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The impact of flexibility on demand-side management and the need for consumer-oriented demand response

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Teresina – PI

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Vitor Augusto Correa Cortez Almeida

The impact of flexibility on demand-side management and the need for consumer-oriented demand response

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Disclaimer: This text was originally written and Portuguese and translated automatically into English using AI. Some of the references may have been lost in translation.

“You miss 100% of the shots you don’t take. – Wayne Gretsky”

– Michael Scott

Resumo

No contexto das redes elétricas inteligentes, o gerenciamento pelo lado da demanda é um conjunto de medidas para motivar os consumidores finais a adaptar sua demanda de energia aos recursos de geração disponíveis. Para atingir esse objetivo, as soluções de gerenciamento do lado da demanda recompensam os consumidores flexíveis por meio de programas de resposta da demanda. Tendências recentes apontam para o desenvolvimento de sistemas de gerenciamento de energia residencial para aproveitar o potencial dos consumidores residenciais a contribuir com os esforços de resposta da demanda. No entanto, estudos ainda estão em andamento e são necessárias mais pesquisas sobre como projetar programas de resposta da demanda com sistemas de gerenciamento de energia residencial que atraiam os consumidores finais. Este estudo aborda limitações dos sistemas de gerenciamento de energia residencial na literatura e propõe uma abordagem de gerenciamento pelo lado da demanda centrada no consumidor com base num modelo de otimização de dois níveis. Primeiro, os consumidores resolvem um problema de nível inferior multiobjetivo de programação de cargas para otimizar sua economia e conforto individuais. Em seguida, os agregadores de demanda resolvem um problema de nível superior de agregação de perfil de demanda para otimizar sua relação entre pico e média. Os experimentos investigam o impacto dos métodos de otimização, recursos de energia distribuída, preferências do consumidor e padrões de comportamento na operação do programa de resposta da demanda. Os resultados indicam que, embora os recursos de energia distribuída contribuam para reduzir os custos de consumo e o desconforto, eles incorrem em um efeito negativo sobre a relação entre o pico e a média do perfil de demanda da comunidade. Além disso, a flexibilidade do consumidor, o preço dinâmico e a participação ativa do consumidor no processo de resposta da demanda são fatores fundamentais para o sucesso das soluções de gerenciamento pelo lado da demanda. Trabalhos futuros podem melhorar aspectos como modelagem de incerteza, sustentabilidade e estabilidade da rede, bem como realizar experimentos com comunidades de consumidores reais.

Palavras-chave: redes elétricas inteligentes, gerenciamento pelo lado da demanda, resposta da demanda, sistemas de gerenciamento de energia residencial, flexibilidade do consumidor, otimização multiobjetivo

Abstract

In the context of smart electricity grids, demand-side management is a set of measures to motivate end consumers into adapting their energy demand to the available generation resources. To achieve this goal, demand-side management solutions reward flexible consumers through demand response programs. Recent trends point towards the development of home energy management systems to leverage the potential of residential consumers to contribute to demand response efforts. However, current research is still ongoing and more studies are needed on how to design demand response programs with home energy management systems that appeal to end consumers. This study addresses limitations of home energy management systems in the literature and proposes a consumer-centric demand-side management approach based on a bi-level optimization model. First, consumers solve a lower-level multi-objective load scheduling problem to optimize their individual savings and comfort. Then, demand aggregators solve an upper-level single-objective demand profile aggregation problem to optimize its peak-to-average ratio. Experiments investigate the impact of optimization methods, distributed energy resources, consumer preferences and behavioral patterns on the demand response program's operation. Results indicate that while distributed energy resources contribute to reduce consumption costs and discomfort, they incur a negative effect on the community demand's peak-to-average ratio. In addition, consumer flexibility, dynamic pricing, and active consumer participation in the demand reponse process are key factors to the success of demand-side management solutions. Future work can improve in aspects such as modeling uncertainty, sustainability, and grid stability, as well as experimenting with real consumer communities.

Keywords: smart grids, demand-side management, demand response, home energy management systems, consumer flexibility, multi-objective optimization

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List of abbreviations and acronyms

ACS ant colony system . . . 49

AMI advanced metering infrastructure . . . 19

AS ant system algorithm . . . 49

DER distributed energy resource . . . 27

DR demand response . . . 20

DSM demand-side management . . . 20

ESP energy service provider . . . 35

ESS energy storage system . . . 52

GA genetic algorithm . . . 80

GRASP greedy randomized adaptive search procedure . . . 49

HEMS home energy management system . . . 20

ICTs information and communication technologies . . . 27

MCDM multiple-criteria decision-making . . . 62

NSGA-II non-dominated sorting genetic algorithm . . . 33

PAR peak-to-average ratio (ratio of peak to average demand) . . . 33

PHEV plug-in hybrid electric vehicle . . . 31

PSO particle swarm optimization . . . 80

RES renewable energy source . . . 32

RTP real-time pricing . . . 28

SG smart grid . . . 27

TOPSIS technique for order of preference by similarity to ideal solution . . . 62

TOU time-of-use . . . 28

List of symbols

Indices and sets

k	Index of an end consumer
a	Index of a home appliance or electrical component
t	Index of a discrete time step
w	Index of a time window
i_k	Index of a load schedule's demand profile for the k-th consumer
K	Amount of end consumer indices
A	Amount of electrical component indices
T	Amount of equal-length time steps indices in the planning horizon
W_a	Amount of time window indices for the a-th appliance
I_k	Amount of load schedule's demand profile indices
$\mathcal{K}$	Set of end consumer indices
$\mathcal{A}$	Set of electrical component indices
$\mathcal{T}$	Set of time steps indices
$\mathcal{T}_a$	Set of time window indices for the a-th appliance

Decision variables

$\boldsymbol{M}$	Binary demand-schedule matrix for the main energy grid
$\boldsymbol{R}$	Binary demand-schedule matrix for the renewable energy source
$\boldsymbol{S}$	Binary demand-schedule matrix for the energy storage system
$x_{k,a}$	Flexible appliance's start-up time

