

Research paper

Rating the participation in Demand Response events with a contextual approach to improve accuracy of aggregated schedule

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ABSTRACT

The flexibility provided by the demand side will be crucial to take a step forward to increase the penetration of renewable energy resources in the system. The proposed methodology provides the aggregator with information about the most reliable consumers, attributing a trustworthy rate that characterizes their performance on Demand Response (DR) events. The innovation relies on applying rates and evaluating the context in which the event is triggered and the factors that influence such rates. The authors find that context is essential to understand which participants are available for the event and achieve the reduction target successfully. Also, the proposed methodology focuses on the performance and the proper motivation for continuous participation, reducing the uncertainty of the response in DR events by giving higher economic compensation to the active consumers with better results. Distributed generation is also optimally managed by the aggregator. Findings prove the feasibility of the proposed methodology supporting the Aggregator in communities and smart cities management.

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1. Introduction

The consequences of greenhouse gases and air pollution created an urgent and essential movement on environmental awareness worldwide. All sectors are now working together to seek environmentally friendly approaches (Canizes et al., 2022). As Ağbulut (2022) mentions, future energy investments must be revised followed by the update of policies, regulations, norms, restrictions, and legislation. Policy-makers should revise these rules to ease the implementation of the smart grids paradigm (Mu et al., 2022). However, as Conchado et al. (2016) refer, introducing new players, such as small consumers, uninformed regarding the transactions requires significant investments and will take time to deal with their uncertain behavior. This section presents the background and motivation and the innovations and contributions of the paper.

1.1. Background and motivation

To reduce the usage of fossil fuels for generation, increase and penetration of Distributed Generation (DG), namely Renewable-based (RE) resources, such as solar and wind technologies, was

one of the main strategies (Cruz et al., 2021; Romanchenko et al., 2021). However, these technologies are volatile due to the uncertainty associated with their primary sources (e.g., wind flow, solar radiation, among others) (Mokhtara et al., 2020).

So, the complexity in the management increases, leading to a reduction of reliability and robustness, resulting in a possible power imbalance between generation and demand (Baum et al., 2019; Zhao et al., 2021). There are already several works and solutions to deal with this problem in the literature.

Demand Response (DR) programs refer to incentives and signals that induce consumers to change their consumption patterns (Mor et al., 2021). In this way, consumer flexibility can optimize market and network operation aspects. Every time a DR program is activated is defined as a DR event. DR programs relate the consumer load elasticity with the market prices and can have several objectives targeting economic, technical, marketing, and environmental issues. Ibrahim et al. (2022) made a review comparing these different aspects coexisting over smart grid platform for a successful deployment of DR. From their conclusions, these authors believe that internet of things, big data and cloud platforms solutions are step forward to allow fast responses of the DR participants when comparing with the other approaches.

Therefore, the flexibility provided must be optimally managed and consider the uncertain behavior from the DR participants. Considering them as “perfect” economic and rational agents may lead to faulty assumptions (Silva et al., 2022). This fact highlights

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Nomenclature

$C_{DG(g,t)}$	Cost from Distributed Generation unit g on period t (m.u.)
$C_{DR(c,t)}$	Cost from Demand Response active consumer c on period t (m.u.)
$C_{NSP(t)}$	Non-Supplied Power Cost on period t (m.u.)
$C_{Supplier(s,t)}$	Cost from supplier s on period t (m.u.)
$p_{(c,t)}^{initial}$	Initial power from active consumer c on period t (kW)
$P_{DG(g,t)}^{Max}$	Maximum Power from Distributed Generation unit g on period t (kW)
$P_{DG(g,t)}^{Min}$	Minimum Power from Distributed Generation unit g on period t (kW)
$P_{DG(g,t)}^{Total}$	Total Contribution Limit from Distributed Generation unit g on period t (kW)
$P_{DG(g,t)}$	Power from Distributed Generation unit g on period t (kW)
$P_{DR(c,t)}^{Max}$	Maximum Contribution from Demand Response active consumer c on period t (kW)
$P_{DR(c,t)}$	Power from Demand Response active consumer c on period t (kW)
$P_{NSP(t)}$	Non-Supplied power on period t (kW)
$P_{Supplier(s,t)}^{Max}$	Maximum Power from Supplier s on period t (kW)
$P_{Supplier(s,t)}^{Total}$	Total Contribution Limit from Supplier s on period t (kW)
$P_{Supplier(s,t)}$	Power from supplier s on period t (kW)
CBL	Customer Baseline Load
CCR	Contextual Consumer Rate
CR	Context Rate
CRP	Context Rate Period
CRW	Context Rate Weather
DG	Distributed Generation
DR	Demand Response
HR	Historic Rate
LDR	Last Day Rate
LEC	local energy community
LER	Last Event Rate
PR	Preliminary Contextual Consumer Rate
RR	Response Rate
UR	Updated Contextual Consumer Rate
ω_{P_CCR}	Weight from CCR in the PR (%)
ω_{P_CHR}	Weight from CHR in the PR (%)
ω_{P_CLER}	Weight from CLER in the PR (%)
ω_{P_CLR}	Weight from CLR in the PR (%)
ω_{U_CCER}	Weight from CCER in the UR (%)
ω_{U_CCR}	Weight from CCR in the UR (%)
ω_{U_CHR}	Weight from CHR in the UR (%)
ω_{U_CLER}	Weight from CLER in the UR (%)
ω_{U_CSR}	Weight from CSR in the UR (%)

the role of the aggregator when dealing with this complex task. Although the resources participation on market transactions can bring several benefits such as the improvement of grid reliability, higher operation flexibility of the community, peak shaving, reduced energy cost or load balancing achievement, methods

must be developed for dealing with these new resources in the grid (Habib et al., 2022). For instance, in Pfeifer et al. (2021), a flexibility vector was created to do important energy transition steps to achieve a 100% renewable energy sources system. The authors consider the flexible operation of thermal power plants, the flexible heat, the flexible electrified transport, the elastic demand, the flexible short and mid-term storage, and the flexible long-term storage. The main goal is to gather information regarding the amount of flexibility used compared to maximal identified flexibility on disposal for the given system – the availability percentage. The number of flexibility options must increase dramatically to integrate renewable technologies into the system fully.

The consumer profile and its load diagram behavior are also important topics to be highlighted. Regarding the residential perspective, Lazzari et al. (2022) highlight the highly irregular human behavior, which plays a significant role in forecasting day-ahead consumption. These authors then considered a robust combination of machine-learning techniques to deal with missing data and outliers. Mor et al. (2021) considered the interaction with the user an important way to learn about the energy consumption, so these authors use the characterization of the electricity consumption of the whole province of Lleida, located in northeast Spain, as a dataset. However, waiting for active consumers to respond to the signals as rational and economic agents can be misleading since it is still little or no information regarding market transactions. In the Judge et al. (2021) work, these authors opt for interruptible loads and thermostatically controlled loads to obtain optimal schedules in uncertainty, studying different parameters in different intervals to control the degree of conservatism.

In this way, Haghghi and Krishnaswamy (2011) it was highlighted another topic: context-awareness. According to the authors, this matter is important to enhance energy management approaches within urban communities – since the uncertainty of response from these new active players is high. The work presented studied the DR energy management systems for residential consumers and highlighted that the context concept enables the DR control actions to be more personalized and adaptive. Mao et al. (2022) also mention the importance of DR to improve the system stability and awake the demand-side resources and the context inserted. In China, the authors remember that these methods are implemented in a centralized model – easier to supervise but harder to deal with due to several factors. With this, these authors proposed a bidding transaction process based on the repeated verification mechanism and tried to prove the effectiveness of blockchain in DR – a decentralized method.

The context-awareness topic opens the door for new and improved solutions to apply the DR concept and increase its potential (Müller and Möst, 2018). The future of the energy sector walks towards a smarter electricity grid with more advanced technology, namely the introduction of bidirectionality for communication with consumers, leading to more control from the demand side – playing a vital role in achieving balance. Load consumption is crucial with the uncertainty associated with DG penetration monitoring (Wang et al., 2022). For example, at peak hours, with the prior approach, generation means would have to follow the demand needs and satisfy them. However, the roles are reversed in this new reality, making the consumers' flexibility vital for balancing generation and consumption. The authors believe that active consumers must be the center of all attention to successfully opt for this new “greener” approach (Siano and Sarno, 2016).

Based on the study conducted by Benegiamo et al. (2018), a detailed analysis of approaches that rely on the macroscopic description of the population, may hide important assumptions that can jeopardize the mechanisms' implementation. These authors

refer that aggregate active population may be convenient. Still, it is also crucial to understand how the active consumer takes the decisions and how players are supposed to interact. However, they also assume that an active consumer chooses the option that maximizes profit as rational agents. From the authors of the present paper's perspective, the residential sector is still inexperienced and unprepared to act as "perfect" economic and rational agents with complete awareness of the market environment. This assumption may be faulty since their response to DR events is uncertain. Faria and Vale (2022) highlight the large amount of uncertainty that could come from the consumers' response and propose a methodology in which diverse DR programs are activated and deactivated during an event to cover the deviations from the target. Three DR programs were activated, presenting how the consumers are activated and remunerated.

The current deterministic methods may be suitable for commercial consumers but fail with the residential due to the uncertainties associated with their unique behaviors. For example, Zeng et al. (2020) based their study on Capacity Credit, paying special attention to the role of human-related uncertainties in DR programs and their potential effects. These authors highlight the difficulty of representing the uncertainties concerning customers' willingness for DR participation since it relies on various factors. However, beyond the operation characteristics of load appliances and the contribution rate of consumers, these authors did not mention the context where the event was triggered. Zhang et al. (2022) went into a more detailed level and studied a flexible smart home appliance load participating in DR constructing a regulation architecture. These authors focused on the air-conditioner as the adjustable potential of this load during the event. Mention that generally, industrial consumers use interruptible loads, which affect the state of the industrial production if they participate in demand response events. Tabandeh et al. (2016) also emphasize the uncertainty of consumers' participation in response to DR programs referring that advanced metering infrastructure is crucial and can highly influence their participation. By considering their historical data from previous events, proving their uncertainty and the tendency to fail, different scenarios for consumers' participation were created, proving the viability of DR programs to reduce congestion costs.

The following points represent the main innovative aspects of the methodology proposed in the present paper regarding previous approaches:

- In Pfeifer et al. (2021), a global perspective on the several flexibility options was presented, estimating that 50% of electricity demand can offer a flexible demand response divided into daily, weekly, and monthly. As so, intra-day aspects (contexts) are neglected. Different rates have been proposed in Silva et al. (2020a), also neglecting contexts. The authors of the present paper classify the participants according to their actual response in a specific context, introducing context-awareness to the solution and giving more accurate information to the aggregator.
- In Niu et al. (2020), the authors believe that economic motivation is crucial to compensate for the active consumers' comfort "sacrifice". In this way, better performance will result in higher rates and better compensation. In the present paper, the DR event context considers the active consumers' willingness and availability, simulating the real environment. Also, the consumer performance from past DR events is considered, but only in the same context to better describe the individual active consumer behavior.
- In Faria and Vale (2022), three different DR programs were applied to deal with the response uncertainty of a DR event participant. In other words, the actual response of consumers can be different from the requested to achieve a

reduction target, so additional programs are activated. In the present paper, the aggregator, before the request, has information on the previous performance of the DR participants and, in this way, can call the more trustworthy, avoiding the triggering of other DR programs.

