Hindawi
International Journal of Energy Research
Volume 2024, Article ID 8831617, 15 pages
https://doi.org/10.1155/2024/8831617

Research Article

On the Impact of Flexibility on Demand-Side Management: Understanding the Need for Consumer-Oriented Demand Response Programs

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Received 26 June 2023; Revised 22 January 2024; Accepted 30 January 2024; Published 9 March 2024

Academic Editor: Subhashree Choudhury

While demand response programs inherently depend on consumer acceptance in order to be successful, consumer behavior is often overlooked when designing such programs. This paper addresses the impact of consumer flexibility in terms of appliance use on the success of a demand response program, measured through the overall grid stability assessed by the demand's peak-to-average ratio. We employ a bootstrapping approach to simulate energy communities from real-life consumer data and implement a state-of-the-art demand response system. Results suggest that higher consumer flexibility under real-time energy tariffs implies higher degrees of grid stability, with real-time pricing decreasing the average peak-to-average ratio by 4.6% compared to time-of-use tariff and with highly flexible consumers showing a 23% lower peak-to-average ratio than regular consumers on average. Yet, it is possible for higher flexibility to be detrimental to grid stability by increasing the peak-to-average ratio under a time-of-use tariff. This result highlights the importance of understanding the interplay between different factors that influence energy consumer behavior, a research stream that has been under investigated thus far.

1. Introduction

The core idea behind demand-side management (DSM) resembles the management of energy generation resources. Although electric utilities have historically had to adapt their generation resources to demand estimates [1], DSM flips the narrative by offering a collection of actions taken by utilities with the aim of altering the load shape of end consumers so as to match energy production [2]. Examples of such actions include compensating consumers for keeping their energy use below a certain level [3], increasing public awareness of how energy is used and possibly wasted [4], and encouraging consumers to replace their old equipment with more energy-efficient versions.

DSM effects are expected to extend beyond utilities. In particular, the key advantages of DSM when helping utilities to balance supply and demand include (1) an increase in the efficiency of energy generation resources since consumer needs can be fulfilled with less generation; (2) a possible delay in investments in costly infrastructure to boost energy production as DSM can reduce peak demand, which is often the driving factor for infrastructure investments; and (3) a possible decrease in total operational costs since, for example, lower demand translates to less wear and tear on generation equipment and a reduced need for maintenance [5]. In turn, the above advantages may reduce wholesale electricity prices, boost retailer profits, and possibly lower end consumer energy costs [6]. In other words, both from the utility and end consumer levels, there are tangible benefits to a successful implementation of DSM practices.

End consumers traditionally participate in DSM programs through demand response (DR) initiatives, where they are able to make well-informed decisions about their energy consumption practices and play a crucial role when shifting loads [2]. A popular DR initiative is to promote energy consumption outside of peak hours through different time-varying rates, such as time-of-use (TOU), critical peak pricing, and real-time pricing (RTP) [7]. These initiatives provide an alternative to the energy market models based on prices fixed throughout the day. The above discussion highlights the need to incentivize end consumers to participate in DR programs, which also explains the growing body of literature on the applications of incentive-design techniques, such as from game theory, to create DR programs [8, 9].

A common trend in DSM research and programs is the use of automated home energy management systems (HEMS) [10, 11]. Specifically, the core premise behind these systems is that humans are (or should be) passive instead of active players in a demand response program. In other words, technological solutions should act on behalf of consumers when shifting energy loads according to the DR goals. However, some social science researchers have challenged this perspective [12]. For example, it has been suggested that energy consumer preferences evolve in complex ways [13]. Additionally, it has been demonstrated that one of the major obstacles to the adoption of autonomous DR systems by residential users is the failure to recognize their disruptive nature [14]. As a consequence, there have been calls for end consumers to be involved in the design of HEMS [15] to mitigate a range of issues such as discomfort, privacy and security concerns, and technology anxiety. We thus posit that DSM research must take into account the possibility of active consumer involvement with the operation of demand response systems because the success of any DR program depends on user engagement.

In this paper, we highlight issues in the operation of a DR system when user preferences and proactive behavior are not taken into account. We do so by modeling an energy community based on a cutting-edge DR system [16] instantiated with real-life data about consumer appliances and flexibility regarding load shifts [17]. More specifically, flexibility is assessed in terms of the amount of time a consumer is willing to shift an appliance's operation start-up time from their habitual time. That combination allows us to investigate our main research question, namely, *how do inflexible consumers impact the aggregate demand profile of an energy community*? We note that our research focus is on residential buildings, as opposed to, for example, industrial ones. Overall, we find that a naive assumption that consumers are all flexible regarding load shifts statistically significantly and favorably impacts a DR program aiming at flattening the aggregate (community) load by reducing the peak-to-average demand ratio (PAR) [18]. In other words, a more realistic condition of having inflexible end consumers negatively affects the demand profile's shape by resulting in a higher PAR value. This result further emphasizes the need for realistic, human-centered models within DR programs.

Besides this introductory section, the rest of this paper is organized as follows. In Section 2, we provide an overview of research on HEMS and our approach's contributions. Section 3 details the model we use in our experiments. We discuss the data set and experimental design in Section 4. Section 5 introduces and elaborates on the results of our experiments. We finally conclude in Section 6.

2. Research Background and Literature Review

Recent years have seen a surge of DSM studies and solutions targeting the residential sector through HEMS [19–23]. A classic formulation of the DSM problem is to minimize costs and/or the demand's peak-to-average ratio [24]. A thorough review of the progress in the field and the evolution of solutions to optimize the PAR is presented in [25]. Modern energy management systems use hybrid optimization strategies to optimize important grid metrics, including the PAR, while considering different model aspects of loads and residential distributed energy resources [26, 27]. Although these solutions can capture some consumer preferences, they still often ignore crucial human elements, such as the potential for consumer discomfort and interventions or noncompliance with the proposed load schedules [10]. For instance, [28] suggests a hybrid DR mechanism based on real-time incentives and pricing that minimizes both consumption and consumer dissatisfaction costs. Even though consumer preferences are captured in the form of utility and dissatisfaction factors, the proposed HEMS requires consumers to passively accept the optimal demand schedules in order for them to receive any benefits from the DR program. A bilevel mixed-integer linear programming model is suggested by [29] for scheduling microgrid loads as part of a DR program that considers the flexibility of appliances, potentially distributed energy resources, and the stability of the grid. In particular, that model takes into account consumers' preferences for usage schedules, uninterrupted consumption patterns, and dependencies between various appliances in a range of scenarios. However, similar to the previously referenced work, the model in [29] does not contemplate the possibility that consumers may reject the suggested load plans. Similar to the above, [16] constructs a DR program based on a multiobjective optimization problem with competing goals. Their bilevel model captures the desired features of handling dynamic pricing, a variety of energy sources, and programmable consumption preferences for specific time periods. However, it prevents rigid consumers from objecting to the load decisions that the energy service provider imposes.

Although some suggested DR models allow for a rich representation of consumer preferences and consumer flexibility in accepting/rejecting proposed loads, they nonetheless fail to take into account other crucial factors for the successful operation of a DR program, such as decentralized energy generation. That is the case of the DR model proposed by [30], where consumer preferences are ascertained by nonintrusive load monitoring, and a Pareto optimization approach is subsequently used to solve a multiobjective optimization problem having two conflicting goals, namely, minimizing costs and user dissatisfaction. Even though the proposed approach allows for the automatic collection of consumption patterns and the possibility of customizing the satisfaction objective by enabling consumers to prioritize their appliances, the underlying model nonetheless does not consider the effects of multiple energy sources on consumer preferences and optimized loads. This is a crucial point, as one can see the increase in the share of renewable energy production as a movement toward bringing energy technologies closer to people's lives.