Parameters

Δt	Length of the time steps (h) in the planning horizon
P_a	Nominal power consumption rating (kW) for the a-th electrical component
P_t^{res}	Output power (kW) of renewable energy source at the t-th time step
$\alpha_{a,w}$, $\omega_{a,w}$	Start- and end-time steps for the a-th electrical component's w-th time window respectively
$d_{a,w}^{min}$, $d_{a,w}^{cur}$	Base and maximum curtailable amount of time steps demanded by the a-th electrical component within the w-th time window respectively
$p_{a,w}^{def}$, $p_{a,w}^{int}$	Deferrable and interruptible binary states of a-th electrical component within w-th time window respectively
p_t, p'_t	Energy purchase and sale tariffs at the t-th time step respectively
$\boldsymbol{B}$	Binary demand-schedule matrix representing the most comfortable schedule
$\gamma_{a,w}$	Inflexibility weight for the a-th electrical component within the w-th time window
$u_{k,a}$	Consumer's preferred start-up time for a-th flexible appliance
$w_{k,a}^A$, $w_{k,a}^D$	Cost factors for when the suggested schedule advances or delays the start-up time respectively

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1 Introduction

The idea of smart electricity grids paints a picture in which energy systems are equipped with modern information and communication technologies. In this scenario, homes and other buildings have access to smart metering devices that read and communicate energy consumption in real time. This access to information enables computer systems to help consumers optimize their energy use, for example, to save money on energy bills. However, research in this area is still ongoing and more studies are needed on how to design consumer programs that appeal to end users. This introductory chapter seeks to answer three questions to help the reader understand this study:

1. What is the topic of the study? The information necessary for the reader to understand the context and motivation behind this study is summarized in Section 1.1;
2. Why is the study necessary? The research problem outlining the knowledge gap is defined in Section 1.2 and the research rationale is given in Section 1.5;
3. How was the study conducted? The research aims and method are presented in Sections 1.3 and 1.4, and the thesis' structure is shown in Section 1.6.

Throughout this document, the first person plural is frequently used, sometimes to refer to the author and the reader, sometimes to refer to the author and the coauthors of the published scientific papers that make up the body of this thesis.

1.1 Context and motivation

Smart grids are built on top of an advanced metering infrastructure that employs information and communication technologies within the generation, transmission and distribution sectors of electric energy systems (RASHED MOHASSEL et al., 2014). A key example of such technologies are the smart meters that replace traditional analog energy meters in consumer facilities (homes, commercial buildings, condos, factories) and enable the reading and transmission of information on energy consumption and the state of the grid in real time. Other examples include devices such as smart plugs and switches that monitor the status of appliances and enable their remote control over a local computer network or even the Internet. In this context, it is through the advanced metering infrastructure (AMI) that smart meters communicate bidirectionally with the organizations responsible for the energy distribution or marketing (utilities, aggregators) in a smart grid scenario.

The purpose of the technological integration of the AMI is to enable measures and processes that benefit the energy system and the various entities connected to it. For example, one could imagine that a smart meter, with the help of a user-friendly display, could facilitate the access to energy consumption information to end consumers, thereby encouraging more conscious consumption habits (OPREA et al., 2021). In addition, energy consumption data allows marketing organizations to offer consumer-centric consumption programs to meet their demands, aiming for energy efficiency and sustainability. In short, the AMI enables demand monitoring to support decision making related to the planning and operation of electric energy systems.

In the literature, demand-side management (DSM) is a collection of actions taken by utilities to change consumer demand. The key idea behind DSM is analogous to the management of generation resources. Historically, electric energy utilities have needed to adapt their generation resources to demand estimates (GELLINGS, 1985). DSM inverts this narrative by influencing the demand to adjust to generation resources, a change that promises benefits not only for utilities, but also for other energy trading entities and end consumers. Employing DSM as another tool to balance energy supply and demand allows for improved efficiency of generation resources, which makes it possible to defer investments in new generation capacity, reduce operating costs, increase profit margins and reduce costs for end consumers. (ESTHER et al., 2016; STRBAC, 2008).

Consumers traditionally partake in DSM initiatives through demand response (DR) programs, where they are able to make well-informed decisions about their energy consumption, playing a central role in load shifting (DAVITO et al., 2010). A typical goal of DR programs is to promote off-peak energy consumption. In turn, this can be achieved through time-varying rate initiatives, such as time-of-use, and real-time pricing (PALENSKY et al., 2011). These initiatives provide an alternative to the traditional energy market models based on fixed prices throughout the day. Still, consumer participation remains a challenge and the DR problem is approached in a variety of ways with a growing body of literature in applications and incentive design techniques, ranging from mathematical programming to artificial intelligence and game theory (KHAN, M. A. et al., 2023; MOHSENIAN-RAD et al., 2010; SAAD et al., 2012). The above discussion highlights the importance of providing an incentive to end consumers to participate in demand response programs.

1.2 Problem definition

A growing trend among DR studies is the use of home energy management systems (HEMSs) for residential consumers. These systems are located near or inside the consumer facilities and work as an interface between the smart meter and the consumer, providing services such as load scheduling, data compression, and power quality monitoring (JAVADI et al., 2020; MENDES et al., 2020; RODRIGUES JUNIOR et al., 2019). The load scheduling problem in DR programs with time-varying rates is particularly challenging as it consists of discovering an optimal schedule for the consumer's programmable loads taking into account the constraints of the DR program and other complexities such as the presence of distributed energy resources, the impact of consumer preferences and actions, and the modeling of conflicting objectives among distinct entities (SILVA et al., 2020; VERAS et al., 2018). For this reason, HEMSs are key pieces in encouraging residential consumer participation in DR programs.

The challenges of developing demand-side management systems come down to identify the needs or intentions of the various entities involved in the problem and modeling mechanisms to meet them. For example, we can conceive that the utility or energy provider entity has the intention to control demand, especially at peak times, reduce operational costs with generation and grid maintenance, prevent peak demand rebounds, and ensure grid stability (SAFDARIAN et al., 2016). Other needs explored in the literature are optimizing the management of distributed energy resources and dealing with the uncertainty of resources such as renewable generation sources. On the other hand, we can conceive that the end-consumer entity wants to decrease energy consumption expenses without having their usage preferences ignored, avoiding inconvenience with load shifting. As new objectives are elicited and modeled in the literature, the complexity of the problem grows and the requirement for new proposals to bring more and more realistic models increases.