- In Rodríguez et al. (2021), the value of the aggregator is studied. Promoting synergistic cooperation between the community manager and the active consumer is beneficial, but no reduction target was defined. By identifying a goal, the Aggregator/ community manager has a clearer view regarding the attitude that should be employed: call all the participants to participate in the event, increase the remuneration value or use a different DR program. So, the authors of the present paper set DR targets for the community in the DR event, which is essential to understanding which consumers the aggregator can rely on to achieve the goals in a specific context.
- In Vuelvas et al. (2021), the authors represent the active consumers as rational agents in their study. However, being a new role in the electricity market, considering that participants will always be active and willing to change their strategy as "perfect" economical and rational agents with complete awareness of the market environment and always seeking the optimal decision may be a faulty assumption and not yet feasible in the real world. The authors of the present paper consider that active consumers' response is very uncertain and needs further study and ways to motivate continuous participation. The definition of a trustworthy rate will give crucial information to the aggregator regarding the community.
- In Conchado et al. (2016), the authors show that a full deployment of DR for a range of 10 years could reduce the overall energy demand by 1.3% and the load peak by 1.9% using both energy conservation and load shifting. However, the authors mention that DR signals are based on whole-system prices, which can be a problem in reducing residential peaks. Therefore, the authors believe that an approach should be designed to deal with both perspectives. The proposed methodology by the authors in the present paper has no restrictions regarding this topic: it can be used in both perspectives since a DR target is included. In the study, the aggregator manages a local community, so the most reliable consumers have been triggered to participate in the DR event.

Context can be sensed, obtained, reasoned, computed, determined, or explicitly entered by the active consumers. As in Azari et al. (2019), the authors of the present paper believe that all the knowledge from the active consumers, with the proper treatment and further analysis, can be useful and have a positive impact to develop a better solution for the DR concept implementation. In this way, as a continuity from previous works, the context concept is inserted to optimally select the participants in a DR event resorting to a ranking according to previous performances. Liang and Ma (2020) and Qi et al. (2020) support the ranking approach's idea. Furthermore, building a solution considering the uncertainty of the response such as Tabandeh et al. (2016), paying special attention to the role of human-related uncertainties (Zeng et al., 2020) like the context, but not going into the detail of just one type of appliance such as Liang and Ma (2020) and Qi et al. (2020), focusing on the DR event participation selection perspective. Thus, the proposed methodology approaches this important topic, gathering all the ideas into one concept and building a useful solution to implement DR in future Smart Cities.

1.2. Innovations and contributions

The methodology proposed by the authors in this paper provides innovative contributions for DR deployment in the system, namely when dealing with the uncertainty of consumer response in events bringing context-awareness to the solution. With this, the aggregator identifies the most likely and reliable consumers to react according to the current context. The temperature, day of the week, and time of day were considered key to designing this new trustworthy rate to be assigned to a participant in the DR program. The core innovation points from the present paper are:

- Classification of DR participants according to their actual response in a specific context.
- Active consumers' historical performance, willingness, and availability, simulating the real environment, is considered to describe the individual active consumer behavior better.
- Give the proper use to Aggregator information on the previous performance of the DR participants and, with this, can call the more trustworthy, avoiding the triggering of other DR programs to achieve the DR reduction target.
- Not consider the active consumers as rational and economic agents since their knowledge regarding market transactions is still poor. The definition of a trustworthy rate will give crucial information to the aggregator regarding the community

The present paper is organized as follows. The first section introduces the background, main motivations, and related literature to compare with the innovation and contributions of the proposed methodology. Section 2 presents a detailed explanation of the method and its application to a case study with several scenarios. The results and main discussion are revealed in Section 3, finishing with the conclusions in Section 4.

2. Proposed contextual consumer rate definition for an aggregator

Flexibility can be seen as a service from the consumers to other players in the power and energy market, namely, in this paper, to the aggregator. An aggregator can procure flexibility by triggering a DR event, where the consumers receive a notification with a certain amount of required flexibility and the offered incentive payment. This paper does not target whether this communication is made by SMS or other means, and with one-hour anticipation or another period.

The authors developed a trustworthy rate by resorting to a context-awareness concept by gathering the right information to select the event participants and achieve the expected results. The several steps from the proposed methodology can be seen in Fig. 1.

However, a flowchart was included to complement this information, highlighting the main steps to implement the proposed method.

Firstly, the DR event is triggered, the aggregator identifies the groups to be activated resorting to the event context and the flexibility and only after the most reliable consumers resorting to the CCR. Now, a consumption reduction request can be sent. Comparing the requested and the actual reduction makes it possible to understand if the target was achieved. For a positive case, the CCR must be updated. Otherwise, the aggregator must add the consumers with less reliable rates, selecting the participants and making the reduction request until the goal is achieved.

The formulation of the trustworthy rate is presented further, and a supporting diagram is presented in Fig. 3 for better visualization of the concept. Between the available consumers

of the urban community, it is necessary to choose those with higher levels of trust from the aggregator's perspective to decrease the risk of larger losses in DR events. In other words, the active consumers' performance in DR events, in a certain context, will impact the selection process. So, the authors created the Contextual Consumer Rate (CCR). Fig. 3 represents a visual explanation of the formulation of each dependent rate resorting to the independent rates.

An important step is to identify the contexts, which can be seen in the top diagram of Fig. 3. Considering the yellow example, the event happens on a Sunday between 10 and 11 AM, when there is warm weather. The aggregator must consider historic performances from all the consumers in the same conditions: the last event and the historical data regarding other previous events in the context. With this information, the CCR can be defined as seen in the bottom diagram of Fig. 3, considering each consumer's performance and flexibility. CCR is divided into two dependent rates according to the phase used: Preliminary Contextual Consumer Rate (PR) and Updated Contextual Consumer Rate (UR). In Fig. 1, these phases can be visualized, and a detailed explanation will be provided further. Then, these two rates depend on several factors regarding consumer characteristics: Context Rate (CR), Historic Rate (HR), Last Event Rate (LER), and Response Rate (RR), mentioned as independent rates. If a consumer does not have any previous information, for instance, when it is the first time participating in DR events, the lowest rate is assigned, and from there, the consumer can improve the CCR. This assumption is applied to all independent rates in the same situation. It also includes a Historic Contextual Consumer Rates database that collects all the information and makes it available.

Firstly, CR, represented with the continuous red line in Fig. 3, considers two perspectives: Context Rate Period (CRP) and Context Rate Weather (CRW). These two independent rates represent the performance (good or bad) for a specific context without considering the other one. CRP represents only the performance according to when the DR event was triggered. CRW represents only the performance according to the weather. In this case, the temperature felt when the DR event was triggered. So, both CRP and CRW receive either the maximum rate value for good performance or the minimum rate value for poor performance. Eq. (1) represents the formulation of CR, attributing weights to both CRP and CRW. The weights assigned to each of these independent rates are defined through ω . Both have a major influence on active consumer response. Particularly during working hours, holidays, weekends, or extreme temperatures, the consumer may not give up his comfort and jeopardize participation in these contexts.

$$CR = \omega_{CRP}CRP + \omega_{CRW}CRW \quad (1)$$

As can be seen, the period, the day of the week, and the weather conditions are highlighted with the color that represents CR. For instance, the event represented by a yellow color is triggered on a Sunday, between 10 and 11, in sunny weather. The previous data gathered must follow the same context. To represent this information, CRP changes according to the daily availability of the consumer — which can be different for a certain day and period of the day. CRW changes according to the willingness to participate in certain weather conditions — in this case, the temperature recorded in the period of the event.

HR is represented with a double black borderline, focusing on the Historic Data column, the event on Sunday between 10 and 11 AM, and the remaining. This rate presents historical information on each consumer and the respective performance in previous events in similar contexts. To select the proper moments to consider, information such as the day of the current week and the temperature recorded at the event are gathered. A dataset search is performed to find consumer samples that can meet

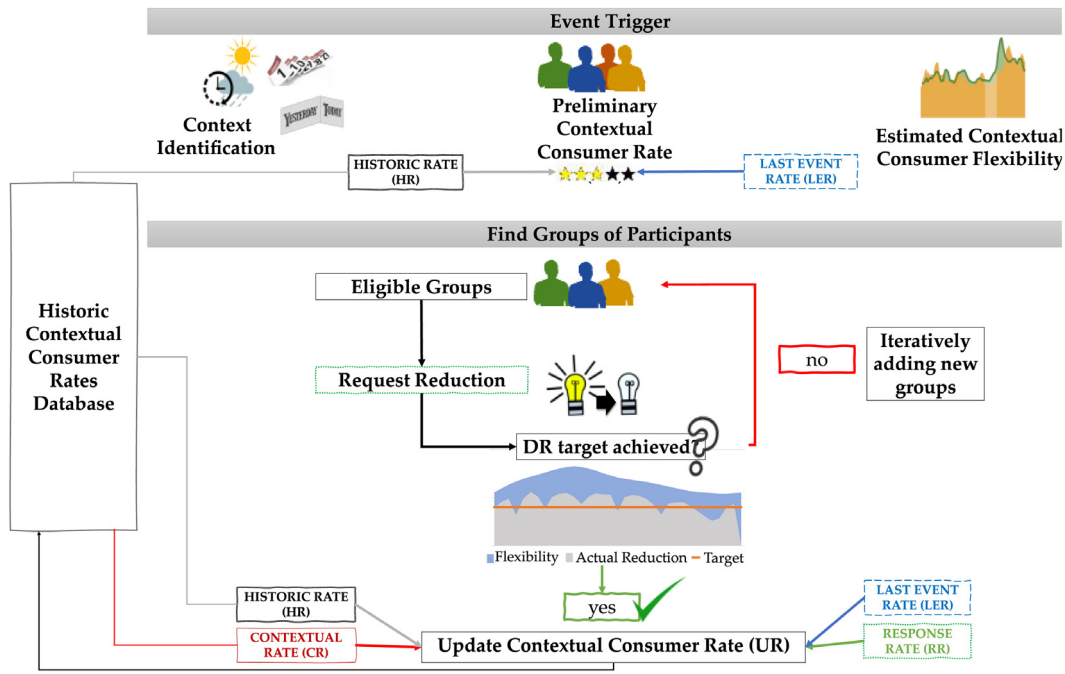


Fig. 1. Proposed methodology – Aggregator activities.

the requirements. A comparison between the current temperature within a defined temperature range is performed for the weather conditions. As Eq. (2) refers, HR is defined by the average performance in the same context.

$$HR = \text{average}(\text{previous performances same context}) \quad (2)$$

For LER, represented with a discontinuous blue borderline, displays the performance of the active consumer in the last event of the same context (weekday, period, and temperature), as can be seen in Eq. (3) and the Last Event column from Fig. 2. This performance rate is important to understand and update the consumer's behavior. Alone, it could misrepresent the active consumer performance since it can be very volatile. With HR, a complete understanding of the performance tendency could be represented. In other words, and for better understanding, HR represents the average performance from previous events in the same context, without the last one – which is represented by LER. For instance, although with high-performance values, a participant could not once participate in a certain context. Therefore, this value should not represent its actual performance because it will jeopardize the continuous work done in previous events.

$$LER = UR \text{ last event in the same context} \quad (3)$$

Finally, the RR, presented with a green dotted line, represents the rate according to the actual response of the consumer to the event. If responded as requested, the resulting rate is the highest. The opposite applies, and the active consumer is penalized with the lowest value of RR.