The above discussion highlights the complexity of designing DR programs and, in particular, how hard it is to capture human preferences and nuances. The failure to do so can have an undeniable impact on a DR program's success since its core promise is one of an energy system with active consumer participation. This observation has led to a flurry of energy-related research in humanities and social science aiming at understanding the role of people as end consumers on, for instance, low-carbon energy transitions [12]. For example, there are many published articles on how key individual traits such as attitude toward the environment and policies, household attributes, and socioeconomic status can impact a transition to low-carbon societies [31–33]. Some of these works challenge the main assumption behind several DR programs, namely, that consumers are solely economic agents interested in maximizing their benefits. In particular, it has been suggested that consumers hardly ever actively think about how much energy they use. Instead, energy use is a derived demand intertwined with various activities, e.g., traveling to work or preparing a meal, and is connected to goals like maintaining cleanliness or comfort [34–38].

We contribute to the above discussion by investigating the consequences of assuming energy consumer flexibility in practice. Specifically, we focus on a modern DR model that (1) captures consumer preferences regarding when and which appliances should be turned on, (2) incorporates the possibility of consumers using renewable energy sources; (3) suggests individual load schedules by maximizing comfort while minimizing costs, and (4) tolerates changes to schedules after consumer interventions. We apply such a model to a realistic data set that contains user preferences regarding appliance usage [17], and we simulate what happens with a key grid stability metric when consumers are and are not flexible. Ultimately, our simulation results contribute to the literature by highlighting the need to design DR programs that can effectively capture consumer preferences and behavior.

Table 1 compares different aspects of the most relevant literature papers and our proposed approach. The relevant aspects to compare the approaches were as follows: (a) whether flexible appliances and consumer preferences are modeled, (b) whether distributed energy resources are considered, (c) does it address response coordination (rebound peaks), (d) whether schedule trade-off is evaluated, (e) does it consider consumer noncompliance, (f) are there any sustainability concerns, (g) does it consider grid stability, and (h) does it model uncertainties.

3. Mathematical Model

In this section, we detail the demand-side management system modeled in [16], which we adapt and subsequently use in our experiments to enable demand response for a community of residential consumers. A key entity in the system is the *demand aggregator*, which is responsible for encouraging and managing the demand flexibility of a community while representing them as a single resource before an energy service provider or utility. Communities, in turn, are analogous to microgrids in the sense that they can potentially supply their own demand through *distributed energy resources* (DERs), such as renewable energy sources or energy storage systems. However, they nonetheless may still rely on the main power grid to cover some of the energy demand, and thus, they partake in the demand response program. Figure 1 illustrates this scenario and the links between the entities involved, which are supported by the information and communication technologies of the advanced metering infrastructure (AMI) of the smart grid, including smart meters.

The proposed demand response system is formulated as a bilevel optimization problem. In the first level (inner problem), a consumer-centric approach is adopted in which each consumer optimizes the load allocation from their own household, focusing on changing the consumption patterns of home appliances. The optimization process at this stage is distributed, and each consumer solves a multiobjective optimization problem using an optimization technique. The conflicting objectives are to minimize the household's energy consumption costs while minimizing the discomfort of rescheduling appliances. The decision variables indicate when each appliance should be operating throughout the scheduling horizon and which energy source should supply their demand. The inputs to the second and final level (outer problem) of the optimization problem are the Pareto set of load schedules of all consumers. This final stage is centralized and managed by the demand aggregator, which determines the best combination of solutions that will benefit the community as a whole. At this stage, the objective function consists in minimizing the peak-to-average ratio of the community by finding an optimal combination of demand profiles. Sections 3.1 and 3.2 further detail both levels of the optimization problem.

3.1. Consumer-Level Optimization. One of the main assumptions behind the model in [16] is that residential consumers are concerned with minimizing their utility expenses. However, reducing energy expenses often implies changing consumption habits, thus leading to discomfort. For example, while a consumer may prefer to do laundry in the afternoon, the optimal time cost-wise to use a dishwasher could be found to be in the early morning; if the consumer weighs their options, changing their preference to save energy could be uncomfortable. The proposed optimization model takes into consideration these conflicting aspects of residential load optimization by formulating a multiobjective problem.

From the perspective of a given consumer k with access to DERs, the utility expenses of their residence can be expressed as its energy consumption cost minus the savings from its power generation system. We denote the consumption of consumer k regarding energy coming from the main grid at time t as $c_{k,t}$, which is formally defined as

$$c_{k,t} = \sum_{\alpha \in \mathscr{A}_k} \Delta t P_{k,a} M_{k,a,t}. \quad (1)$$

Table 1: Comparison between related work and proposed approach.

Approach	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
[17]	Yes	Partially	No	No	Yes	Partially	No	No
[18]	Yes	Partially	Yes	No	No	Partially	Partially	No
[11]	Yes	No	No	No	No	No	Partially	No
[39]	Partially	No	Partially	No	Yes	No	Partially	No
[20, 23]	Yes	Yes	No	No	Yes	Yes	Partially	No
[40]	Yes	Yes	Partially	Partially	No	Partially	Partially	No
[30]	Yes	No	No	Yes	No	No	No	No
[41]	Yes	Partially	Yes	No	Partially	No	No	No
[42]	No	Yes	No	No	No	Yes	Partially	Yes
[43]	Yes	Yes	No	No	No	Yes	Yes	Yes
[28]	No	No	Yes	No	No	No	Partially	No
[44]	Partially	No	No	No	No	No	No	No
[29]	Yes	Yes	Partially	No	No	Yes	Yes	Yes
Proposed	Yes	Yes	Yes	Yes	Yes	Partially	No	No

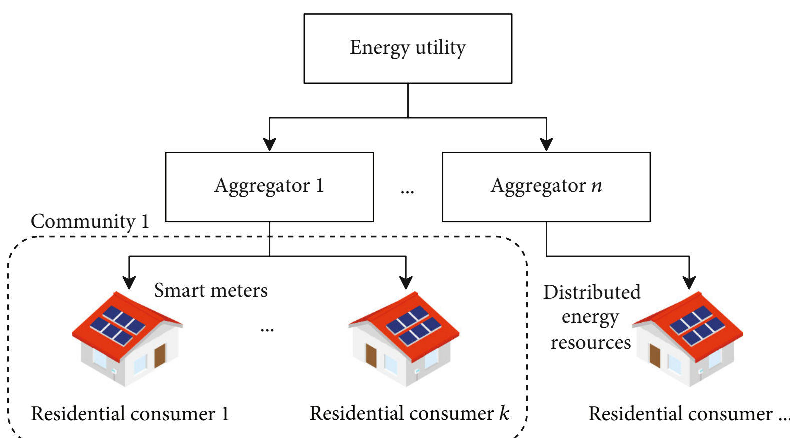

Figure 1: Overview of the smart grid scenario and entities involved.

In Eq. (1), $\mathscr{A}_k$ represents the set of all appliances under consumer k's control. The parameter Δt denotes the discrete time step size in hours, while $P_{k,a}$ refers to the nominal power rate in kilowatts of the α-th appliance of consumer k. The term $M_{k,a,t}$ represents one of the decision variables of the problem: the consumer k's load state of appliance a at time t with respect to the main grid. The decision variables encoded as binary values indicate whether an appliance is turned on or off at a given time slot. When a variable equals one, it indicates that a load should operate, or demand energy, at that time period; otherwise, it equals zero.