Currently, many HEMSs consider the end consumer to be a passive participant in the DR program. In other words, a large part of the proposed solutions consider that HEMSs should act on behalf of the end consumer when shifting household loads, while they merely inform their preferences before the scheduling procedure starts. According to McIlvennie et al. (2020), this trend reveals a technological bias in studies in the field that has been criticized by researchers calling for more attention to the study of human and social factors in the adoption of these systems. Indeed, the failure to recognize the disruptive nature of the end consumer is seen as one of the biggest obstacles to mass adoption of DR programs by residential consumers (LI, W. et al., 2021). As a result, new research is encouraged to engage these consumers in designing HEMSs to mitigate a number of issues pertinent to them, such as discomfort, privacy, security, and technology anxiety (INGEBORGRUD et al., 2020).

1.3 Research aims

The key aim of this research is to model a home energy management system-based demand-side management approach that prioritizes the needs of end consumers and considers their personal preferences and energy consumption habits to enable and motivate their active participation in demand response programs. To achieve this aim, we seek to accomplish the following objectives:

1. Review the models and approaches in the literature to solve the DR problem;
2. Identify the characteristics and aspects modeled by these approaches to meet consumer needs;
3. Develop a model that includes relevant aspects to promote flexibility and active consumer participation;
4. Compare the model developed with other state-of-the-art solutions;
5. Assess the impact of consumer flexibility and participation on the DR program.

1.4 Method overview

To achieve the objectives and aim of this research, we first identified limitations in other HEMS-based demand-side management approaches in the literature and proposed a solution to address these limitations. By further reviewing new studies and identifying limitations both in other state-of-the-art approaches and in our own, we were able to continue a process of improving the proposed model throughout the research. For each milestone in our approach, we strive to publish our progress and findings to further receive feedback.

Besides the literature review, we searched for methods to compare DSM approaches given the different optimization models in the literature. We chose to compare the aspects considered by the models and evaluate the effects of these aspects through simulations by verifying the results through statistical tests.

1.5 Research rationale

The main rationale behind this study is that understanding how potentially inflexible residential consumers may behave in demand response programs is vital for us to assess what works in terms of practices and aspects currently modeled in the state of the art, and to inform and improve future decision-making on the design of home energy management systems. Since the success of any DR program depends on consumer participation and engagement, we believe that further studies on demand-side management with demand response programs should focus on addressing the active involvement of consumers in the operation of home energy management systems. The proposed method was intended for this area of research specifically because there is no simple way to directly compare different optimization models that consider more or less variables and parameters, but it is still possible to observe the modeled aspects and evaluate the impact of these aspects through experiments and case studies.

1.6 Document structure

The following chapters of this document are organized as follows: in Chapter 2 we introduce the research background and review the research gaps, related works and contributions; in Chapter 3 we present the proposed approach and the evolution and limitations of the demand response models and experimental designs throughout the study; then, we discuss the results of the experiments in Chapter 4. These chapters begin with a presentation of their respective contents and end with a concluding remarks section that can be read together as a chapter summary. Finally, we conclude the thesis in Chapter 5 with our final considerations and highlight the method limitations, future work and scientific production.

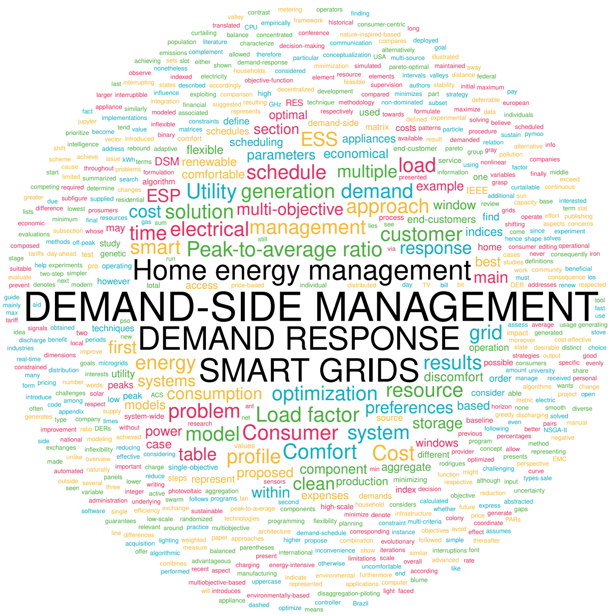
2 Literature Review

This chapter is organized in two parts. First, we present the theoretical framework or research background of this study in Section 2.1, that is, a presentation of the main concepts required to understand the present study that could serve as future reference for eventual readers who are not experts in the subject. Then, in Section 2.2 we introduce and discuss the works in the literature that are related to the proposed approach and compare the different aspects considered by state-of-the-art solutions. (WAZLAWICK, 2014).

2.1 Research background

This research covers different areas of knowledge and proposes a computational system model for electric power systems. In writing this section, the author sought to list the most important concepts frequently mentioned by related works to present them in a didactic and succinct way. A collection of words related to this research background is shown in Figure 1.

Figure 1 – Word cloud related to the present research



Source: Desined by the author

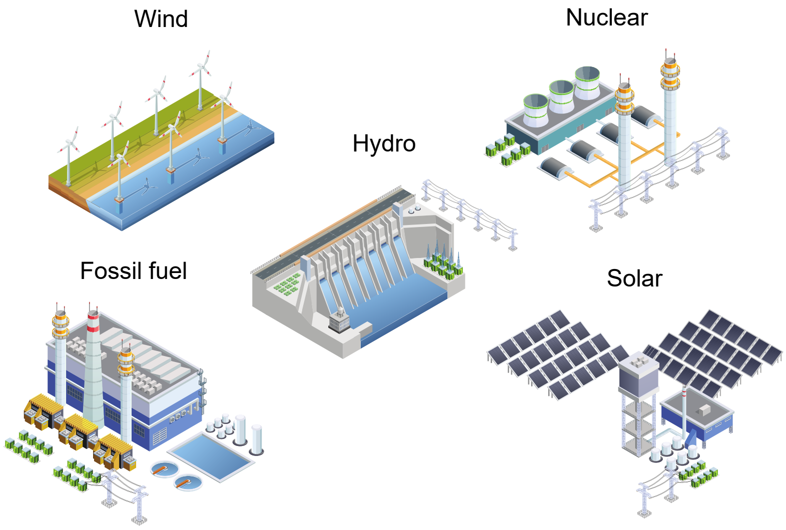
Perhaps the most important concept to understand the heart of this research is that of demand-side management, seen in Section 2.1.1. This concept may or may not be related to the concept of smart grids which in turn references the concept of advanced metering infrastructure, introduced in Section 2.1.2. These concepts support and help us understand the so-called demand response programs in Section 2.1.3. At last, we summarize the concept of home energy management systems in Section 2.1.4.