With the components that formulate the CCR introduced and properly explained, the process that defines the methodology is presented in Fig. 3. Initially, the CCR is defined considering Eq. (4), labeled as (PR).

$$PR = \omega_{HR} * HR + \omega_{LER} * LER \quad (4)$$

This rate considers past information (HR) and performance in the last DR event in the same context (LER). PR is used at the beginning of the event to define the initial rate for each consumer, as can be seen in Fig. 1. After the event is triggered, PR, context

identification, and load flexibility provided by each participant define groups of event participants.

The authors opted to form groups finding a similar pattern among consumers. The group that gathers the highest value of flexibility in the study context is selected, and the elements are called to participate in the event. The approach chosen is an unsupervised machine learning method: clustering. One of the best-known partitioning methods was selected for the present paper - k-means. Generally, this method supposes that a dataset can be defined by finite cluster prototypes, each with its objective functions. In other words, the algorithm consists of finding the centroid value that represents each group being achieved when the distance between an element and the rest is minimal. Several functions can be used to find this distance, namely Euclidean distance. A detailed explanation of this method is now presented (Singh et al., 2013). Let X be the set of data points and V the set of centers. Then, the number of clusters k must be provided. Finally, it was calculated, resorting to Eq. (5), the distance between each data point and cluster centers using the Euclidean distance.

$$Dist_{xv} = \sqrt{\sum_{k=1}^K (X_{ik} - X_{jk})^2} \quad (5)$$

A data point is assigned to the cluster center whose distance is the minimum of all cluster centers. So, the new cluster center should be calculated according to Eq. (6), where c_i denotes the number of data points in the i th cluster.

$$V_i = \frac{1}{c_i} \sum_{c=1}^{c_i} x_i \quad (6)$$

The distance between each data point and the new cluster center is recalculated. If no datapoint was reassigned, the process stops. Otherwise, repeat the previous steps.

The k-means clustering method was already studied and widely used with various extensions in the literature (Sinaga and Yang, 2020). One of the main problems is initialization since it needs the number of clusters from a dataset a priori, which is

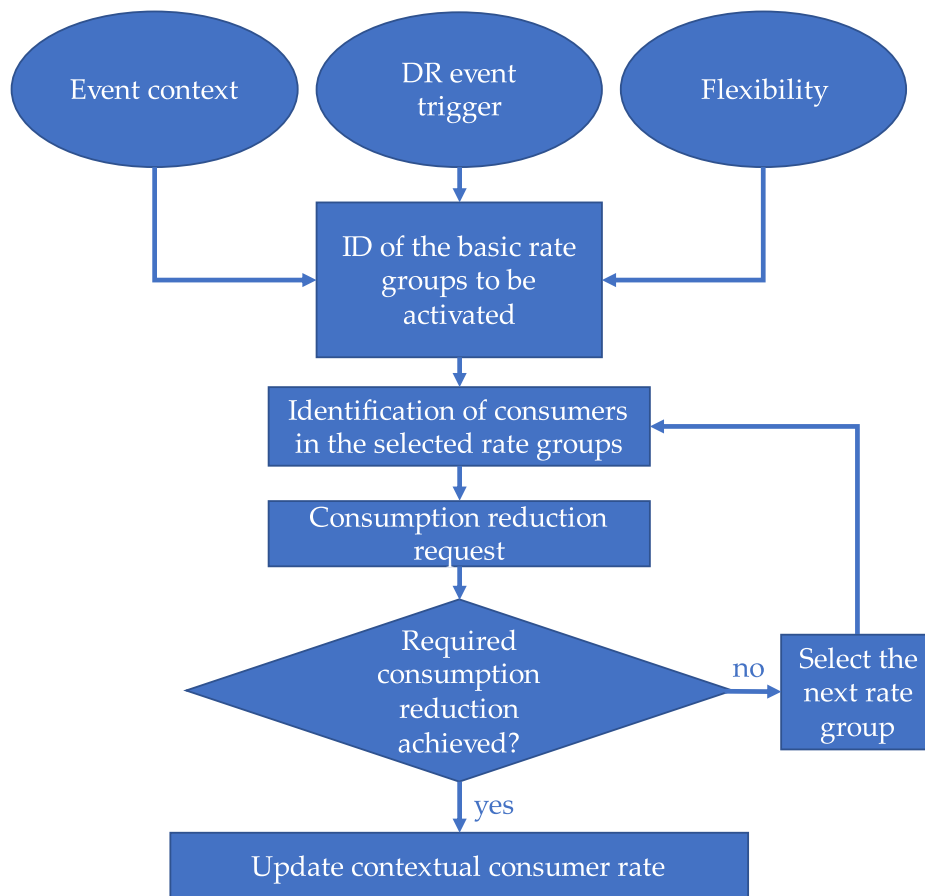


Fig. 2. Proposed methodology – Flowchart. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

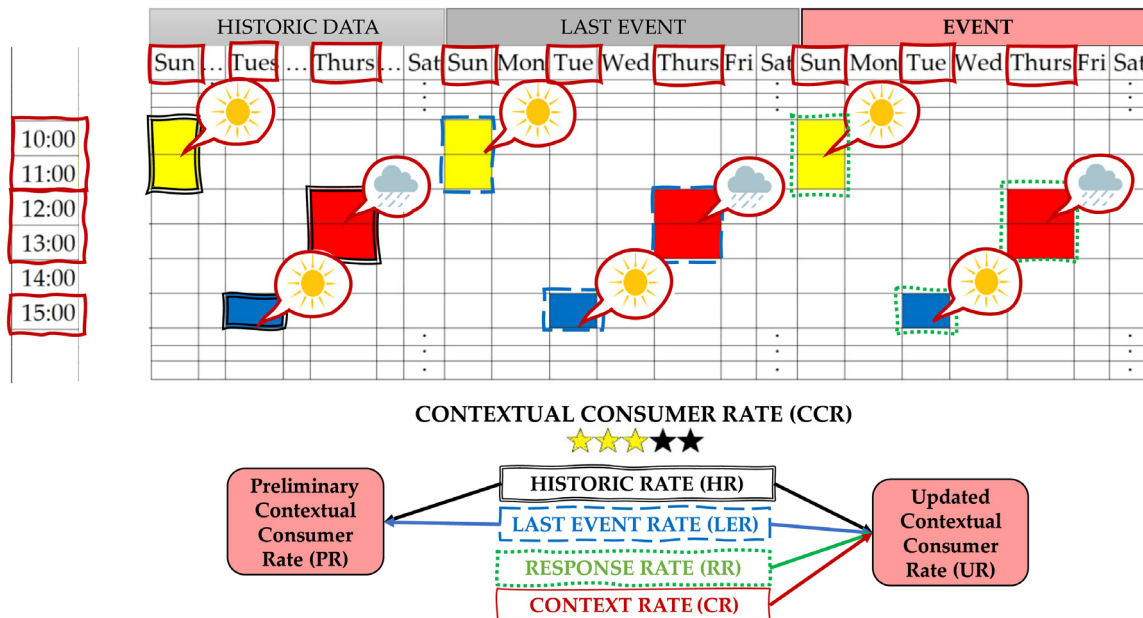


Fig. 3. Proposed methodology – Contextual Consumer Rate definition.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

normally unknown. However, validity indices are used to find the optimal number of clusters for a dataset, aiding the decision-maker (Silva et al., 2019). The database is organized in matrix form, where the columns correspond to the inputs (PR and

flexibility from each consumer) and the rows to the different participants.

As a result, the aggregator finds the group to which each consumer belongs and the centroid of each group. Then, one group

of consumers is selected for the DR event to achieve the required reduction target. In this case, the group that accumulates more flexibility is chosen first, and members are called to participate in the event (Requested Reduction step). A linear approach is employed, and the objective function minimizes operational costs from the Aggregator perspective, as seen in Eq. (7). Let c be the number of consumers, t be the number of periods, g the number of Distributed Generation (DG) units, and s be the number of external suppliers. The authors in this paper obtained the results by using lpSolve in RStudio, taking 30 s for the optimization of each period.

The objective function is represented by the sum of the product between all the power from DG units g on period t ($P_{DG(g,t)}$) and the respective cost ($C_{DG(g,t)}$) plus the sum of the product between all the power from DR active consumer c on period t ($P_{DR(c,t)}$) and the respective cost ($C_{DR(c,t)}$) plus the sum of the product between all the power from supplier s on period t ($P_{Supplier(s,t)}$) plus the product between the NSP on period t ($P_{NSP(t)}$) and the respective cost ($C_{NSP(t)}$).

$$\begin{aligned} \text{Min. OF} &= \sum_{p=1}^P [P_{DG(g,t)} C_{DG(g,t)}] + \sum_{c=1}^C [P_{DR(c,t)} C_{DR(c,t)}] \\ &+ \sum_{s=1}^S [P_{Supplier(s,t)} C_{Supplier(s,t)}] + P_{NSP(t)} C_{NSP(t)} \\ &c, t, g, s \in \mathbb{Z}: c, t, g, s > 0 \end{aligned} \quad (7)$$

The objective function represented in Eq. (7) is subjected to several constraints—(8) to (14). Firstly, to achieve the network power balance, in other words, the equilibrium between consumption and generation (8) is defined. Then, the sum of the difference between the initial load ($P_{(c,t)}^{initial}$) and the requested reduction should equalize the value to the total generation within DG units, external suppliers, and the NSP.

$$\begin{aligned} \sum_{c=1}^C [P_{(c,t)}^{initial} - P_{DR(c,t)}] &= \sum_{g=1}^G [P_{DG(g,t)}] + \sum_{s=1}^S [P_{Supplier(s,t)}] \\ &+ P_{NSP(t)} \quad c, t, g, s \in \mathbb{Z}: c, t, g, s > 0 \end{aligned} \quad (8)$$

Eq. (9) represents the maximum contribution requested ($P_{DG(g,t)}^{Max}$) from each active consumer to a DR event. Since they have a contract with the aggregator, it is expected that each participant will contribute the amount requested. The CTR was defined to reduce uncertainty but not guarantee that the requested reduction equals the actual reduction.