Given the consumer's generation system's power output $P^{\mathrm{res}}_{k,t}$ in kilowatts, we calculate the amount of energy surplus that can be sold back to the utility—henceforth referred to as $g_{k,t}$—as described below:

$$g_{k,t} = \Delta t P^{\mathrm{res}}_{k,t} - \sum_{\alpha \in \mathscr{A}_k} \Delta t P_{k,a} R_{k,a,t}. \quad (2)$$

From left to right, the terms on the right-hand side of Eq. (2) denote the available energy from generation sources minus the energy demanded from consumer k's appliances. Here, we introduce the decision variable $R_{k,a,t}$, denoting the demand of the residential loads for the consumer's distributed generation resources. In other words, we use different symbols to represent the decisions with respect to the two main energy sources considered in this model, namely, the main grid resources $M_{k,a,t}$ and the distributed generation resources $R_{k,a,t}$. It is worth noting that these parameters are obtained through the smart meter infrastructure in the consumer's household [45, 46].

Based on the previous definitions, we define the first objective function, f^k_{cost}, as the total expenses of a residential consumer k, as seen in the following equation:

$$f^k_{\mathrm{cost}} = \sum_{t \in \mathscr{T}} \left(c_{k,t} p_t - \beta_{k,t} g_{k,t} P'_t \right). \quad (3)$$

In the above equation, p_t and P_t' represent the tariffs for purchasing and selling energy at a time slot t, respectively. Additionally, the term $\beta_{k,t}$ is an auxiliary binary variable that equals one when consumer k is able to sell energy at time t, or zero otherwise. Finally, $\mathcal{T}$ denotes the set of all time intervals.

As previously discussed, the discomfort of following a suggested load schedule is another aspect that directly influences consumers in residential load management. The discomfort associated with a given load when scheduled at a different time slot than the one preferred by the consumer is defined next as the difference between an appliance's programmed start-up time and the consumer's preferred start-up time.

$$f_{\text{disc}}^{k} = \sum_{a \in \mathcal{A}_k^{\text{flex}}} (x_{k,a} - u_{k,a}) \left[(1 - \delta_{k,a}) w_{k,a}^{D} - \delta_{k,a} w_{k,a}^{A} \right]. \quad (4)$$

In Eq. (4), $\mathcal{A}_k^{\text{flex}}$ is consumer k's subset of appliances that are flexible, for which their programmed start-up time $x_{k,a}$ can be shifted away from the consumer's preferred start-up time $u_{k,a}$. The difference between these two start-up times is computed in terms of time intervals, which in turn is converted into a cost when multiplied by an appropriate cost factor. Here, $w_{k,a}^{A}$ represents the cost factor for when the suggested schedule advances the start-up time of a flexible appliance, while $w_{k,a}^{D}$ represents the cost factor for when it gets delayed. We use an auxiliary binary variable $\delta_{k,a}$ to apply the appropriate cost factor to the difference between the start-up times, meaning $\delta_{k,a}$ equals one when $x_{k,a}$ is less than $u_{k,a}$, or zero otherwise.

We must consider some constraints regarding the state of the decision variables and the distributed generation system. First, due to the binary encoding of the decision variables, a load cannot be supplied by more than one energy source at once in the same time interval. Therefore, let $X_{k,a,t}$ of a given consumer k be the sum of the decision matrices of the energy sources, i.e., $X_{k,a,t} = M_{k,a,t} + R_{k,a,t}$, for a given appliance a consuming energy at time t. Then, the following constraint must be respected:

$$X_{k,a,t} \leq 1. \quad (5)$$

Additionally, any consumer's generation system's power output must be greater than or equal to zero ($P_{k,t}^{\text{res}} \geq 0$), and the consumer's demand cannot exceed the energy coming from DERs. Formally,

$$\Delta t P_{k,t}^{\text{res}} \geq \sum_{\alpha \in \mathcal{A}_k} \Delta t P_{k,a} R_{k,a,t}. \quad (6)$$

For the sake of conciseness, we refer the reader interested in DER modeling and related constraints to [16].

3.2. Aggregator-Level Optimization. As the inner level of the optimization problem finds a set of equally optimal (i.e., nondominated) load schedules for each consumer through a multiobjective optimization method, it then becomes possible to define an additional procedure to determine which schedule would be the most advantageous to the whole community if performed in practice. The demand aggregator is in a privileged position to perform this procedure, as it can gather the relevant information about the schedules from all consumers and make a globally informed decision. This section details how the aggregator is able to determine which solution from its consumers should benefit the community as a whole.

In this context, a load schedule is simply a set of instructions to either keep an appliance on or off for each discrete time step of the planning horizon. Thus, it is important to know the number of distinct load schedules that a given consumer has as options. This number depends on several factors regarding consumer preferences, such that it is not possible to expect all consumers to have the same number of options. Additionally, we consider that a consumer may deliberately prefer to exclude a subset of their load schedules for any reason so that the reported number of schedules they are willing to assign to their appliances is smaller than the initial number of optimal schedules found by the previous optimization level. That said, we define S_k as the number of schedules informed by consumer k, with $S_k \geq 1$. Moving forward, these are the only schedules that will be taken into account by the aggregator.

It is important to note that at this stage of the problem, the nature of the system changes from distributed to centralized. More precisely, the optimization problem is no longer distributed among the consumer's HEMS, and instead, it is solved by the aggregator's central controller. This centralization implies that the input data for the next optimization procedure will be transmitted to the aggregator via AMI, which raises concerns about data privacy and security [47]. Although the issue of secure protocols and infrastructure is outside the scope of this paper, privacy is an important factor that can be addressed at this optimization level. In particular, to prevent sharing sensitive information that could reveal consumer habits, the optimal load schedules from each consumer are not sent directly to the aggregator. Instead, for each schedule, the aggregator receives the aggregated consumption of all the appliances expected to be turned on during a time window. Thus, we define the term $l_{k,t}^{i}$ to denote the total demand from consumer k given by their i-th optimal load schedule, with $i \in \{1, \cdots, S_k\}$, and satisfied by the main grid (M) at time t, as detailed in

$$l_{k,t}^{i} = \sum_{\alpha \in \mathcal{A}_k} \Delta t P_a M_{k,a,t}^{i}. \quad (7)$$

In Eq. (7), the superscript i is also added to other variables whose state changes depending on the load schedule to which they refer. For example, let $k = 1$ be the index of a consumer who has two valid load schedules $(I_k = 2)$ that program a washing machine (say, $a = 2$) to run at different time intervals: the first $(i = 1)$ at 8:00 a.m. $(t = 8)$ and the second $(i = 2)$ at 9:00 p.m. $(t = 21)$. In this scenario, $M_{1,2,8}^{1}$

is equal to one when $M^1_{1,2,21}$ is equal to zero while, conversely, $M^2_{1,2,8}$ is equal to zero when $M^2_{1,2,21}$ is equal to one.

Given the load profiles from all consumer solutions, the optimization process performed by the aggregator can be expressed as a combinatorial optimization problem, for which the main goal is to find the aggregate demand profile of a community that optimizes a particular metric. At this level, we introduce the load factor as a useful metric of the aggregate demand profile. The load factor is defined as the average load over a specific time period divided by the peak load in that period:

$$\mathrm{LF} = \frac{(1/T)\sum_t L_t}{\max_t L_t}. \tag{8}$$

In the equation above, L_t represents a community's aggregate demand at time interval t. We use the inverse of the load factor, also known as the peak-to-average ratio (PAR), to define a minimization problem. In other words, the aggregator's job is to select a load profile from each consumer such that their aggregate demand profile has the lowest peak-to-average ratio among all possible combinations. Minimizing PAR achieves the goal of securing the grid by avoiding overloading it during peak times. The above model can be formalized as follows.

$$\min_{\vec{i}} \quad f_{\mathrm{PAR}}\left(\vec{i}\right) = \frac{T \cdot \max_{t\in\mathcal{T}} L_t\left(\vec{i}\right)}{\sum_{t\in\mathcal{T}} L_t\left(\vec{i}\right)}. \tag{9}$$

In Eq. (9), $\vec{i}$ represents a vector of K indices, for which the k-th value of $\vec{i}\,(i_k)$ denotes which load profile from consumer k is being selected. The function $L_t(\vec{i})$ can be expressed as follows:

$$L_t\left(\vec{i}\right) = \sum_{k\in\mathcal{K}} l^{i_k}_{k,t}. \tag{10}$$

In other words, $L_t(\vec{i})$ stands for the aggregate demand of all consumers given the indices of the load profiles $(\vec{i})$ to select for each consumer.