2.1.1 Demand-side management

To say that electric power systems are complex is perhaps an understatement. These systems are often broken down into sectors or blocks, typically generation, transmission, and distribution, whose complexities are further unpacked (RABÊLO, 2010). While it is not necessary to comprehend the full complexity of these systems to understand this thesis, before we can grasp the concept of demand-side management, we must at least be familiar with a key challenge in the management of electric power systems, which is how to supply the consumer's energy demand.

Traditionally, electric utility companies have treated consumer demand as largely uncontrollable and bound to fluctuate depending on the time of day (STRBAC, 2008). This means that what determines the consumer's demand is not something that can be managed in the eyes of electric utilities. The job of an electric utility is then to forecast the demand and accordingly manage the generation resources needed to supply it (GELLINGS, 1985). By generation resources, we refer to hydroelectric, wind, solar, nuclear, and fossil fuel-based power plants, as seen in Figure 2. Simply put, to supply the consumer's energy demand means having generation resources ready to output enough power to match any level of consumption that consumers might require.

Figure 2 – Examples of generation resources



Source: Compiled by the author[1]

Generation resources can be classified into two groups: base load generation, and peak load generation. Resources in the first group supply most of the demand

[1] Images from *macrovector* at Freepik

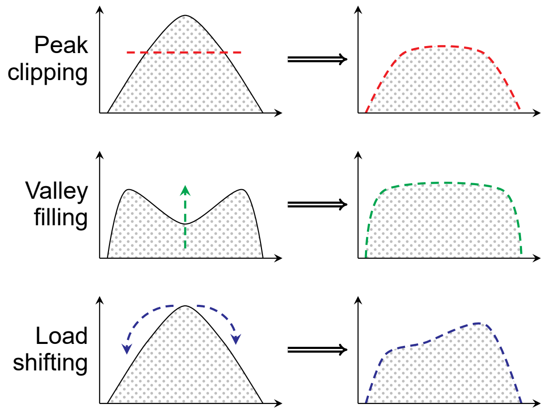
while those in the second group serve to supplement base load generation at times of high demand (DAVITO et al., 2010). For example, at times near the end of the workday, when most consumers are coming back home, daily demand tends to peak as many household appliances are turned on simultaneously. In these situations, it is common for utilities to activate more expensive and less efficient power plants to meet peak demand, such as those based on fossil fuels, which then go back to idle during off-peak periods (WARREN, 2014). Here we see an optimization opportunity: the less demand peaks there are, the more loads could be supplied by the base generation resources, reducing costs and improving efficiency.

In this context, demand-side management emerges as a tool to help electric utilities. As best defined by Gellings (1985), “Demand-side management is the planning and implementation of those electric utility activities designed to influence customer uses of electricity in ways that will produce desired changes in the utility’s load shape”. According to Warren (2014), DSM activities designed to match supply and demand appeal to electric utilities because they are a cheaper alternative than investing in new generation capacity. While the term may have been coined by Gellings in the 80s, DSM remains a topic of interest to industry and academia (PALENSKY et al., 2011).

Demand-side management activities can be seen in terms of load shaping goals. Figure 3 illustrates three examples of these goals, where each graph indicates the demand level on the y-axis over a time period along the x-axis. The goals describe the ways in which the demand profile can change – from the left-side graph to the right-side one – as a result of the utility’s efforts to direct or indirectly influence the demand. For example, utilities can achieve peak clipping by offering energy bill rebates to consumers who do not exceed a certain consumption level or who are willing to curtail loads during peak demand periods. Valley filling can be attained by offering bill discounts or other incentives to increase demand during off-peak periods. At last, load shifting can be accomplished with a combination of the previous efforts or by offering alternative energy rates to consumers who are willing to shift loads away from peak demand periods. (GELLINGS; CHAMBERLIN, 1993).

In summary, demand-side management encompasses actions, measures, programs and policies promoted on the demand side to achieve utility goals while emphasizing the importance of the end consumer for the future of electric energy systems (WARREN, 2014). As a matter of fact, having the consumer at the center of the DSM actions is a must. Demand-side management is all about breaking the traditional one-way communication utility-centric paradigm and establishing a two-way communication consumer-centric partnership that gives consumers more information on their energy consumption and a sense of control over their energy bills (GELLINGS, 1985). However, due to technological limitations, early DSM efforts did not reach beyond the largest con-

Figure 3 – Load shaping goals in demand-side management



Source: Adapted from (ESTHER et al., 2016)

sumers as measures were too expensive and time-consuming to implement properly (DAVITO et al., 2010). This scenario is expected to change with the advent of smart grids as we will see in the next section.

2.1.2 Smart grids

The concept of smart grids refers to the next generation of electricity grids that are equipped with information and communication technologies (ICTs). The smart grid (SG) is expected to address major challenges faced by the traditional electricity grid infrastructure (FARHANGI, 2010). According to the United Kingdom's Department of Energy and Climate Change (2009), the transition to a smarter grid should be an incremental process, and SGs should be observable (real-time monitoring), controllable (fully manageable and optimized), automated (intelligent and self-healing), and fully integrated (interoperable and backwards compatible). In other words, the role of technology in the future electricity grid is essentially to bring real-time monitoring, control, automation and computational intelligence to the grid's management processes and components. Table 1 summarizes the key differences between traditional electricity grids and smart grids.

Behind the innovative potential of smart grids is an advanced metering infrastructure that makes it all possible. The AMI leverages ICTs to establish a connection between utilities and consumers through the so-called smart meters (RASHED MOHASSEL et al., 2014). Smart meters, which replace traditional energy meters in consumer units, are able to receive information remotely, measure energy consumption data, and allow it to be transmitted or even displayed on a home device (DILEEP, 2020). As a result, utilities can collect, monitor and analyze information concerning the state of the grid and consumer demand in real time, enabling systems and applications.

The expectations surrounding smart grids have contributed to a resurgence of

Table 1 – Comparison between traditional grid and smart grid

Traditional grid	Smart grid
Electromechanical	Digital
One-way communication	Two-way communication
Centralized generation	Distributed generation
Few sensors	Sensors throughout
Limited monitoring	Self-monitoring
Manual restoration	Self-healing
Limited control	Pervasive control
Few consumer choices	Many consumer choices

Source: (FARHANGI, 2010)

the discussion on DSM. Smart grids are a key piece of the puzzle towards making the vision of demand-side management become reality as the AMI enables cost-effective real-time measurement and verification efforts (DAVITO et al., 2010). Additionally, the integration of distributed energy resources (DERs) enabled by the SG upholds the vision of a consumer-centric grid of DSM, making room for interconnected networks of distributed energy systems that can operate in both connected or islanded mode from the main grid, also known as microgrids (FARHANGI, 2010). A step towards realizing this vision lies in demand response, discussed in the following section.