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

To define limits for the DG units' contribution, (10) to (12) allow the aggregator to control the upper ($P_{DR(c,t)}^{Max}$) and lower bounds ($P_{DG(g,t)}^{Min}$) and the total value of generation provided from each different technology ($P_{DG(g,t)}^{Total}$).

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

$$P_{DG(g,t)} > P_{DG(g,t)}^{Min} \quad g, t, \in \mathbb{Z}: g, t > 0 \quad (11)$$

$$\sum_{g=1}^G [P_{DG(g,t)}] \leq P_{DG(g,t)}^{Total} \quad g, t, \in \mathbb{Z}: g, t > 0 \quad (12)$$

Eqs. (13) and (14) represent the external suppliers' constraints, constraining the maximum capacity ($P_{Supplier(s,t)}^{Max}$) and the total amount of generation provided from this source to suppress the demand side needs ($P_{Supplier(s,t)}^{Total}$).

$$P_{Supplier(s,t)} \leq P_{Supplier(s,t)}^{Max} \quad s, t, \in \mathbb{Z}: s, t > 0 \quad (13)$$

$$\sum_{s=1}^S [P_{Supplier(s,t)}] \leq P_{Supplier(s,t)}^{Total} \quad s, t, \in \mathbb{Z}: s, t > 0 \quad (14)$$

It is highlighted those high values of CCR represent a high probability of the consumer responding in this context but do not guarantee. Responses are collected, and the current reduction of the event is compared with the DR target. The DR target is defined according to upper-level managers who request a load reduction from the aggregator's urban community manager. The goal is to achieve this value of load reduction, for instance, when the Distribution System Operator detects a voltage limit violation a priori. The evaluation procedure is defined according to the comparison between the expected/requested reduction value and the current one. A signal is sent to the selected participants before the event to understand their availability. If the value of flexibility is lower than the target, the remaining consumers are called until the target reaches the desired value. The CCR of each of them is updated according to the answers given at the end of each event - (UR). This rate is further called LER, as mentioned earlier, and is used in the next event that happens in the same context. After the first time, this method was used in the same context, and the UR will be used as LER at the beginning of the next event and in the update. Eq. (15) represents the UR formulation, as shown in Fig. 3, through the independent rates and their weights assigned to them.

$$UR = \omega_{HR} * HR + \omega_{LER} * LER + \omega_{RR} * RR + \omega_{CR} * CR \quad (15)$$

According to the weight given to each independent rate, the importance given to each of the independent rates influences both actual events and the following. What the consumer reduces in this event is important (RR), but should it be considered the independent rate with the greatest influence? It may have been when they would not be available to respond. However, the historical data affirms that previous participation in similar contexts has been high. Should your previous effort and proven loyalty to the aggregator be penalized in this way? What is the best approach to assigned weights? This paper aims to prove the feasibility of the proposed methodology and make a sensitivity test of these values, i.e., how will it influence consumers over a month of testing. This topic is relevant in situations that impact the grid's good functioning, which may require a consumption reduction from an active community. For instance, a Distribution System Operator (DSO) detects a voltage limit violation of the network. A DR event is triggered to overcome, and DSO requests a reduction from the aggregator. For instance, the amount of requested reduction can be 100 kW. The timeline of the DR event starts with the event announcement (can go from a day ahead to some minutes before the event starts). In the face of the conditions settled in the announcement, the participating consumers are expected to ensure their demand reduction, after the ramping period, during the full sustained response period (Abrishambaf et al., 2020).

3. Case study and scenarios definition

Thus, a case study was designed considering one month as a timeline – April 2019. The database contained information from ten randomly generated urban communities and was already used in several studies by the authors and works as the base for this paper (Faria et al., 2016). Table 1 shows all elements in the urban communities composed of residential consumers. The dataset used is divided into 15-minute periods.

Only one urban community was chosen for the case study presented in this paper. It has 406 consumers and was the community with the highest CCR performance rate average (Silva

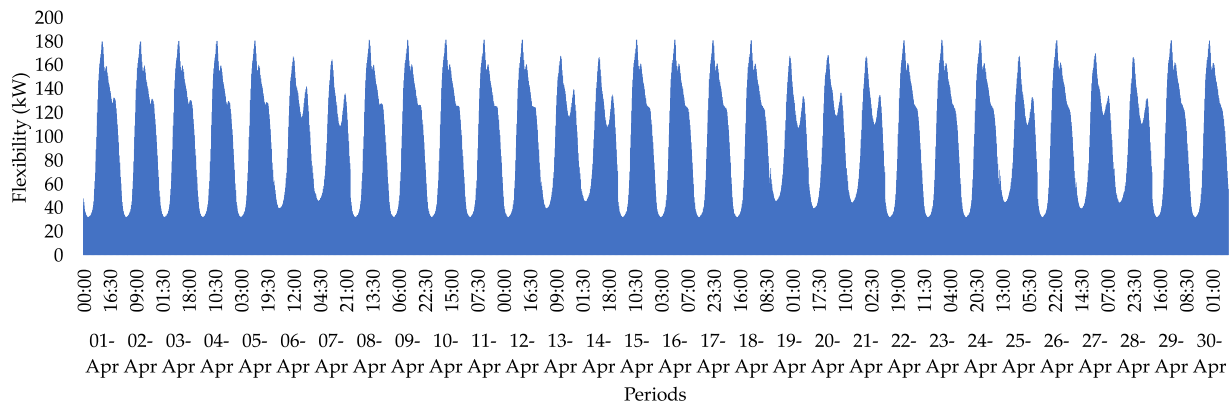


Fig. 4. Selected urban community flexibility throughout April 2019.

First Week			Remaining Weeks	
Phase	Rate	Weight	Rate	Weight
Preliminary Contextual Consumer Rate (PR)	HISTORIC RATE (HR)	ω_{HR}	HISTORIC RATE (HR)	ω_{HR}
			LAST EVENT RATE (LER)	ω_{LER}
Update Contextual Consumer Rate (UR)	HISTORIC RATE (HR)	ω_{HR}	HISTORIC RATE (HR)	ω_{HR}
	RESPONSE RATE (RR)	ω_{RR}	LAST EVENT RATE (LER)	ω_{LER}
	CONTEXT RATE (CR)	ω_{CR}	RESPONSE RATE (RR)	ω_{RR}
			CONTEXT RATE (CR)	ω_{CR}

Fig. 5. Rate definition according to the timeline for each methodology phase and scenario definition.

Table 1

Characterization of the consumers from all the ten urban communities.

Type	Residential
# elements	10,168
Energy (kWh)	9369.35
Max load reduction (kW)	4684.7
Initial price (m.u./kWh)	0.12

et al., 2020a). The flexibility provided by the selected urban community throughout the month can be seen in Fig. 4.

Moving to the definition of the case study regarding the CCR, the value of each rate goes between 1 and 5. The first is the one with lower performance. A denominated minimum was considered for participation in previous works: consumers with values higher than three were selected first, given participation priority. Here, all the consumers are selected as input for the clustering phase.

The focus of the study is a weight sensitivity for each of the independent rates in the formation of the CCR, understanding how each independent rate can influence the result. Therefore, it was necessary to perceive the total number of permutations, considering a fixed step of 0.25 in a range between 0 and 1. In addition, scenarios in which the independent rate weight was equal to zero were also studied, perceiving the need for this specific rate in the definition of the CCR. Also, it was assumed that for cases where two or more independent rates could define the CCR, at least two should have a weight higher than 0, and the sum should equal 1. Fig. 5 presents the method to obtain the number of scenarios.

As mentioned earlier, in the first week, the independent rate LER could not be a part of the definition of the PR – still no

information relating to the previous event using this specific methodology. For a better understanding, an example of a scenario definition: in the first week, PR was only formed by HR being the ω_{HR} equal to 1, and the UR was formed by HR (being the ω_{HR} equal to 0.5) plus CR (being the ω_{CR} equal to 0.25) and RR (being the ω_{RR} equal to 0.25); in the remaining weeks PR was formed by HR (being the ω_{HR} equal to 0.5) plus LER (being the ω_{LER} equal to 0.5) and the UR was formed by HR (being the ω_{HR} equal to 0.5) plus CR (being the ω_{CR} equal to 0.25) plus RR (being the ω_{RR} equal to 0.25) and LER (being the ω_{LER} equal to 0).

Thanks to the resulting high number of permutations (116) to the limited space, scenarios were created for only two days of the week: one during the working week (Monday) and the other during the weekend (Saturday). Throughout the month, the results from these days were tested, analyzed, and compared – four samples from each of the days of the week – were 1, 6, 8, 13, 15, 20, 22, and 27.

To ease the treatment of historical information, the day was divided into 11 periods, as shown in Table 2. Intervals may not always have the same duration. Depending on these periods and the day of the week the event was triggered, the CRP was defined, where performance in these periods was evaluated, and the rate value was assigned.

The CRW depends on the temperature recorded at the time of the event. Also, HR is the average of historical values in similar contexts (including temperature). Therefore, since there may not be the same temperature in that period, temperature intervals were also designed in the database and are presented in Table 3.

The temperatures recorded in the three months preceding the month studied – April 2019, were considered for independent

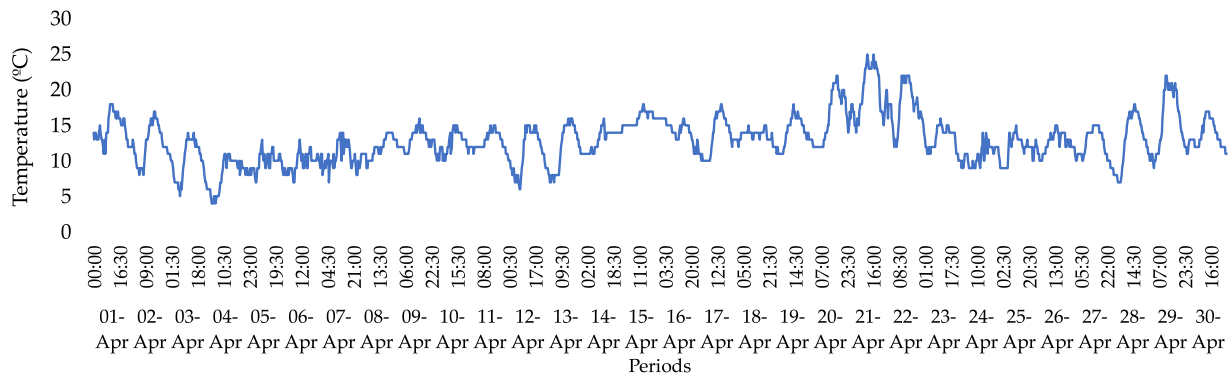


Fig. 6. Temperature value throughout April 2019 for the definition of the independent rate.