4. Experiments

As some authors discussed in Section 2, the model we discussed in the previous section relies on the behavioral assumption that consumers are flexible. In our experiments, we investigate the consequences when that assumption is invalid. The model by [16] is particularly suitable for our purposes in that it allows one to naturally measure how changes in individual preferences (consumer-level optimization) affect the whole community (aggregator-level optimization). More precisely, in what follows, we describe the design of experiments to assess the effect of flexible consumers on the final PAR of an energy community using the bilevel optimization method described in Section 3. The data set introduced by [17] serves as the base for all consumer profiles within this experiment. This data set is briefly described in Section 4. The data transformation procedures required to fit the model from [16] to that data, the experimental design and optimization tools are detailed in Sections 4.2, 4.3, and 4.4, respectively.

4.1. Data Set. The data set chosen for this experiment was collected from [17]. In that study, a survey was conducted with over 400 subjects to understand how these consumers typically use specific home appliances. The questionnaires asked each subject about when they would prefer to use their home appliances during the day, whether they were willing to postpone or bring forward this usage in exchange for energy bill savings, and how annoyed they would be, on a scale from 1 to 5, if they were asked to shift the time of use such appliances from 30 minutes to 3 hours away from their preference. Then, the collected data was clustered and used to map different consumer annoyance profiles for each appliance and each kind of consumer. Subsequently, this study produced a database with 1000 simulated consumers proportionally representing the types of consumer found in the survey.

In [17], the authors defined four groups of electrical devices used by the simulated consumers: the devices in group one (G1) are household appliances whose use is not flexible and therefore cannot be rescheduled by the system, e.g., fridge, house lights, and computers; group two (G2) features household appliances that can be rescheduled up to three hours before and after the consumer's preferred time, e.g., washing machines and dryers; appliances in group three (G3) are those controlled by a thermostat, i.e., they have a temperature range that is considered acceptable and must be regulated to keep the environment's temperature within that range, such as HVAC and water heaters; and finally, group four (G4) features solar and wind power generation systems represented by a single profile denoting the percentage of the aggregate power output at any given time slot of the day.

4.2. Data Transformation. Although the data set from [17] realistically represents residential consumers, it was nonetheless necessary to adapt that data characterizing weekly usage preferences to the daily preference model expected by the model in [16]. For example, the data available to characterize G1 devices, specifically the operating state (on/off) of the device at each time interval, was originally represented by a time series of probabilities of the device in question being turned on at each time interval over the period corresponding to one week. We proceeded by averaging the probabilities over the week, thus reducing the values to the dimensions of a single day. Then, those values were used as the probabilities of success (of the device being on) in the given time interval, using a binomial probability density function to generate a binary usage profile for the given device. Finally, each continuous usage interval was converted into an inflexible preference window.

For the G2 devices, on the other hand, the operation preference times were not characterized by probabilistic distributions, but by indices of preferred time intervals during the week. We decided to use the time intervals of the weekday with the highest amount of operation preference times for each device, and each interval, together with the predetermined device runtime, was converted into a flexible preference window. In addition, the annoyance levels reported on a scale of 1 to 5 for each 30-minute delay or advance from the consumer's preferred schedule were grouped, and the calculated average was used as the respective delay ($w^D_{k,a}$) or advance factor ($w^A_{k,a}$) of the appliance.

The last two groups of appliances were either partially or completely removed from this experiment. For example, the thermostat-controlled appliances in G3 were not considered because there was not a lot of usage flexibility in the obtained data. A potential explanation for this phenomenon is that the consumers had a reference point regarding temperature levels and HVAC operation times and were not that willing to move away from it. Additionally, since our goal is to analyze the demand and PAR of the main power grid, the wind power systems in G4 were not considered as well because the scale of their power output in the original data set was nearly high enough to supply most remaining loads and even allow some consumers to operate in island mode. Thus, we have converted the percentage output of the generation units from the data set into a power output profile and aggregated all similar units into a single generation profile. Nonetheless, the remaining loads are sufficient to represent the consumers and their range of flexibility as obtained from the original data set.

The above said, we henceforth call devices in G1 and G2 as *inflexible* and *flexible*, respectively, where flexibility means that some consumers are willing to accept delaying the operations of appliances. Figures 2 and 3 show the number of devices per category and the number of consumers who own these devices.

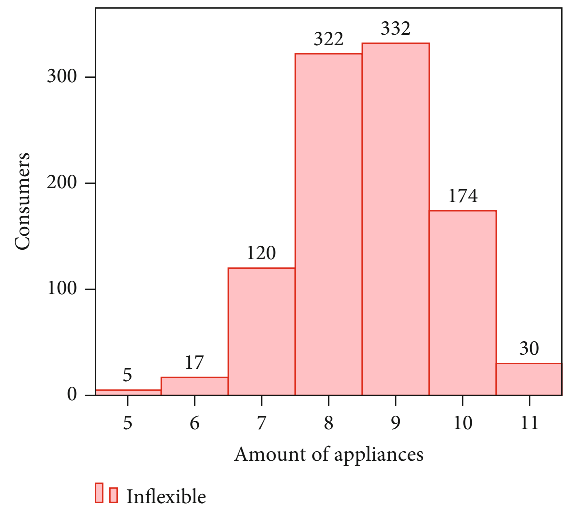

Figure 2: Number of consumers owning inflexible appliances.

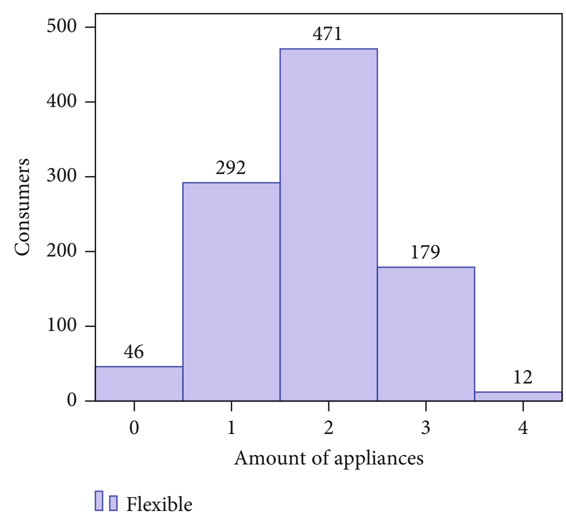

Figure 3: Number of consumers owning flexible appliances.

4.3. Experimental Design. In order to calculate reliable statistics in our data analysis, we used a bootstrapping technique [48] to generate multiple resamples from the initial sample of consumers. Specifically, the initial sample of 1,000 consumers was resampled 100 times, each having 100 consumers. Each consumer in a bootstrap sample would then perform their consumer-level optimization and, subsequently, participate in the aggregator-level optimization together as a community. This process gave us a total of 100 PAR values to analyze, one for each bootstrap sample. We henceforth refer to this group of values as the *base group*.