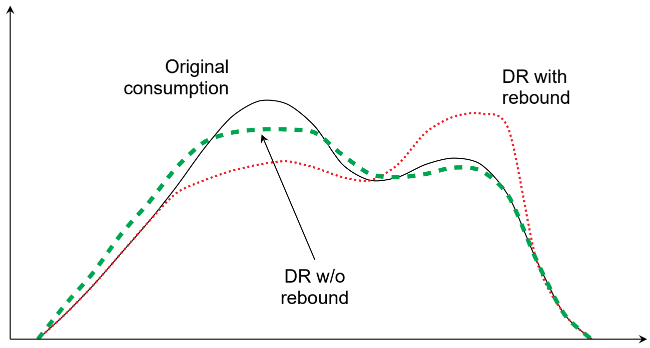
2.1.3 Demand response

Demand response is one of the most studied demand-side management efforts in the literature. According to Albadi et al. (2008), the concept of DR describes the behavior of end consumers as they change electricity consumption patterns from their normal habits in response to messages from utilities signaling the need to alter the demand in exchange for incentive payments or alternative energy prices. In general, these efforts are performed through demand response programs that establish the terms of a contract agreed upon between utility and consumer (PATERAKIS et al., 2017). The focus of DR is therefore on the consumer response.

Demand response programs are commonly distinguished between incentive-based, in which payments are offered to consumers in exchange for a desired change to their consumption patterns, or price-based, in which economic signals are informed to the consumer who gets to decide how to change consumption patterns in response (KHAN, A. A. et al., 2015). Regardless of program type, the end goal is to achieve a load shape change. Figure 4 illustrates a load profile and two shifted versions impacted by DR efforts, with and without creating a peak demand rebound (SAFDARIAN et al., 2016).

Examples of incentive-based programs are the direct load control programs, in

Figure 4 – Impact of demand response on load profile



Source: Adapted from (PALENSKY et al., 2011)

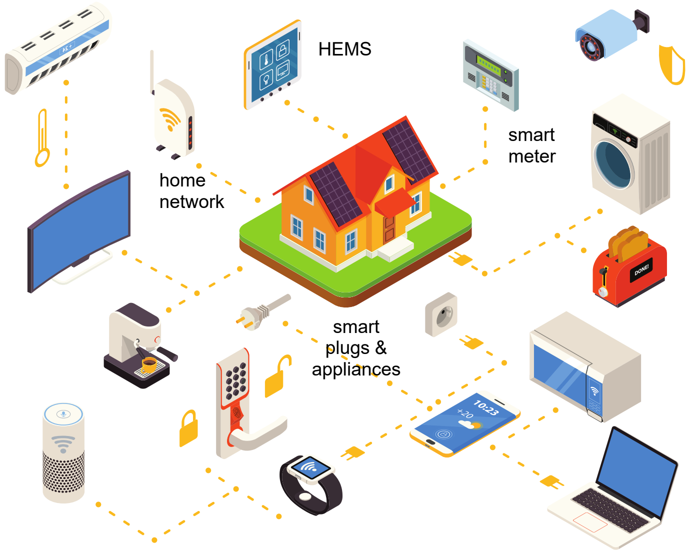
which the utility is allowed to control loads directly in accordance with consumer restrictions, or *interruptible/curtailable* load programs, which are similar to the previous program but the utility cannot control loads directly and consumers have to respond to signals instead (ALBADI et al., 2008). On the other hand, price-based programs generally seek to reflect the actual wholesale energy costs. For example, time-of-use (TOU) pricing programs define price regions to reflect the average cost of electricity in peak and off-peak hours, while real-time pricing (RTP) programs can have energy costs varying hourly (AGGARWAL et al., 2021). In all programs, the degree of advance notice of the utility signals is also part of the agreement between the parties, and can be monthly, daily or even hours in advance.

Ideally, DR programs bring together consumers who are interested in savings or incentive payments on their energy bills in exchange for their flexibility in load management. However, the tasks of educating end users, in particular residential consumers, about energy management (DAVITO et al., 2010), and motivating them to actively participate in DR programs remains a challenge (LI, W. et al., 2021). In the next section, we introduce home energy management systems and their role in enabling consumer acceptance and engagement.

2.1.4 Home energy management systems

Energy management systems automate consumer participation in DR programs. They are responsible for gathering all the input information needed to optimize an operating strategy for the end consumer (PATERAKIS et al., 2017). When these systems are aimed at residential consumers, they are known as home energy management systems. HEMSs effectively act as a home interface between consumer and DR program, facilitating communications and responsiveness to utility signals (AMER et al., 2021). Figure 5 illustrates a home energy management system scenario.

Figure 5 – Consumer household with HEMS



Source: Compiled by the author[2]

According to Aftab Ahmed Khan et al. (2015), the role of a HEMS is to automate the processes of optimizing consumer goals as well as monitoring and controlling power flow. Indeed, several applications can benefit from the kind of information that a HEMSs have access to, such as data compression and power quality monitoring (MENDES et al., 2020; RODRIGUES JUNIOR et al., 2019). In this study, the application of interest is residential load scheduling, which consists of determining an optimal schedule of appliances and other components of a home's electrical grid in order to benefit the consumer under a price-based demand response program. In Section 2.2 we present an overview of the related work on home energy management systems.

2.2 Related works

In this section, we present solutions aimed at load scheduling with energy management systems. With the advent of smart grids, there has been a surge of demand-side management studies on demand response solutions targeting the residential sector through home energy management systems (BEHRANGRAD, 2015; GELAZANSKAS et al., 2014; MEYABADI et al., 2017; SILVA et al., 2020). Although these solutions can capture consumer preferences, they still often ignore crucial human elements, such as the potential for consumer intervention and non-compliance with the proposed load schedules (MCILVENNIE et al., 2020). As stated by Gellings (1985), "while the objective of any DSM activity is to produce a load-shape change, the art of successful implementation and the ultimate success of the program rests within the balancing of

2 Images from *macrovector* at Freepik

utility and consumer needs". Since DR programs depend on customer participation, it is a must to consider consumers as equally important actors within the system.

