be profitable for both sides, like in DR4 (Fig. 5(d)). This scenario shifts the load from 24h to 48h after the DR event. The time range size is slightly superior to the one in scenario DR2 (total of 3h). This interval changed the maximum load attributed in one period – going from 10.68 kW in DR2 to 8.25 kW in DR4. The distinction can be seen in Fig. 5(d) when comparing with the results from scenario DR2. The curve is flatter in the first.

The Remuneration Step results are presented in Fig. 6, considering the incentives presented in Table III and according to the Schedule and different zones from Table II. The load allocation curves, and the schedule zones are clearer, easing the analysis. To complement Fig. 6, Table IV presents the total remuneration values from each scenario throughout the study week.

Fig. 6(a), which represents the results from the DR1 scenario, shows that the maximum value was achieved in period 285 with a total incentive of 2.45 m.u. for the reduction. This period is in the valley zone.

Regarding the results from the DR2 scenario, the total value from the period where the total incentive achieved the maximum was 0.23 m.u. lower than the previous one in period 113. The maximum period was in a valley zone. DR3 achieved the lowest value from the scenario comparison on this matter – in period 406, the real incentive was 1.12 m.u. – once again in a valley zone. Finally, in the last scenario, the maximum incentive value was noticed in period 198, with a value of 1.83 m.u. For the week overall, the minimum value was achieved on the DR1 scenario because most of the periods' allocated load was on a peak or off-valley zone.

Since the load was more accumulated in these periods, the aggregator could allocate the same amount and save on incentives. However, this approach can be dangerous since it can trigger other voltage-bound limit violations.

From the authors' perspective, to keep the network secure and reliable, giving the option of a lower range to allocate the load could be the proper solution. A higher benefit can be withdrawn if both parties can achieve an agreement.

VI. CONCLUSION

The volatile behavior from DG requires flexibility from the consumers. The authors created a Trustworthy Rate (TR) to understand the more reliable consumers in each context. Consider several aspects influencing the participants' behavior to gather accurate knowledge about the community.

Following the study performed in [1], the current paper evaluates different ranges for load allocation using the DR program load shifting. As mentioned in referred work, compensating the participants for renouncing their comfort to aid in the network transactions is an important step. It acts as motivation for continuous participation in the future. However, the periods in which this load is allocated are important and can be critical to avoid other limit load violations.

The authors compared four different time ranges for the load allocation. Although the one with the lower time range available resulted in savings regarding the incentives from the Aggregator perspective, higher amounts of load were added to a new period. For instance, if this period is at a peak moment, the reliability and security of the network can be jeopardized. From the results, the authors consider that giving more time range for the load allocation can be beneficial despite spending more on incentives.

In future works, since the aggregator must be capable of dealing with DG and other resources, the authors intend to evolve the method to include storage units and electric vehicles. Also, since new violations may be detected, it was not the focus of the current study and will be considered.

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