Besides that control group, we also created two treatment groups by varying the proportion of flexible to inflexible appliances. That process helps us assess the impact of more or less flexibility on the final PAR of a given community and, thus, answer our research question. To show the robustness of our results, we also analyzed the impact of flexibility under two DR pricing strategies/tariffs adopted by the aggregator. Beyond helping to determine how robust our findings are, analyzing two different tariffs enables us to measure how much influence the pricing strategy used in the first optimization level influences the schedules of each consumer and, consequently, the final PAR value.

We varied the ratio of flexible to inflexible devices by randomly selecting up to a given number of devices and switching consumer preferences from flexible to inflexible or vice versa. The chosen amount of appliances to convert was four, as this is the maximum number of flexible appliances for any consumer in the data set, as seen in Figure 3. For the pricing strategy, we have adopted two pricing tariffs, the time-of-use (TOU) tariff from [17] and the real-time price (RTP) tariff from [16]. We highlight these tariffs in Figure 4 for a given day.

4.4. Optimization Methods. We next discuss the optimization methods selected to solve the bilevel optimization problem introduced in Section 3. We note that any optimization method suitable for solving combinatorial problems can be employed to solve the aggregate-level optimization problem. In our experiments, we adopted a simple genetic algorithm. Alternatively, it is necessary to be more careful with the

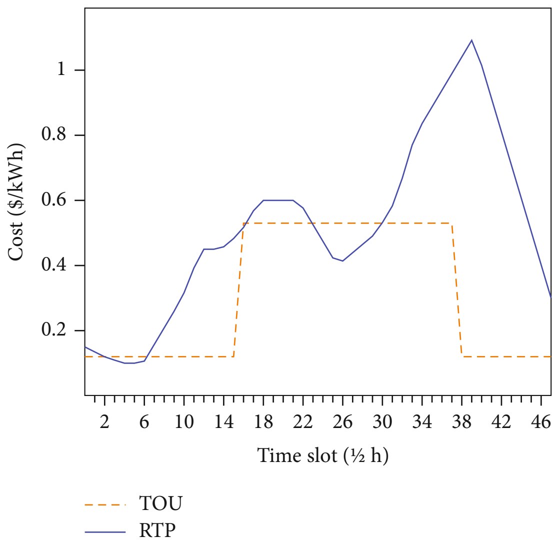

Figure 4: TOU and RTP tariffs.

model selection for the consumer-level optimization problem as it has multiple and conflicting objectives. In our experiments, we require an optimization method that can provide us with a set of nondominated solutions that reveal a spectrum of load schedules ranging from the schedule with the lowest cost but highest discomfort to the schedule with the least discomfort but highest cost. To this end, we use the Nondominated Sorting Genetic Algorithm (NSGA-II) optimization metaheuristic [49]. This evolutionary algorithm allows us to observe a population of individual solutions that are recombined and mutated in an attempt to move toward a global optimum. NSGA-II is well-suited for the proposed mathematical model because it is a fast and effective algorithm designed for multiobjective optimization problems [50].

5. Results and Discussion

Having described our experimental setting, we next present the results of our data analyses. Specifically, we first discuss our findings for the inner level of the optimization problem (consumer-level optimization). In this step, the parameters applied to NSGA-II were (1) population of 100 individuals, (2) iteration of 500 generations, (3) polynomial mutation with probability of 0.01 and crowding degree of 3.0, and (4) simulated binary crossover with crowding degree of 3.0. Next, Section 5.2 introduces the results of the outer level of the optimization problem (aggregator-level optimization). In this step, the genetic algorithm operated with a population of 50 individuals over 100 generations, using integer adaptations of the simulated binary crossover and polynomial mutation methods [50]. Finally, Section 5.3 presents the results of statistical tests performed on the PAR values of the bootstrap samples.

5.1. Individual Optimization. Since we cannot yet measure the impact of different degrees of consumer flexibility on the PAR values during the first consumer-level optimization phase, this subsection, thus, focuses on explaining the differences between the intermediary results found under the RTP and TOU tariffs. The individual optimization results are summarized in Table 2. First, we can observe the variation in the number of solutions—referred to as “count” in the table—between test cases. The results suggest that both the pricing method and the number of flexible loads contribute to increasing the average number of schedules on the consumers' Pareto front. On average, the number of solutions per test case with the RTP tariff was 235.02% higher than their TOU counterpart. A possible explanation for this finding is that the flattened TOU price curve (see Figure 4) reduces the potential amount of load shifting that would result in cost reductions compared to a typical RTP price curve. In other words, a load shift that would certainly result in a cost change under the RTP tariff does not necessarily result in a cost change under the TOU tariff. This means that more load schedules under TOU can be eliminated from the population of nondominated solutions by multiobjective optimization methods.

Another way to visualize the difference created by the tariffs is by observing the spread of the solutions within the base test case on the two-dimensional histograms illustrated in Figures 5 and 6 with the TOU and RTP tariffs, respectively. We binned the range of solution space values within a 50×50 grid. One can see that the range of values occupied by the solutions under the TOU tariff (Figure 5) is less comprehensive than the range under the RTP tariff (Figure 6). Moreover, despite covering a larger area, the density of the solutions under RTP is more prominent than the one under TOU, as evidenced by the dark-colored bins. Considering that the number of nondominated solutions under RTP was almost four times larger than the number of solutions under TOU, this difference in the spread in the solution space was expected. Nevertheless, these results demonstrate the role of tariffs in influencing the behavior of potential consumers regarding a shift in their consumption patterns.

We illustrate a consumer's Pareto front under each pricing method in Figures 7 and 8. In particular, the figures show the Pareto fronts of consumer #655 under TOU and RTP, respectively. We chose this consumer specifically because they presented a greater than average number of flexible appliances (4) and an average number of inflexible appliances (10). Figure 7 shows eight solutions that are seemingly paired in terms of cost and vary more clearly in terms of discomfort. In reality, the pairs of solutions have different but very close costs; otherwise, the solution with the least discomfort would have dominated the other and caused it to be out of the Pareto front. That reflects the nature of the TOU price curve with only two pricing regions, which makes many load shifts equivalent in cost. The same cannot be said about the pricing curve of the RTP tariff. Figure 8 shows a more typical Pareto front with 30 solutions and an elbow region in orange and yellow. The leaps in cost and discomfort from one solution to another are smoother in this graph. It is also noticeable that the Pareto front under RTP spans a wider range of values than under TOU.

TABLE 2: Summary of the resulting load schedules from the first-level optimization problem.

	Base		Flexible		Inflexible	
	Cost	Discomfort	Cost	Discomfort	Cost	Discomfort
p = TOU	count = 4,292		count = 12,202		count = 1,286	
Mean	2.56	12.95	2.36	17.47	2.46	0.00
SD	1.38	13.62	1.30	13.15	1.28	0.00
Min	0.23	0.00	0.20	0.00	0.23	0.00
Max	8.78	92.38	8.76	107.29	8.92	0.00
p = RTP	count = 17,088		count = 61,787		count = 1,293	
Mean	6.55	26.14	5.56	35.43	6.37	0.00
SD	2.83	20.43	2.58	22.09	3.06	0.00
Min	0.72	0.00	0.57	0.00	0.75	0.00
Max	18.34	119.69	17.76	142.00	17.81	0.00

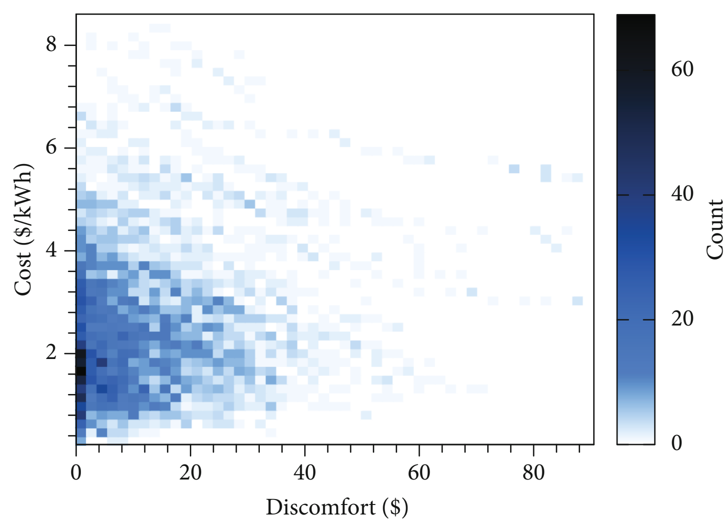

FIGURE 5: 2D histogram of all base case solutions under the TOU tariff.