Table 2
Time intervals definition to ease the independent rates assignment.

Interval	1	2	3	4	5	6	7	8	9	10	11
Initial	00:15	07:15	09:30	10:30	11:30	12:45	14:00	15:30	17:30	18:15	21:30
Final	07:00	09:15	10:15	11:15	12:30	13:45	15:15	17:15	18:00	21:15	00:00

Table 3
Temperature Intervals definition to ease the independent rates assignment.

Interval	1	2	3	4	5	6	7	8
Initial (°C)	-05	11	16	19	23	26	31	36
Final (°C)	10	15	18	22	25	30	35	45

rate definition. Therefore, weather data from the Oporto Airport station were considered a reference point, and the values can be seen in Fig. 6 (Underground, 2020).

In this case study, 100 kW of reduction is requested and updated on a 15-minute basis.

4. Results for a global perspective and selected consumers

Several DR events were triggered, analyzed, and evaluated throughout the selected month. Although the sensibility of the weights from each independent rate was performed for the 116 created scenarios, only four were selected to be presented in this section, as Table 4 shows.

The scenarios were chosen considering that each independent rate would have a higher percentage in one of them: Scenario 21 represents the one where LER has a higher impact than the remaining; in Scenario 30, the CR has a higher impact; in Scenario 51, the RR has higher impact; in Scenario 94 the HR has higher impact. Section 4 is divided into two subsections: first, the community results with a global perspective, and finally, two consumers are selected to understand how the CCR impacts the group of participants over the month according to each scenario. Section 4.1 presents the evolution from the four tested weeks and comparison between four chosen scenarios (each one with an independent rate with a higher percentage than the others in both phases of the event).

4.1. Global perspective – Community results

The current sub-section is divided according to the two days chosen for the study: Monday and Saturday. In other words, the different responses from the selected active consumers were analyzed for all the selected scenarios and compared for similar days of the month. Therefore, all the scenarios implemented (different configurations of weights) have been tested on the same days.

Firstly, Fig. 7 exhibits the actual reduction from the community for the four sample days. A wide range of DR events was

Table 4
Weights for the independent rates in each selected scenario – fixed step of 0.25.

	CCR	ω				Scenario
		HR	LER	RR	CR	
First week	PR	1	-	-	-	21
	UR	0.25	-	0.25	0.50	
Remaining weeks	PR	0.50	0.50	-	-	21
	UR	0.00	0.50	0.25	0.25	
First week	PR	1	-	-	-	30
	UR	0.25	-	0.25	0.50	
Remaining weeks	PR	0.50	0.50	-	-	30
	UR	0.00	0.25	0.25	0.50	
First week	PR	1	-	-	-	51
	UR	0.25	-	0.50	0.25	
Remaining weeks	PR	0.50	0.50	-	-	51
	UR	0.25	0.00	0.50	0.25	
First week	PR	1	-	-	-	94
	UR	0.50	-	0.25	0.25	
Remaining weeks	PR	0.50	0.50	-	-	94
	UR	0.50	0.00	0.25	0.25	

presented to understand the behavior in that period and how the scenarios differ. It must be highlighted for this simulation the DR target was 100 kW, and every 15 min, the value was updated. From the Aggregator perspective, the goal is to select the right DR event participants to reduce the target amount altogether. Scenario 21 is a green line, Scenario 30 represents a red line, Scenario 51 represents a blue line, and Scenario 94 is a yellow line. The scenarios are consistent between the charts shown in Fig. 7 when the DR target is not achieved.

In the first week, since the PR depended only on HR, the actual reduction was equal to all scenarios. Then, the distinctions begin to be observed in the following samples with the UR for the next event. For example, in the first 45 min in Fig. 7(b), scenarios follow almost the same tendency. However, from that point, Scenario 51 and Scenario 94 differ from the remaining until 16:15:00.

Scenario 51, where the RR had more influence than the remaining, had more discrepancy. For instance, between 12:30 and 13:45 or 15:15 and 16:15, the actual reduction value was lower than the remaining but still above the target. Scenario 21 (higher LER) and Scenario 30 (higher CR) kept equal the entire period. Although the influence of LER exists in this second week of the

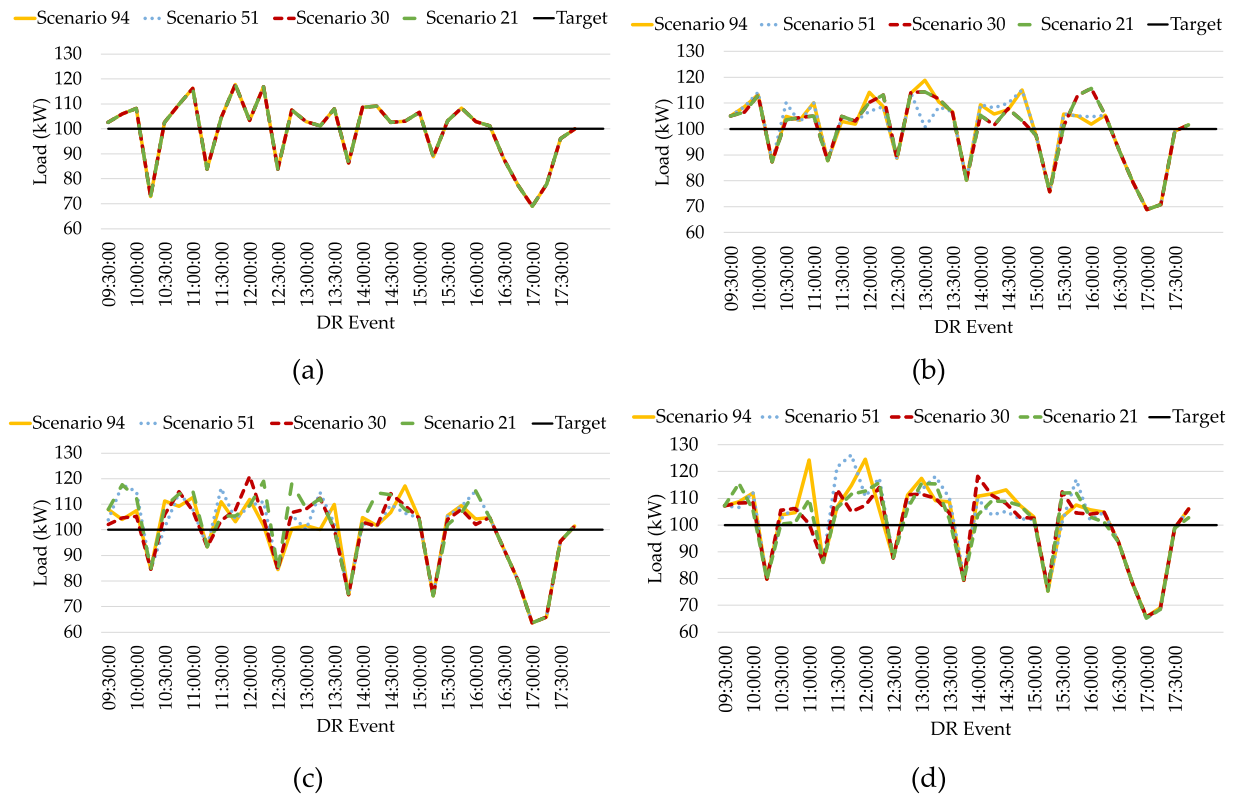


Fig. 7. Actual Reduction for each weight combination (a) Monday, 1 April; (b) Monday, 8 April; (c) Monday, 15 April; (d) Monday, 22 April.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

month, it is equal to all scenarios in PR, and only the update has a stronger influence; in this way, Scenario 21 and Scenario 30 are like the weights, the exhibit result is reasonable.

Fig. 7 (c) the divergence from scenarios is highly noticed – except from 16:15 until 17:30, where they all remain equal, and the DR target is not achieved. Scenario 30 achieves the higher reduction value from all the scenarios in this example at 11:45, slightly above 120 kW. Scenario 94 had a lower actual reduction but always achieved the target most of the time.

Finally, in Fig. 7(d), between 11:45 and 13:00, the value of actual reduction was higher than in the other periods, and Scenario 51 is again highlighted.

The PR and UP influence the actual reduction results (previous event results). Four periods of the DR event observed in the previous figure were studied in detail: 12:00 until 12:45. Remembering the fact that the method was updated every 15 min. Table 5 compares the PR and UR for Scenario 21, where the LDR has a greater impact on the update phase of CCR. Only the first and the final sample were compared – Figs. 7(a) and 7(b) days. The table shows the number of elements from all group rates in each period.

On the first day, between 12:00 and 12:15, only Group Rate 4 increased the number of elements – superior to 100 participants seemed to increase their value of CCR. Between 12:30 and 12:45, none of the participants had Rate 1 or Rate 5 on PR, and the number of participants was concentrated on Rate 3. However, in the update phase, most consumers increase their CCR to Rate 4.

For the sample regarding the last day (Sample 4), there was consistency in all the observed periods: Rate 1 and 5 stayed the same; Rate 2 decreased, and Rate 3 and Rate 4 increased the number of elements.

Table 6 demonstrates the results for Scenario 30, where the CR impact was superior.

As already mentioned, Scenario 21 and Scenario 30 were similar in the first week, so the results are the same for Sample 1.

In the last sample, the result was slightly different on Rate 4 and Rate 5. In periods 12:15 and 12:45, the number of elements in Rate 4 decreases for Rate 5 in periods 12:00 and 12:15.

Table 7 demonstrates the results for Scenario 51, where the RR impact was superior.

In Sample 1, Rate 4 increased in all the periods, although only the first two were the most aggregated in this group. In the remaining cases, the consumers stayed on Rate 3.

For Sample 4 in Scenario 51, one of the highlights was in period 12:00 PM, where the number of participants with Rate 5 increased from 0 to 35, the highest increase in all the examples in this rate. The consumers were condensed between Rate 3 and Rate 4.

Finally, Table 8 demonstrates the results for Scenario 94, where the HR impact was superior.

In the first week, the number of consumers is mainly concentrated above Rate 3, with more participants.

Compared with the remaining scenarios in the final week, Scenario 94 was where Rate 4 had fewer elements between periods. When the HR has more influence, the CCR stays mostly on Rate 3. Now, results from Saturday and its reunited samples are demonstrated. Like the previous study, Fig. 8 presents the actual reduction from the whole community between the stipulated period of the day. The conclusions from Figs. 8(a) and 8(b) are pretty to the previous study: the same curves in the first week and a slight discrepancy between Scenario 51 and Scenario 94 in the second. Another important conclusion is the fact of less non-achieved targets. The range between 9:30 and 13:15 was a good example of the aggregator maintaining the reduction above the objective for more or less than 4 h. Looking at each scenario, Table 9 shows the results between 12:00 and 12:45 in the first and last week for Scenario 21 the comparison.