As our literature review progressed, we identified several aspects of the solutions found in the literature, which we used to formulate 11 questions that help us characterize them. The first two questions are more general and help us summarize the method and experiments of the reviewed study: (i) how is the control approach? and (ii) how is the validation approach? The remaining questions inquire about specific aspects considered by each solution: (iii) does it manage household appliances? (iv) does it manage distributed energy resources? (v) does it consider consumer preferences? (vi) does it consider response coordination? (vii) does it consider sustainability aspects? (viii) does it consider uncertainty? (ix) does it consider grid stability? (x) does it consider consumer interference or non-compliance? (xi) does it evaluate trade-off solutions? In Section 2.2.1, we attempt to answer these questions as we introduce the studies more closely related to our proposed approach. Then in Section 2.2.2, we summarize our main contributions.

2.2.1 Energy management solutions

The work by Conejo et al. (2010) presents a linear programming robust optimization model to minimize energy consumption costs minus consumer utility with respect to a RTP tariff. This model considered demand as a continuous variable without considering individual home appliances, which is a common trait of early DSM studies not aimed at residential consumers. A rolling window approach is used to re-evaluate the optimal strategy on an hourly basis, planning future demand while considering past energy prices and energy consumption as fixed. As a model parameter, minimum consumer daily consumption can be considered a consumer preference, besides the consumer-defined utility function itself. The uncertainty of future energy prices from retailer market was modeled using an autoregressive integrated moving average model to calculate confidence intervals for the remaining energy prices throughout the planning horizon. Some grid stability constraints in the form of demand ramp limits and maximum peak consumption were considered.

Further studies focusing on the residential sector rely on optimization models that incorporate constraints targeting specific household appliances. For example, in Qian et al. (2013), the authors propose a day-ahead solution in two steps using simulated annealing. The first step is a local optimization of the consumer, while the second step is an iterative process where the utility optimizes a price vector for the incoming scheduling horizon. Home appliances are modeled in three groups: the first group contains inelastic or background appliances, the second describes appliances with a utility function of the energy consumption for each time step, and the third group represents semi-inelastic appliances that have a fixed demand that can be shifted and interrupted within a specified subset of the scheduling horizon. Distributed energy resources are not modeled, but plug-in hybrid electric vehicles (PHEVs) are envisioned as semi-inelastic loads. Consumer preferences are expressed in terms of elastic appliance utility function, minimum demand and preferred time steps for the operation of semi-inelastic appliances. Regarding response coordination, the simulated annealing price control algorithm tries to optimize utility profits by flattening the load curve, which improves the peak-to-average ratio. The uncertainty of consumer demand is worked around using the iterative approach. As for grid stability, appliances have to respect retailer imposed maximum energy consumption limits.

With the modeling of household appliances, constraints regarding consumer preferences lead to the concept of schedule inconvenience. Setlhaolo et al. (2014) present a mixed-integer nonlinear programming model to minimize consumer expenses and inconvenience from load shifts. The decision variables are binary and reflect the state of loads at each time step. The inconvenience of a schedule is measured in terms of the total differences between the optimal schedule and a baseline schedule, and both objective functions are combined as a weighted sum. All home appliances are modeled as flexible and consumer preferences are expressed in terms of allowed time intervals and minimum consumption of each appliance, baseline schedule, and constraints to enforce uninterrupted and/or consecutive operation.

In Pilloni et al. (2016), a centralized energy management system controls neighborhood loads using two algorithms: first an appliance scheduling algorithm uses a greedy approach to shift appliances with highest consumption; then a renewable source scheduling algorithm detects energy surplus and decides whether to re-shift appliances. Simulations are performed with 1000 consumers based on preferences surveyed from real consumers. The authors implement a state-of-the-art system and compare it with their quality of experience-aware system under two settings, with and without renewable energy source (RES), to conclude that their approach can have higher costs for some appliances (the ones that users are least likely to make flexible) but always achieve the least amount of “annoyance” rates. Appliances are classified in one of four groups: G1 are not controllable; G2 are “switching” controllable; G3 are thermostatically controllable; and G4 are energy sources. G2 and G3 appliances have simple linear models relating their energy consumption with the amount of time it needs to complete a task (usage time window). Only renewable energy sources (solar, wind) are considered, and no specific model for energy storage systems was found, with water heaters considered as thermostatically controlled loads only. Consumer preferences are implied in the consumer profiles obtained from surveys and also collected daily when users manually change their preferred load starting times. Non-compliance is considered as consumers that refuse to participate in DR events for extended periods of time get profiled as inflexible and do not benefit from the cost savings.

Another aspect considered by HEMS studies is the minimization of the demand's peak-to-average ratio (PAR) in an effort to prevent demand peak rebounds. Safdarian et al. (2016) propose a decentralized approach to coordinate consumer load scheduling efforts in order to improve their system-wide demand profile. The problem is formulated as a bi-level optimization problem, the lower level problem is a distributed optimization of each consumer household schedule. The optimal cost is saved and later used as a constraint within the upper level problem. In the upper level, an aggregator computes the aggregate demand profile and broadcasts it to consumers. Consumers try to improve the profile by re-optimizing their load schedule with the added constraint that a cost no worse than the previous result can be used. This process is iterative and repeats until it converges. Although their solution guarantees minimal energy expenses for all consumers, the coordination method between consumers and utility requires repeated executions and message exchanges to converge towards a solution. They consider one type of responsive appliance whose energy consumption and time of use can be freely adjusted within some constraints. Responsive appliances can have a set minimum energy consumption, allowed time interval, and not be interrupted as consumer preferences such as allowed time intervals and minimum appliance demands. Distributed generation output is considered, yet PHEVs are only considered as loads with a battery capacity model. The upper level of this approach is a perfect example of response coordination, an attempt to coordinate the optimal load schedule from the lower level problem and find the best alternative load profiles that maximize the load factor of a consumer community.