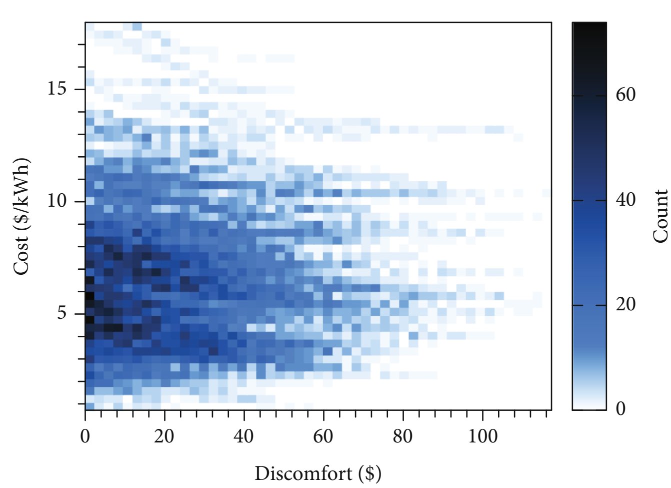

FIGURE 6: 2D histogram of all base case solutions under the RTP tariff.

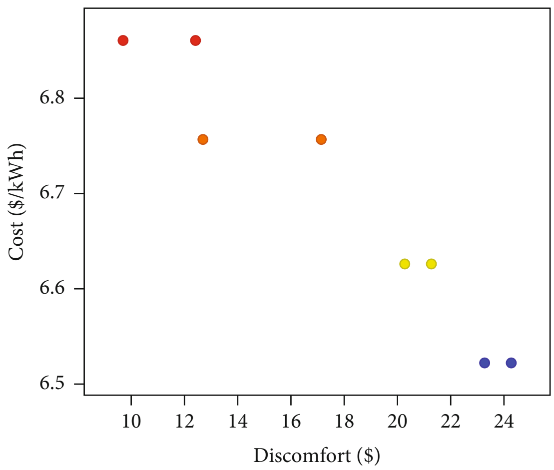

FIGURE 7: Consumer's base case Pareto front under the TOU tariff.

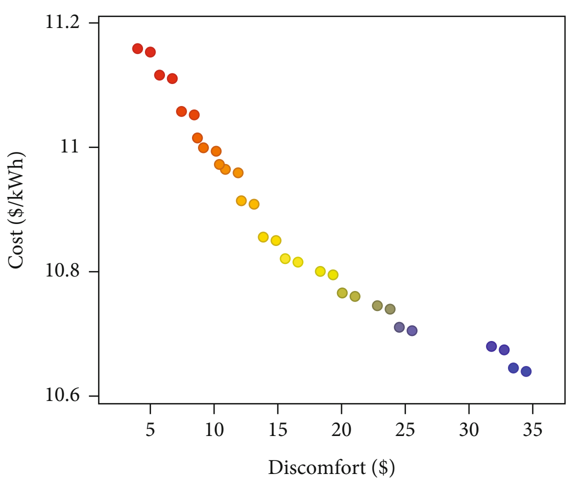

FIGURE 8: Consumer's base case Pareto front under the RTP tariff.

Besides differences produced by distinct tariffs, we can also see in Table 2 that there was a significant increase in the number of solutions for the flexible treatment group. In fact, the number of solutions in that group was, on average, 222.94% greater than the respective number in the base case. To illustrate this finding, Figure 9 shows 87 solutions in the Pareto front for the consumer #655, the same consumer we highlighted in Figures 7 and 8, but now under the flexible treatment.

The results for the inflexible treatment group showed a very low number of solutions compared to the other groups. Moreover, we can see in Table 2 that the solutions for the inflexible treatment group did not have a discomfort value greater than zero. That result was expected due to the proposed experimental design. Specifically, it happened because all consumers had up to four flexible devices transformed into inflexible ones, meaning the load-shifting flexibility of all consumers was removed by design. Thus, the problem for these consumers reduces to a single-objective cost minimization problem where the costs are determined solely based on the utilized energy source, i.e., whether energy comes from distributed generation resources or the main grid.

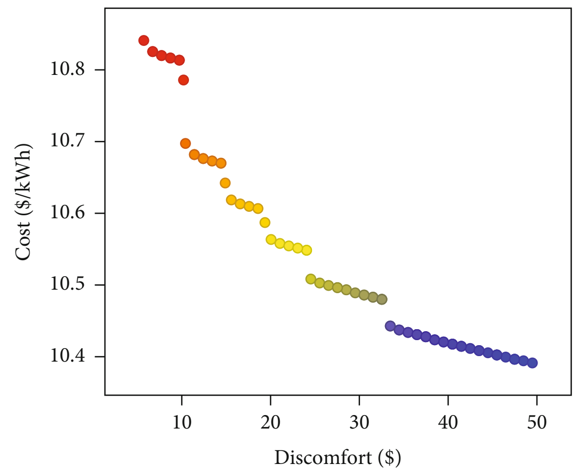

FIGURE 9: Consumer's Pareto front under the RTP tariff and flexible treatment group.

5.2. Community Optimization. The previous subsection highlights that the higher the flexibility in terms of appliance usage and the more dynamic the energy tariff, the higher the number of optimal solutions that will be found on the consumer's Pareto front. In this subsection, we discuss the impact of flexibility and tariffs on PAR values, i.e., on grid stability and, consequently, on the community of consumers. Table 3 summarizes the PAR values resulting from each group. Recall that we obtained these values by following the bootstrapping procedure previously described in Section 4.3; i.e., these results refer to the 100 trials based on randomly selected groups of 100 (out of 1,000) consumers.

At a first glance, one can see that the average PAR for the flexible group is 23% lower than the base group's PAR, and the results under the RTP tariff seem either similar or slightly better (lower) than the results under the TOU tariff. Figure 10 highlights that difference in average PAR values. Based on Figure 10, communities under RTP pricing achieved a 4.6% lower PAR on average when compared to communities under the TOU tariff. As we suggested in the previous subsection, that finding can be explained by the greater diversity of solutions presented by consumers under RTP, which contributes to increasing the combinatorial search space of the second optimization stage under the utilized model. This result highlights the impact energy tariffs can have on consumer behavior and, consequently, on a community of energy consumers.

To further corroborate the above point, we next illustrate some aggregate load profiles under different tariffs. Starting with the base case, Figures 11 and 12 illustrate the aggregate load profiles for the first bootstrap sample under the TOU and RTP pricing schemes, respectively. In both charts, flexible demand is highlighted in red over inflexible demand in blue. At first glance, the differences between the two demand profiles are not immediately obvious. Both profiles peak at the timeslot $t = 43$, at 135.52 kW under TOU and 131.74 kW

Table 3: Summary of the PAR results for different groups.