The number of elements with Rate 1 and Rate 5 decreased in the first week; on the contrary, Rate 4. Rate 3 agglomerated

Table 5
Community results – Scenario 21 when the LDR is superior to the other independent rates.

Sample	Period	CCR	Rate									
			1		2		3		4		5	
1	12:00	PR	47	↘	97	↘	104	↘	99	↗	59	↘
		UR	0		69	↘	70	↘	264	↗	3	↘
	12:15	PR	39	↘	102	↘	103	↘	104	↗	58	↘
		UR	0		95	↘	97	↘	208	↗	6	↘
	12:30	PR	0	=	38	↗	328	↘	40	↗	0	=
		UR	0		57	↗	88	↘	261	↗	0	=
	12:45	PR	0	=	27	↗	350	↘	29	↗	0	↗
		UR	0		54	↗	86	↘	265	↗	1	↗
4	12:00	PR	0	=	109	↘	74	↗	223	↗	0	=
		UR	0		75	↘	81	↗	250	↗	0	=
	12:15	PR	0	=	125	↘	62	↗	219	↗	0	=
		UR	0		87	↘	63	↗	256	↗	0	=
	12:30	PR	0	=	64	↘	98	↗	244	↗	0	=
		UR	0		57	↘	99	↗	250	↗	0	=
	12:45	PR	0	=	71	↘	83	↗	252	↗	0	=
		UR	0		62	↘	92	↗	252	↗	0	=

Table 6
Community results – Scenario 30 when the CR is superior to the other independent rates.

Sample	Period	CCR	Rate									
			1		2		3		4		5	
1	12:00	PR	47	↘	97	↘	104	↘	99	↗	59	↘
		UR	0		69	↘	70	↘	264	↗	3	↘
	12:15	PR	39	↘	102	↘	103	↘	104	↗	58	↘
		UR	0		95	↘	97	↘	208	↗	6	↘
	12:30	PR	0	=	38		328		40		0	=
		UR	0		95	↗	97	↘	208	↗	0	
	12:45	PR	0	=	27	↗	350	↘	29	↗	0	↗
		UR	0		54	↗	86	↘	265	↗	1	↗
4	12:00	PR	0	=	154	↘	43	↗	204	↗	5	↘
		UR	0		43	↘	134	↗	229	↗	0	↘
	12:15	PR	0	=	123	↘	62	↗	214	↘	7	↘
		UR	0		52	↘	159	↗	195	↘	0	↘
	12:30	PR	0	=	82	↘	128	↗	196	↗	0	=
		UR	0		48	↘	150	↗	208	↗	0	=
	12:45	PR	0	=	82	↘	113	↗	211	↘	0	=
		UR	0		35	↘	170	↗	201	↘	0	=

the most participants in periods 12:00 and 12:15, although the number of elements reduced between PR and UR. In the last sample, none of the participants had Rate 1 or Rate 5. Instead, the majority was concentrated on Rate 4.

Table 10 demonstrates the results for Scenario 30, where the CR impact was superior.

The first sample is equal to the previous scenario. In Sample 4, Rate 3 increased the number of elements in all the periods. The opposite happens on Rate 4. Rate 1 and Rate 5 maintain the same.

Table 11 demonstrates the results for Scenario 51, where the RR impact was superior.

In the first week, it is possible to see a decrease from Rate 1 and Rate 2, but between 12:15 and 12:30, the elements in Rate 3 stay the same. So, Rate 4 saw the number of elements increase. In the last week, the number of participants with Rate 1 stays the same – zero. Therefore, the number of elements with Rate 3 and

Rate 4 increased in the first period. In the second period, Rate 3 decreased, and both Rate 2 and Rate 4 increased. The increase in Rate 2 defined the last two periods despite the majority being concentrated on Rate 4.

Finally, Table 12 demonstrates the results for Scenario 94, where the HR impact was superior.

In the first week, the only rate that did not decrease the number of elements was Rate 3 (in some periods) and Rate 4, the significant number of elements concentrated around these rates. However, in the last week, none of the participants had Rate 1 or 5.

Table 13 shows the results from applying the basic methodology without considering comparing the proposed approach with previous works and understanding the evolution. In this case, the LER had more influence in PR ($\omega_{HR} = 0.40$; $\omega_{LER} = 0.60$), and for UR, all the independent rates had the same percentage ($\omega_{RR} = 0.33$;

Table 7
Community results – Scenario 51 when RR is superior to the other independent rates.

Sample	Period	CCR	Rate									
			1		2		3		4		5	
1	12:00	PR	47	↘	97	↘	104	↘	99	↗	59	↘
		UR	6		55	↘	97	↘	211	↗	37	↘
	12:15	PR	39	↘	102	↗	103	↘	104	↗	58	↘
		UR	10		123	↗	101	↘	134	↗	38	↘
	12:30	PR	0	=	38	↘	328	↘	40	↗	0	=
		UR	0		37	↘	303	↘	66	↗	0	=
	12:45	PR	0	=	27	↘	350	↘	29	↗	0	↗
		UR	0		26	↘	315	↘	64	↗	1	↗
4	12:00	PR	0	=	115	↘	105	↗	186	↘	0	↗
		UR	0		98	↘	109	↗	164	↘	35	↗
	12:15	PR	0	=	144	↘	59	↘	192	↗	11	↘
		UR	0		67	↘	58	↘	273	↗	8	↘
	12:30	PR	0	=	26	↘	275	↘	105	↗	0	=
		UR	0		10	↘	222	↘	174	↗	0	=
	12:45	PR	0	=	46	↘	272	↘	88	↗	0	=
		UR	0		4	↘	231	↘	171	↗	0	=

Table 8
Community results – Scenario 94 when HR is superior to the other independent rates.

Sample	Period	CCR	Rate									
			1		2		3		4		5	
1	12:00	PR	47	↘	97	↘	104	↗	99	↗	59	↘
		UR	6		55	↘	172	↗	136	↗	37	↘
4	12:15	PR	39	↘	102	↗	103	↘	104	↗	58	↘
		UR	10		123	↗	101	↘	135	↗	37	↘
	12:30	PR	0	=	38	↘	328	↘	40	↗	0	=
		UR	0		37	↘	303	↘	66	↗	0	=
	12:45	PR	0	=	27	↘	350	↘	29	↗	0	=
		UR	0		26	↘	315	↘	65	↗	0	=
4	12:00	PR	0	=	145	↘	81	↘	175	↗	5	↘
		UR	0		143	↘	57	↘	202	↗	4	↘
	12:15	PR	0	=	141	↘	85	↗	166	↘	14	↘
		UR	0		115	↘	122	↗	161	↘	8	↘
	12:30	PR	0	=	37	↗	277	↗	92	↘	0	=
		UR	0		38	↗	302	↗	66	↘	0	=
	12:45	PR	0	=	29	↘	280	↗	97	↘	0	=
		UR	0		28	↘	283	↗	95	↘	0	=

$\omega_{HR} = 0.33$; $\omega_{LER} = 0.33$). Although more samples were provided in the previous study, only the first and the fourth were considered.

One of the highlights is the number of participants in Rate 1 and Rate 5. Although in the present study, the value tends to zero, Table 13 increases while Rate 3 and Rate 4 decrease. However, two main differences separate both methods, which may be the source of the disparities:

- Last Day Rate (LDR) vs. Last Event Rate (LER): firstly, the authors considered the actual last event without context (for instance, it could be used the performance from a Sunday on a Friday event). With the contextual approach, the LER contemplates the day of the week and the period and temperature.

- Selection of Participants: in the previous work, three different approaches were compared to select trustworthy participants, considering scheduling only the ones with a higher rate. All the consumers can join in the scheduling phase by being selected through a clustering method (participants with similar performances are integrated into the same group). In this way, the need for several re-scheduling is avoided.

Section 4.2 goes into a more specific study, selecting consumers to compare their behavior and the impact of each scenario on their performance throughout the 4 tested weeks.

4.2. Selected consumers

As already mentioned, each consumer has different behaviors in specific contexts. Two consumers were selected to study

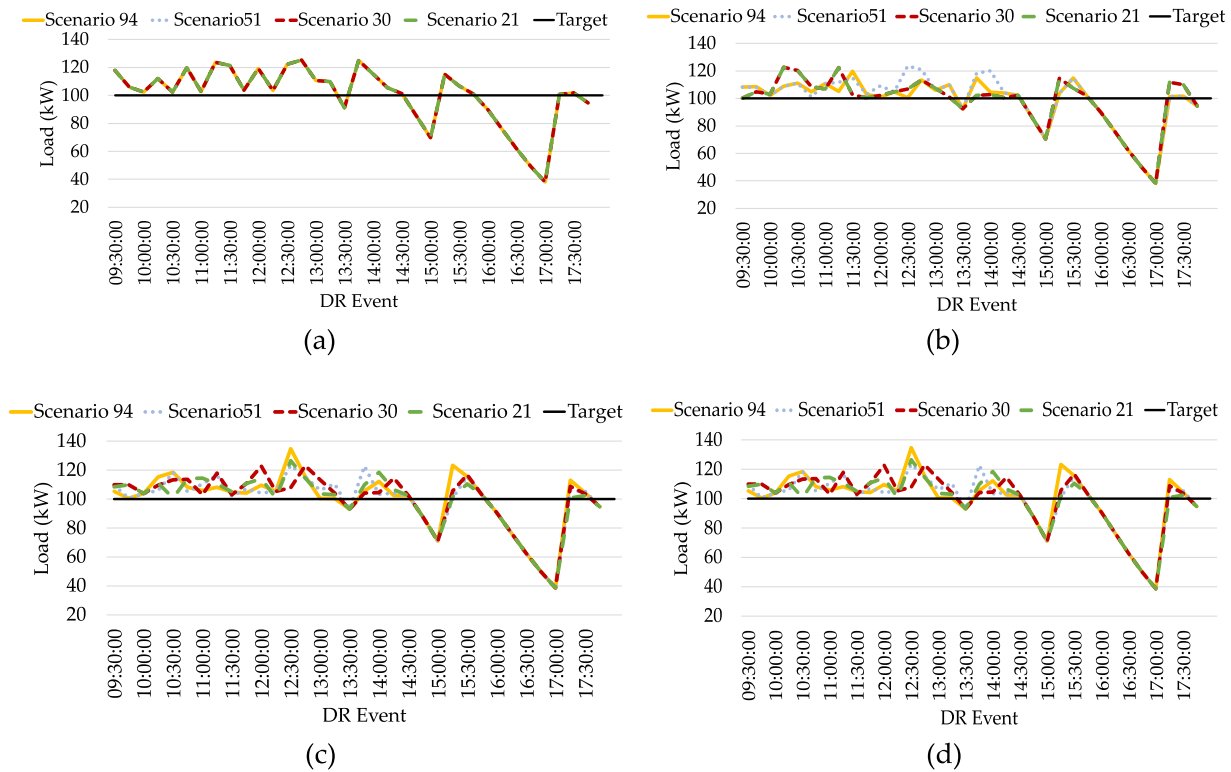


Fig. 8. Actual Reduction from Community (a) Saturday, 6 April; (b) Saturday, 13 April; (c) Saturday, 20 April; (d) Saturday, 27 April.