In Veras et al. (2018), the authors propose a multi-objective DSM model to optimize a load schedule by minimizing energy expenses and consumer inconvenience. The authors employ a non-dominated sorting genetic algorithm (NSGA-II) implementation to solve the consumer load schedule problem with binary decision variables. Three types of home appliances are considered to describe the scheduling patterns they are allowed to exhibit: type I that can be interrupted and deferred; type II, only *deferrable*; and type III, inflexible. DERs are not considered in the mathematical formulation. Consumer preferences are expressed in terms of appliance type, baseline schedule, minimum demand per appliance and minimum daily energy consumption. Demand ramping constraints are considered, but no response coordination, sustainability, uncertainty, non-compliance, nor evaluation of multi-objective solution trade-offs are considered.

The study by Lin et al. (2018) automatically determines home appliance preferences with an energy *disaggregation* method using historical data, and optimizes load schedule cost and comfort for a day-ahead price-based program. The authors combine both optimization functions with a weighted sum and use a constrained particle swarm optimization algorithm to solve the optimization problem. Only one type of programmable appliances with deferrable and uninterruptible operation are considered. Deterministic renewable generation output is considered. Consumer can express their preferences for when each appliance can operate, which can also be collected from historical energy consumption data. The authors attempt to reduce the PAR using an inclining block rate energy tariff.

Z. A. Khan et al. (2019) propose a day-ahead and real-time DSM approach for residential load scheduling to minimize the distance to an ideal load curve, appliance usage waiting time, and energy consumption cost. The authors employ two nature-inspired metaheuristic techniques to find a Pareto set of suitable solutions, plus an additional step to select a multi-criteria solution. Appliances are all shiftable, however the formulation does not consider consumer preferences nor multiple energy sources. Some level of coordination is considered by minimizing each consumer's load profile PAR, which is also a way to improve grid stability. A real-time approach is used to complement the load schedule algorithm and respond to consumer non-compliance. Although Pareto optimization is considered, the procedure to select a trade-off solution is completely random.

The solution proposed by Silva et al. (2020) considers multiple energy sources, schedule interference, and a load schedule problem with two conflicting objectives solved by an evolutionary Pareto optimization method. The inconvenience function considers two types of discomfort, appliance waiting time and thermal discomfort. Appliance model and most constraints are based on the work by Veras et al. (2018). Consumer preferences indicate multiple time windows in which appliances can operate with a minimum energy consumption constraint. DERs are properly modeled, considering multiple generation sources, renewable sources, battery capacity model and vehicle to grid integration. Pollution minimization is considered as a sustainability objective. However, the authors do not address response coordination nor determine which multi-criteria solution should be followed in practice by the end consumer.

In Chiu et al. (2020), the approach employs Pareto optimization to create a demand response program that minimizes the consumer's individual energy expenses and maximizes their load factor. The appliance model is limited to three types of home appliances considering flexibility in start time and total demand: type I are fixed in time and demand; type II are shiftable in time and inflexible in demand; and type III are shiftable and flexible. The authors consider DERs with renewable generation and electric vehicle charging. Response coordination is somewhat investigated as the solution maximizes the load factor of individual consumers, however, much like Z. A. Khan et al. (2019), this does not guarantee that the aggregate demand profile will have a good load factor. The authors do attempt to evaluate the trade-off between multi-criteria solutions by selecting the elbow solution from a Pareto front.

In Pamulapati et al. (2020), consumer preferences are inferred by non-intrusive load monitoring with energy disaggregation, and a Pareto optimization approach is subsequently used to solve a multi-objective optimization problem having two conflicting goals, namely minimizing costs and user dissatisfaction. The authors address the issue of suggesting a load schedule from a Pareto set based on a trade-off worth metric and a *niching* technique. 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.

Latifi et al. (2020) propose a distributed DSM framework to reduce consumer expenses, preserve utility, and improve the system-wide PAR. The multi-objective optimization problem is reduced to a single-objective problem via a weighted sum approach, meaning the trade-off between solutions is not addressed. The underlying diffusion approach makes use of adaptive network models and preserves consumer privacy while minimizing information exchange. The authors consider a variety of appliance flexibility patterns in their appliance model, from inflexible to three levels of flexibility and even curtailable loads. This model does not consider multiple energy sources, but it models battery capacity for PHEVs. Response coordination is implemented by the diffusion method to minimize a community's PAR. Consumer non-compliance is theoretically considered as the iterative diffusion approach allows consumer preferences to change mid optimization, but this aspect was not investigated.

Several recent studies present more robust models contemplating grid stability aspects while abstracting away other aspects addressed in the literature. For example, the studies by Jafari et al. (2020) and Zeng et al. (2021) consider multiple energy sources when formulating a price-based DR scheme. Moreover, Zeng et al. (2021) consider cost reduction and consumer preferences in their model. However, neither solution considers grid stability aspects and response coordination, i.e. how to avoid peak demand rebounds. Amer et al. (2021) introduce the concept of loss-of-life to reflect transformer degradation costs considered by the HEMSs to benefit both consumers and the energy service provider (ESP). The main limitations of their approach lies in the model's flexibility, which does not consider multiple scheduling windows for a given load, and the simple categorization of flexible loads into either *shiftable* or controllable.

The approach suggested by Barja-Martinez et al. (2021) combines price-based with environmentally-based DR programs and reduces the multi-objective optimization problem to a single-objective optimization, thus ignoring the evaluation of schedule trade-off. The same limitation is present in Amer et al. (2021), Latifi et al. (2020), Lin et al. (2018) and Setlhaolo et al. (2014). In general, weighted sum approaches for solving multi-objective load schedule problems should be avoided as they hinder the system's ability to find Pareto-optimal solutions, each of which having a distinct demand profile, with respect to evolutionary techniques (JAKOB et al., 2014; SHUKLA et al., 2007).

Some studies consider end consumers as strictly passive agents, this ignoring their non-compliance potential. In Xu et al. (2021), the authors suggest a hybrid DR mechanism based on real-time incentives and pricing that minimizes both consumption and consumer dissatisfaction costs. The authors use an iterative approach to gather decision variables from three entities (grid operator, retailer, and consumers). In reality, consumers do not actively participate in this process and the HEMS automates everything. The retailer (who is aware of consumer preferences) represents them to the grid operator. The grid operator sets incentive prices to retailers, who set real-time electricity prices to consumers, who reschedule their loads in response. This process is repeated for a range of incentive rates the operator is willing to share with retailers, and at the end of it, after testing what the demand would be like for each incentive rate, they pick the one that minimizes its costs. Experiments run simulations considering a time resolution of 5 minutes and compare the results of 4 test cases: (1) the proposed hybrid approach (incentives and real-time price); (2) only real-time price; (3) only incentives; and (4) non-DR (flat tariff). Two sets of parameters for a set of users and two retailers were used and results are compared in terms of peak load reduction, PAR, operator cost, retailer profits, and consumer electricity bills. Response coordination is addressed as the proposed approach seeks to reduce peak load and flatten the aggregate demand profile, reducing the PAR. Even though consumer preferences are captured in the form of utility and dissatisfaction factors, consumer appliances are not considered within the model, and the proposed HEMS requires consumers to passively accept the optimal demand schedules to benefit from the DR program.