	Base PAR	Inflexible PAR	Flexible PAR
p = TOU			
Mean	6.048	5.920	4.871
SD	0.001	≈0	0.009
Min	6.047	5.920	4.868
Max	6.051	5.920	4.906
p = RTP			
Mean	5.890	5.923	4.321
SD	0.004	≈0	0.004
Min	5.883	5.923	4.314
Max	5.902	5.923	4.332

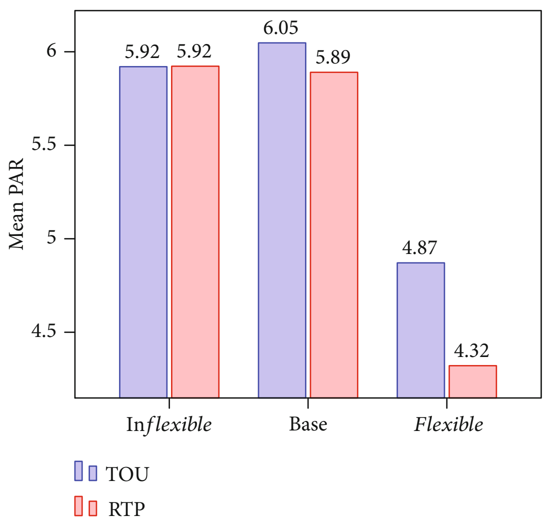

Figure 10: Bar chart comparing the mean PAR values for all groups.

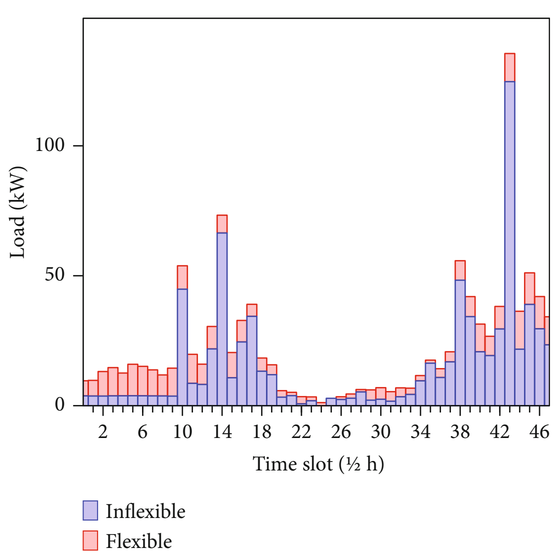

Figure 11: Sample aggregate load profile of the base group under the TOU tariff.

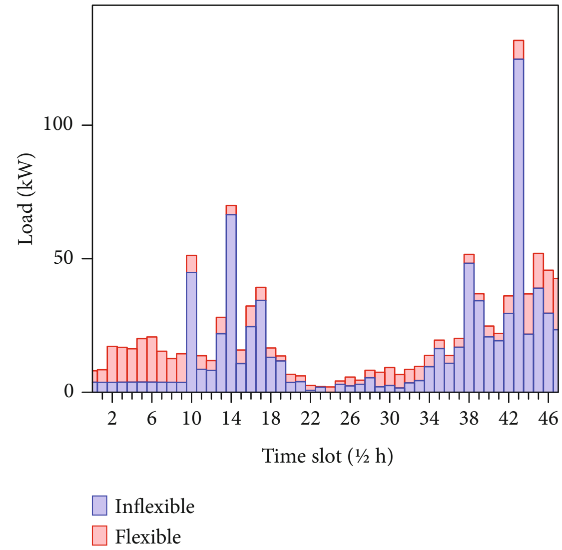

Figure 12: Sample aggregate load profile of the base group under the RTP tariff.

under RTP. However, the aggregate RTP profile achieves a PAR of 5.89, while the TOU profile reaches 6.05.

For the flexible treatment group in Figures 13 and 14, the effects of the greater diversity of load profiles are more noticeable. The aggregate profile under the TOU tariff achieves a PAR of 4.87, while the profile under the RTP tariff achieves 4.32. There are some potential explanations for the differences in Figures 13 and 14. For example, focusing on the time slot at around 40, we notice that there is more flexibility under the TOU tariff than under RTP. We posit that under RTP, consumers might not respond as quickly to real-time pricing signals, whereas they know about the pricing scheme under the TOU tariff in advance, which allows them to plan accordingly. Another possibility is that the prices might be rather flat and/or peaks may be short-lived under the RTP tariff while being more volatile under TOU, which may cause consumers to take advantage of the price changes in the latter in order to reduce costs.

Finally, as expected, the sample profiles for the inflexible treatment group are nearly identical under both tariffs, as Figures 15 and 16 show, since no flexible devices are used by consumers in this scenario.

5.3. Statistical Analysis. Having discussed the effects of tariffs on PAR values, we next discuss the impact that flexibility in terms of appliance use can have on grid stability and, thus, provide an answer to our research question, namely, *how do inflexible consumers impact the aggregate demand profile of an energy community*? To answer that question, we compared the flexible and inflexible treatment groups against the base case to determine whether the differences in PAR values reported in Table 3 are statistically significant. In particular, we performed two-sample, two-sided t-tests, whose results are presented in Table 4.

Focusing first on the results under the RTP tariff, the p values from all statistical tests reject the null hypothesis that the PAR values are the same for any reasonable statistical

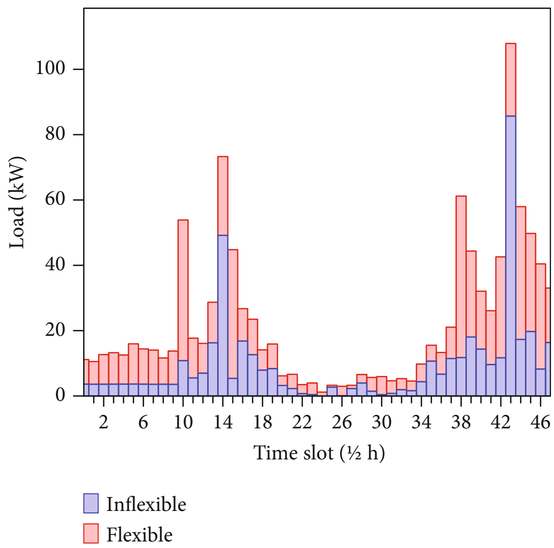

FIGURE 13: Sample aggregate load profile of the flexible treatment group under the TOU tariff.

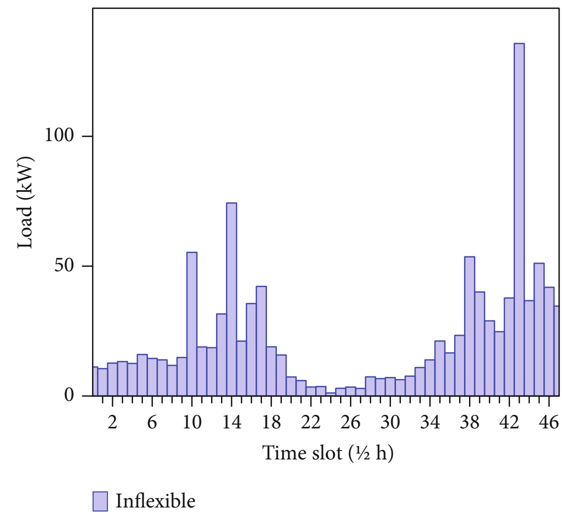

FIGURE 15: Sample aggregate load profile of the inflexible treatment group under the TOU tariff.