Table 9
Community results – Scenario 21 when LDR is superior to the other independent rates.

Sample	Period	CCR	Rate									
			1	2	3	4	5					
1	12:00	PR	3	↘	91	↗	204	↘	101	↗	7	↘
		UR	0		127	↗	147	↘	132	↗	0	
	12:15	PR	6	↘	98	↗	205	↘	89	↗	8	↘
		UR	0		142	↗	154	↘	110	↗	0	
	12:30	PR	8	↘	142	↘	98	↗	154	↗	4	↘
		UR	0		73		139	↗	194	↗	0	
12:45	PR	3	↘	164	↘	81	↗	150	↗	8	↘	
	UR	0		98		138	↗	170	↗	0		
4	12:00	PR	0	=	123	↘	112	↗	171	↗	0	=
		UR	0	=	64	↘	121	↗	221	↗	0	=
	12:15	PR	0	=	110	↘	142	↗	154	↗	0	=
		UR	0	=	71		144	↗	191	↗	0	=
	12:30	PR	0	=	100	↘	74	↘	232	↗	0	=
		UR	0	=	96		7		303	↗	0	=
	12:45	PR	0	=	137	↘	51	↗	218	↗	0	=
		UR	0	=	47		134	↗	225	↗	0	=

their CCR and how the independent rates impact their results throughout the month. The four scenarios are presented between Tables 15 and 21 for the two participants. The green color represents the consumer’s availability to respond, and the red represents the non-response. Remembering the fact that RR depends on PR. If the consumer was not selected to participate, the RR equals PR with a response or a non-response. Only Monday’s results are presented in this section since the one with more periods with actual reduction is different from the DR target – lower. Also, the same period from the previous subsection is

studied: 12:30 is one of the moments where the target was not achieved.

The first participant is residential and is identified as Consumer 55. Fig. 9 represents the daily consumption with different shades of blue and the average from April 2019 with a red dotted curve. The max reduction value from an event through the month was 0.5985 kW.

Table 14 shows the result for the first participant with Scenario 21, where the LER is superior. Focusing on the non-responses, for instance, on the first day, the critical period was 12:30 and 12:45, but although the RR was low, the UR increased

Table 10
Community results – Scenario 30 when CR is superior to the other independent rates.

Sample	Period	CCR	Rate									
			1	2	3	4	5					
1	12:00	PR	3	↘	91	↗	204	↘	101	↗	7	↘
		UR	0		140	↗	119		147	↗	0	
	12:15	PR	6	↘	98	↗	205	↘	89	↗	8	↘
		UR	0		142	↗	154		110	↗	0	
	12:30	PR	8	↘	142	↘	98	↗	154	↗	4	↘
		UR	0		73		139	↗	194	↗	0	
Sample	Period	CCR	Rate									
			1	2	3	4	5					
12:45	PR	3	↘	164	↘	81	↗	150	↗	8	↘	
	UR	0		98		138	↗	170	↗	0		
4	12:00	PR	0	=	95	↘	85	↗	226	↘	0	=
		UR	0		84		158	↗	164		0	
	12:15	PR	0	=	74	↘	98	↗	234	↘	0	=
		UR	0		72		174	↗	160		0	
	12:30	PR	0	=	102	↘	68	↗	236	↘	0	=
		UR	0		77		159	↗	170		0	
	12:45	PR	0	=	32	↗	152	↗	222	↘	0	=
		UR	0		37		195	↗	174		0	

Table 11
Community results – Scenario 51 when RR is superior to the other independent rates.

Sample	Period	CCR	Rate									
			1	2	3	4	5					
1	12:00	PR	3	=	91	=	204	↘	101	↗	7	↘
		UR	3		91		124		186	↗	2	
	12:15	PR	6	↘	98	↘	205	=	89	↗	8	↘
		UR	4		61		205		135	↗	1	
	12:30	PR	8	↘	142	↘	98	=	154	↗	4	↘
		UR	1		79		98		226	↗	2	
12:45	PR	3	↘	164	↘	81	↘	150	↗	8	↘	
	UR	1		166		6		227	↗	6		
4	12:00	PR	0	=	147	↘	65	↗	194	↗	0	=
		UR	0		118		74	↗	214	↗	0	
	12:15	PR	0	=	102	↗	110	↘	194	↗	0	=
		UR	0		106		82		218	↗	0	
	12:30	PR	0	=	36	↗	183	↘	187	↘	0	↗
		UR	0		80		142		183		1	
	12:45	PR	0	=	109	↗	93	↘	204	↘	0	↗
		UR	0		130		77		197		2	

from PR – CR was 5 and 4 and had more influence justifying the increase. When LDR had influence, the only time that UR was different from PR was on Day 8 with a decrease – although RR and HR had a higher value (4), CR was 1.

Table 15 shows the results for Scenario 30, where the CR influence is greater than the remaining. Again, the non-response had a low impact on UR for the first day, and UR decreased from PR when the CR had a low value. For instance, comparing the 12:30 over the month, it started with UR with a Rate 4 and decreased to Rate 2 thanks to the CR. Again, it highlights that the HR was never below Rate 3.

The results from Scenario 51, where the RR has a higher impact, can be seen in Table 16. When comparing with the previous table, for instance, on Day 8, the difference between UR is colossal

– it is the distinction between a good participant and a mediocre, thanks to the impact of the RR. It should also be highlighted that the only scenario where this consumer was able to reach Rate 5.

In the scenario where HR has a higher weight than the remaining independent rates (Table 17), the consumer 55 had the majority values above Rate 3 except at 12:45. For both Scenario 55 and Scenario 94, this period was the one with lower rates.

Now, a participant with more availability, the consumer with identification number 235.

Fig. 10 represents the daily consumption from the second participant, a residential consumer, with different green shades and the average from April 2019 with a red dotted curve. The max reduction value from an event through the month was 0.5421 kW.

Table 12
Community results – Scenario 94 when HR is superior to the other independent rates.

Sample	Period	CCR	Rate									
			1		2		3		4		5	
1	12:00	PR	3	=	91	=	204	↘	101	↗	7	↘
		UR	3	=	91	=	162	↘	148	↗	2	↘
	12:15	PR	6	↘	98	↘	205	↗	89	↗	8	↘
		UR	4	↘	61	↘	244	↗	96	↗	1	↘
	12:30	PR	8	↘	142	↘	98	↗	154	↗	4	↘
		UR	1	↘	79	↘	168	↗	156	↗	2	↘
	12:45	PR	3	↘	164	↘	81	↘	150	↗	8	↘
		UR	1	↘	166	↘	26	↘	207	↗	6	↘
4	12:00	PR	0	=	149	↘	37	↗	220	↘	0	=
		UR	0	=	112	↘	113	↗	181	↘	0	=
	12:15	PR	0	=	130	↘	74	↗	202	↘	0	=
		UR	0	=	102	↘	131	↗	173	↘	0	=
	12:30	PR	0	=	153	↘	89	↘	164	↗	0	=
		UR	0	=	151	↘	33	↘	222	↗	0	=
	12:45	PR	0	=	112	↘	67	↗	227	↘	0	=
		UR	0	=	108	↘	113	↗	185	↘	0	=

Table 13
Community results – Previous studies (Silva et al., 2020a).

Sample	Period	CCR	Rate									
			1		2		3		4		5	
1	12:00	UR	47	↗	109	↗	98	↘	103	↘	49	↗
		PR	55	↗	122	↗	75	↘	83	↘	71	↗
	12:15	UR	42	↗	98	↗	104	↘	113	↘	49	↗
		PR	52	↗	110	↗	80	↘	96	↘	68	↗
	12:30	UR	44	↗	102	↗	93	↘	102	↘	65	↗
		PR	61	↗	109	↗	62	↘	94	↘	80	↗
	12:45	UR	52	↗	111	↗	93	↘	100	↘	50	↗
		PR	56	↗	122	↗	70	↘	93	↘	65	↗
4	12:00	UR	43	↗	116	↗	95	↘	106	↘	46	↗
		PR	54	↗	124	↗	66	↘	96	↘	66	↗
	12:15	UR	14	↗	119	↗	133	↘	117	↘	23	↗
		PR	21	↗	118	↗	114	↘	111	↘	42	↗
	12:30	UR	7	↗	93	↗	193	↘	94	↘	19	↗
		PR	16	↗	106	↗	151	↘	98	↘	35	↗
Sample	Period	CCR	Rate									
			1		2		3		4		5	
12:45	UR	9	↗	89	↗	202	↘	90	↘	16	↗	
	PR	23	↗	100	↗	158	↘	95	↘	30	↗	

Table 14
Results for Consumer 55 – Scenario 21 when LER is superior to the other independent rates.

Period	Day 1					Day 8					Day 15					Day 22				
	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR
12:00	4	3	3	3	4	2	4	3	4	4	4	5	3	4	4	3	5	3	4	4
12:15	4	5	5	5	4	2	4	3	4	4	4	4	5	4	4	3	4	5	4	4
12:30	5	3	3	3	4	1	4	4	4	3	3	3	3	3	3	2	3	3	3	3
12:45	4	3	3	3	4	2	4	3	4	4	3	4	3	4	4	2	4	3	4	4

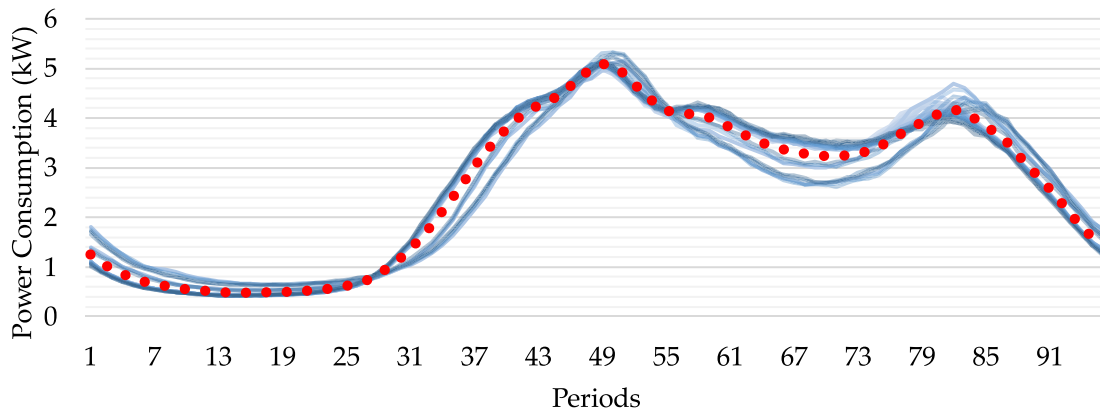


Fig. 9. Average and Daily Consumption from April 2019 for Consumer 55.

Table 15
Results for Consumer 55 – Scenario 30 when CR is superior to the other independent rates.

Period	Day 1					Day 8					Day 15					Day 22				
	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR
12:00	4	3	3	3	4	2	4	3	4	3	4	3	3	3	4	4	4	3	4	4
12:15	4	5	5	5	4	2	4	3	4	3	4	4	5	4	4	4	4	5	4	4
12:30	5	3	3	3	4	1	4	4	4	2	2	2	3	2	2	2	2	3	2	2
12:45	4	3	3	3	4	2	4	3	4	3	3	3	3	3	3	2	5	3	3	3

Table 16
Results for Consumer 55 – Scenario 51 when RR is superior to the other independent rates.

Period	Day 1					Day 8					Day 15					Day 22				
	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR
12:00	4	3	3	3	3	3	3	3	3	3	4	3	3	3	3	4	3	3	3	3
12:15	4	5	5	5	5	2	4	3	4	3	4	5	5	4	5	4	5	5	5	5
12:30	5	3	3	3	4	2	4	4	4	4	3	4	3	4	4	3	4	3	4	4
12:45	4	3	3	3	3	1	3	3	3	2	2	2	3	2	2	3	5	3	2	4

Table 17
Results for Consumer 55 – Scenario 94 when HR is superior to the other independent rates.

Period	Day 1					Day 8					Day 15					Day 22				
	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR
12:00	4	3	3	3	3	3	3	3	3	3	4	3	3	3	3	3	5	3	3	4
12:15	4	5	5	5	5	2	4	3	4	3	4	4	5	4	4	3	4	5	4	4
12:30	5	3	3	3	4	2	4	4	4	4	2	4	3	4	3	2	3	3	3	3
12:45	4	3	3	3	3	1	3	3	3	2	3	2	3	2	3	2	3	3	3	3

The results for this consumer are presented for the four considered scenarios, between Tables 18 and 21. On the first day, this consumer had no availability to participate in the DR event at 12:30 and 12:45. Firstly, as in previous cases, the results from Scenario 21, where the LER has a bigger influence, can be seen in Table 18. Therefore, this player can be classified as a good participant in the majority since the CCR was always above Rate 3.

In Scenario 30, where the results can be seen in Table 19, the worst rate was on day 8, where the CR had the lower values – as can be seen in Fig. 6, the temperature value was near 10 °C, reaching Rate 2 as the final CCR on 12:15 and 12:45. Thus, this scenario was where this consumer had lower CCR rates.

Finally, Scenarios 51 and 94 had similar results, Tables 20 and 21, respectively. The results assigned higher rates to the consumer. However, the CR influenced Day 8, the previous results, and the availability from this consumer guaranteed high CCR.

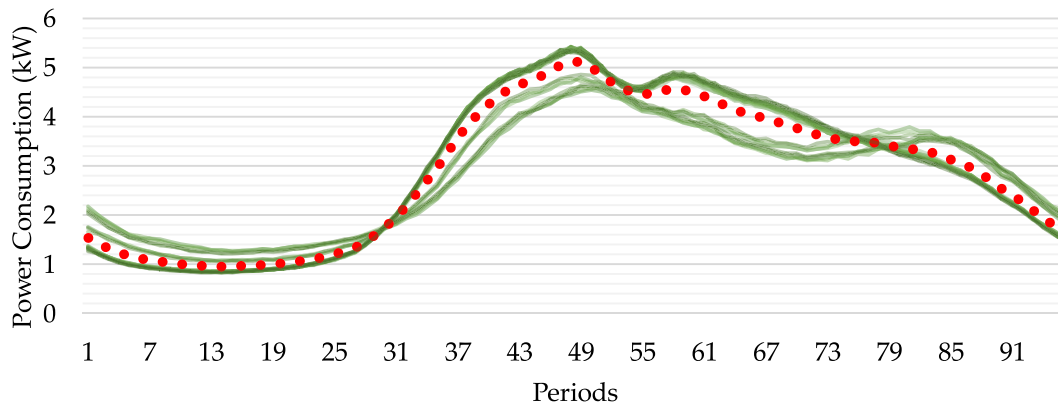


Fig. 10. Average and Daily Consumption from April 2019 for Consumer 235.

Table 18
Results for Consumer 235 – Scenario 21 when LER is superior to the other independent rates.

Period	Day 1					Day 8					Day 15					Day 22				
	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR
12:00	4	3	3	3	4	2	4	3	4	4	4	4	3	4	4	2	4	3	4	4
12:15	4	5	4	4	4	1	4	3	4	3	4	4	4	4	4	2	4	4	4	4
12:30	4	4	4	4	4	2	4	4	4	4	4	4	4	4	4	2	4	4	4	4
12:45	4	4	4	4	4	1	4	3	4	3	4	4	4	4	4	2	4	4	4	4

Table 19
Results for Consumer 235 – Scenario 30 when CR is superior to the other independent rates.

Period	Day 1					Day 8					Day 15					Day 22				
	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR
12:00	4	3	3	3	4	2	4	3	4	3	4	3	3	3	4	2	4	3	4	3
12:15	4	5	4	4	4	1	4	3	4	2	4	3	4	3	4	2	4	4	4	3
12:30	4	4	4	4	4	2	4	4	4	3	4	4	4	4	4	2	4	4	4	3
12:45	4	4	4	4	4	1	4	3	4	2	4	3	4	3	4	2	4	4	4	3

Table 20
Results for Consumer 235 – Scenario 51 when RR is superior to the other independent rates.

Period	Day 1					Day 8					Day 15					Day 22				
	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR
12:00	4	3	3	3	3	2	3	3	3	3	4	3	3	3	3	3	3	3	3	3
12:15	4	5	4	4	4	2	4	3	4	3	4	4	4	4	4	3	4	4	4	4
12:30	4	4	4	4	4	1	4	4	4	3	4	4	4	4	4	3	4	4	4	4
12:45	4	4	4	4	4	1	5	3	4	4	4	5	4	4	4	3	4	4	4	4

It is crucial to refer to the importance of the context in the trustworthy rate designed by the authors. However, assigning a strong influence on this rate may cause unwanted variability. Since the remaining independent rates are already affected by the context, the CR weight should be inferior.

4.3. Summary of findings

Throughout the present study, the authors’ main goal is to select fairly DR participants resorting to the context in which the event is triggered to provide the aggregator with the proper

knowledge to mitigate the possible effects of the response uncertainty. There were already studies, done by the authors confirming that information given to the aggregator on the community behavior throughout the trustworthy rate is important to achieve good results. Furthermore, understanding the willingness to reduce in a specific context is crucial to complex management and avoiding losses.

In this way, and compared with previous works, namely Silva et al. (2020a), there is an improvement in the proposed approach. Although the uncertain response of the consumer in DR events was considered, the context is innovation and a step forward. So,

Table 21
Results for Consumer 235 – Scenario 94 when LER is superior to the other independent rates.

Period	Day 1					Day 8					Day 15					Day 22				
	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR	CR	RR	HR	PR	UR
12:00	4	3	3	3	3	2	3	3	3	3	4	3	3	3	3	2	5	3	3	3
12:15	4	5	4	4	4	2	4	3	4	3	4	4	4	4	4	2	4	4	4	4
12:30	4	4	4	4	4	1	4	4	4	3	4	4	4	4	4	2	4	4	4	4
12:45	4	4	4	4	4	1	5	3	4	3	4	4	4	4	4	2	4	4	4	4

several conclusions can be withdrawn from the present study and when compared with the previous:

- Although the information on the performance from previous events is relevant, the way data is selected is crucial. In this way, the authors carefully selected the same context for all the independent rates in the present study. For instance, the Historic Rate was the average of the participant's performance in the same period, day, and temperature (according to a range).
- Also, stressing the importance of the context, the Last Day Rate (LDR) from Silva et al. (2020a) and Last Event Rate (LER) from the present paper were confronted. Previously, the authors considered the actual last event without context where a different day of the week could be compared, leading to probably an incorrect interpretation since the behaviors of, for instance, a Sunday could be different from a Friday event. However, with the contextual approach, the LER contemplates the day of the week and the period and temperature.
- Regarding selecting event participants, in Silva et al. (2020a), three approaches were designed and compared to choose trustworthy participants for first stage scheduling. So, only the ones with a higher rate were selected, and, in the eventuality of a low number of consumers in these levels, a re-scheduling would be immediately needed. To avoid these situations, all the consumers can join the scheduling phase being selected through a clustering method (participants with similar performances are integrated into the same group).
- From an individual perspective, several consumer results were compared in this paper. Since each consumer has distinct behaviors, the contextual approach must be an important factor when creating a trustworthy rank giving more precise information to the aggregator regarding the community. There is a higher guarantee of their actual response when selecting reliable consumers to participate in DR events. However, assigning a high weight to this independent rate may cause unwanted variability. Therefore, RR and HR should have a higher impact than CR, according to the results found in the study presented. Additionally, future work should consider individual weights for each consumer

5. Concluding remarks

The proposed approach was developed considering the necessity behind the complex task from the aggregator of managing an active community. The idea is to provide this entity with useful information regarding the reliability of the participants according to the actual context of DR events. The literature presents a few approaches where uncertainty and context are considered in this problem. Hence, the authors present as a noble element from their previous work, this approach where a trustworthy rate was designed and, in this study, called Consumer Contextual Rate.

In fact, a numerical comparison of the results with other works in the literature would be beneficial for the validation of the advantages of the proposed methodology. However, numerical comparisons are difficult to perform as the authors cannot find case studies ready to be used, for which the results are published and available from other authors. Several factors influenced the formation of Consumer Contextual Rate, and a sensibility was done to test which one should have more impact. Furthermore, the study presented considers scheduling where a DR target is imposed. Therefore, the methodology must decide which consumers to participate in the event according to their last performance in the same context.

The penalization for non-responses is also an interesting theme in this subject. For example, should the aggregator punish the participants by not selecting them for a certain period or just cutting the compensation percentage? On the other hand, will the consumer be more willing to participate if a fee were withdrawn from their final remuneration? Can it be considered as an “incentive” for their participation? Also, regarding the context topic, the comparison between client nature (domestic, small commerce, industry, among others) and their reaction to different circumstances can be interesting and helpful in understanding their behaviors in fighting against the uncertainty of the response to DR events. The future work from the authors intends to study these issues further.

CRedit authorship contribution statement

Cátia Silva: Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Pedro Faria:** Conceptualization, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Zita Vale:** Conceptualization, Data curation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – review & editing. **José M. Terras:** Data curation, Validation, Writing – review & editing. **Susete Albuquerque:** Project administration, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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