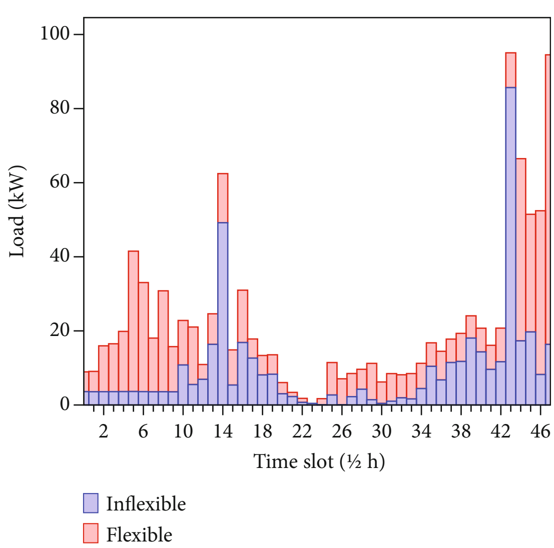

FIGURE 14: Sample aggregate load profile of the flexible treatment group under the RTP tariff.

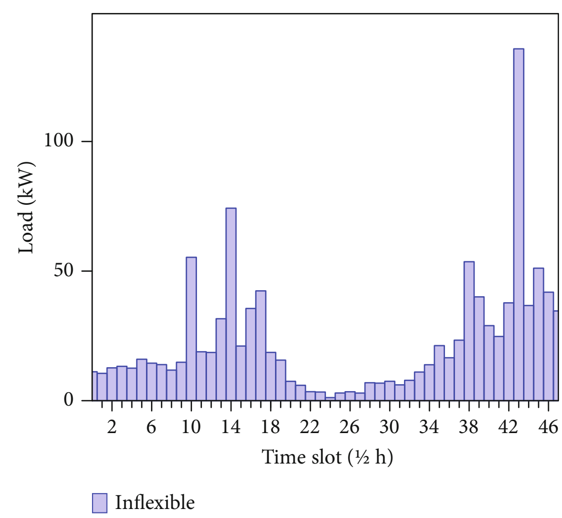

FIGURE 16: Sample aggregate load profile of the inflexible treatment group under the RTP tariff.

TABLE 4: Summary of the results of the two-sample, two-sided t-tests.

	TOU		RTP	
	T score	p value	T score	p value
Inflexible	1,266.99	$<10^{-16}$	-93.12	$<10^{-16}$
Flexible	1,316.66	$<10^{-16}$	3,095.80	$<10^{-16}$

significance threshold. In particular, increasing flexibility directly results in lower average PAR values. Arguably, that is an expected finding because greater flexibility results in more solutions in the Pareto front during the first optimization phase (consumer-level optimization), as we previously discussed in Section 5.1, which may, in turn, likely generate a global solution that has a lower PAR value during the second optimization phase (aggregate-level optimization).

However, the above finding is not robust with respect to different tariffs. In particular, Tables 3 and 4 show that, under the TOU tariff, the average PAR value for the inflexible treatment group *is statistically significantly lower* than the average PAR value for the base group, in which consumers have flexible appliances. That result shows that, under certain tariffs, flexibility can actually be detrimental to grid stability and, thus, be worse for a community of energy consumers. In technical terms, the flexibility consumers have when choosing when to use their appliances can generate solutions that dominate others that are produced by solely minimizing costs while disregarding comfort. However, it turns out that the latter solutions may end up producing lower PAR values.

What the above results show is the inherent need of DSM proponents to take a holistic view when designing DR programs by not only considering individual factors that may affect energy consumer behavior, such as tariffs and flexibility, but also the interplay between them. At the same time, it is important to note, though, that these findings may not apply universally to all types of communities or energy systems. The specific conditions and variables of each community can significantly influence the outcomes of the interplay between energy tariffs and consumption flexibility. This observation naturally calls for more research on human behavior under different DR programs.

Elaborating on the above point, under real-time energy tariffs, consumers have access to real-time information about electricity prices and consumption, and that information allows consumers to make informed decisions about their energy use. In this setting, our studied DR system may successfully incentivize consumers to shift their energy usage to off-peak hours through a combination of strategies, including personalized recommendations, real-time energy usage data, and financial incentives. The result is the effective management of demand and improved grid stability. Alternatively, unlike real-time energy tariffs, time-of-use tariffs can be detrimental to grid stability because consumers with flexible appliances may still choose to use them during peak hours. That happens because time-of-use tariffs do not offer as many opportunities for effective load shifts (i.e., load shifts that lead to a cost reduction) as real-time tariffs, thus causing a higher peak demand and a less stable grid. As we discuss in the following section, to mitigate this negative impact and maintain grid stability while still encouraging consumer flexibility in the context of time-of-use tariffs, DR system designers should ideally provide consumers with the tools and information they need to make informed decisions about their energy usage, even with limited opportunities for load shifting. For example, we conjecture that informing consumers about current grid conditions during peak and sensitive times may still lead to more responsible consumption behavior, regardless of the underlying energy tariff.

6. Conclusion

The practice of demand-side management is all about influencing the demand side of an energy system so as to achieve the primary goal of shifting and/or reducing energy consumption. That goal naturally relies on consumer acceptance and behavioral changes [51]. In this paper, we have investigated the impact of certain behavioral changes—measured in terms of flexible appliance use—on the success of a demand response program, measured in terms of flattening energy consumption by reducing the peak-to-average ratio. Experiments were conducted using a data set of 1,000 residential household profiles based on data from questionnaires offered to real-life consumers [17] and a modern DR model [16]. Our results show that flexibility does increase grid stability under the real-time energy tariff, but surprisingly, that is not necessarily true under the time-of-use tariff. That discrepancy is explained by the peculiar interplay between tariffs and flexibility and their joint influence on consumer behavior. This insight points to the importance of understanding a diverse set of factors that lead to the successful implementation of DR programs.

It is important to acknowledge that our results come from the use of a single DSM model instantiated by a realistic data set. As such, more experiments are required to corroborate our findings. Nonetheless, these initial results shed light on the importance of understanding energy consumers (and prosumers) when designing DR programs. In particular, technology and program designers should be aware of the impact of various factors/interventions as well as their interplay on the behavior of end users. That is in line with prior calls from social science scholars asking for sociotechnical knowledge to be incorporated into technology and design education since energy consumer behavior and DR designers' expectations might not be well-aligned [52]. Overall, we expect the following benefits when actively involving energy consumers in the design of DR programs:

(i) *Enhanced efficiency*: consumers who are actively engaged can provide valuable feedback, helping to optimize DR programs for better performance and efficiency

(ii) *Increased adoption*: when consumers are involved in the DR design and operation, they may feel a sense of ownership and are potentially more likely to participate and adopt energy-saving behaviors

(iii) *Empowerment and education*: engaging consumers educates them about their energy consumption patterns, empowering them to make informed decisions

Naturally, there are some requirements in order to fulfill these expected benefits; e.g., educational resources, support, and feedback mechanisms must be in place to help consumers understand and effectively participate in DR programs and to continuously gather feedback and adjust programs accordingly. After this initial understanding and learning phase, we believe automation through machine learning algorithms embedded into smart appliances might significantly enhance the effectiveness of DR programs by reducing the need for continuous manual intervention. Such a conjecture opens the door to exciting research directions, e.g., on how willing consumers are to accept algorithms acting on their behalf.

Recognizing that users' energy consumption and behavior are just as important to a sustainable energy system as new technologies opens up several other research opportunities for understanding consumer preferences and on how to alter energy behavior. For example, besides flexibility on appliance use and energy tariffs, what other potential factors can influence consumer behavior? And how do these factors work when implemented together instead of individually? We posit that a successful answer to the above questions is crucial for the successful implementation of demand-side management policies and practices.

Data Availability

The appliance consumption data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This study was financed in part by the Brazilian Coordination for the Improvement of Higher Education Personnel (CAPES) (Finance Code 001) and the Brazilian National Council for Research and Development (CNPq) via grant nos. 407274/2021-9 and 307967/2022-0.

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