The study by Bugaje et al. (2022) uses a rule-based strategy using system dynamics to describe systems through diagrams. They consider 4 DR scenarios with different TOU tariffs and go over several metrics to compare simulated data of appliance usage for a year. Delay between preferred start-up time and programmed start-up time is the main metric, which they use to create two "two-dimensional" metrics: delay duration profile and delay time profile. These metrics are used to judge how convenient a DR program is in comparison to others for a specific consumer. Home appliances are managed with a rule-based strategy to shift appliances towards off-peak TOU pricing regions. DERs are not considered. The main consumer preference in consideration is when the consumer prefers to use a DR-enabled appliances such as a dishwasher. They also expect consumers to inform how much delay they are willing to tolerate for each appliance at each time period of the day. The experiments were performed from the perspective of a single consumer and no aggregation or response coordination was investigated. Other aspects are not considered.

A robust bi-level mixed-integer linear programming model is suggested by Khosravi et al. (2022) 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 with distribution feeder reconfiguration and linear AC power flow constraints. The lower level problem considers multiple scenarios based on probability distributions. The objective functions sum the respective values of each scenario weighted by a factor proportional to the likelihood of that scenario. There are two objectives, cost and discomfort. The authors say they use the epsilon constraint method to aggregate both objectives. The upper level problem consists in maximizing social welfare, but it is unclear how this step is performed. The authors claim that after each microgrid solves their individual scheduling problem, they send information about their hourly power shortage/surplus to the distribution system operator, who is supposed to use this information to calculate the deviations from their requested schedules for each microgrid. The data format and how the procedure is performed is not detailed. The problem is solved with a conventional solver (CPLEX in the general algebraic modeling language) and and algorithm to reduce the number of scenarios (SCENRED2). Experiments implement a simulation based on a 33-bus radial distribution network and run 4 case studies examining various aspects of their approach. Their appliance model takes into account consumer preferences for usage schedules, uninterrupted consumption patterns, and dependencies between various appliances in a range of scenarios. Consumers can express their preferred time range of operation for each appliance; a weight factor to the discomfort caused by operating outside each appliance's range; and whether an appliance can be interrupted, or operate within a time period after another appliance. Response coordination is somewhat investigated and peak demand is minimized using a locational marginal pricing-based approach. Uncertainty is modeled for renewable energy resources considering multiple scenarios and they employ a scenario reduction technique. Trade-off between multi-criteria solutions is abstracted away using the epsilon constraint optimization method. Grid stability is considered as they model power flow equations to control the voltage and justify modeling active and reactive power flow inequality constraints for the implementation of distribution feeder reconfiguration. The approach does not consider consumer non-compliance or the possibility that consumers may reject suggested load schedules.

2.2.2 Contributions

With respect to the aforementioned literature, we contribute by investigating the consequences of assuming energy consumer flexibility in practice. Specifically, we propose a modern DR model that: (i) models flexible home appliances with multiple scheduling patterns as consumer preferences; (ii) enables the operation of multiple energy sources; (iii) suggests optimized consumer load schedules by maximizing comfort while minimizing costs; (iv) coordinates consumer response to avoid demand peak rebounds; (v) evaluates the trade-off between Pareto-optimal load schedule solutions; and (vi) investigates the effect of consumer non-compliance and appliance flexibility. By studying how consumer non-compliance impacts the aggregate load profile of a consumer community, we expect to highlight the need to design DR programs that can effectively capture consumer preferences and behavior.

As recommended by Wazlawick (2014), we summarize the studies presented in Section 2.2.1 comparing different aspects of all solutions in Table 2. The most relevant aspects to differentiate the approaches were: (a) flexible appliances & consumer preferences; (b) distributed energy resource; (c) response coordination; (d) schedule trade-off; (e) consumer non-compliance; (f) sustainability; (g) grid stability; (h) uncertainty. A check mark symbol (✓) indicates that an aspect was fully considered, and a cross symbol (✗) indicates otherwise; the minus symbol (⊖) is used to indicate that an aspect was only partially considered.

Table 2 – Comparison between related work and proposed approach

#	Paper	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
01	Conejo, 2010	✗	✗	✗	✗	✗	✗	⊖	⊖
02	Qian, 2013	⊖	✗	⊖	✗	✗	✗	✗	✗
03	Setlhaolo, 2014	✓	✗	✗	✗	✗	✗	✗	✗
04	Pilloni, 2016	✓	⊖	✗	✗	✓	⊖	✗	✗
05	Safdarian, 2016	✓	⊖	✓	✗	✗	⊖	⊖	✗
06	Veras, 2018	✓	✗	✗	✗	✗	✗	⊖	✗
07	Lin, 2018	⊖	⊖	✗	✗	✗	✗	⊖	✗
08	Z. A. Khan, 2019	⊖	✗	⊖	✗	✓	✗	⊖	✗
09	Silva, 2020	✓	✓	✗	✗	✓	✓	⊖	✗
10	Chiu, 2020	✓	✓	⊖	⊖	✗	⊖	⊖	✗
11	Pamulapati, 2020	✓	✗	✗	✓	✗	✗	✗	✗
12	Latifi, 2020	✓	⊖	✓	✗	⊖	✗	✗	✗
13	Jafari, 2020	✗	✓	✗	✗	✗	✓	⊖	✓
14	Zeng, 2021	✓	✓	✗	✗	✗	✓	✓	✓
15	Amer, 2021	✓	✓	⊖	✗	✗	✗	⊖	✗
16	Barja-Martinez, 2021	✗	✓	✗	✗	✗	✓	⊖	✗
17	Xu, 2021	✗	✗	✓	✗	✗	✗	⊖	✗
18	Bugaje, 2022	⊖	✗	✗	✗	✗	✗	✗	✗
19	Khosravi, 2022	✓	✓	⊖	✗	✗	✓	✓	✓
20	Our approach	✓	✓	✓	✓	✓	⊖	✗	✗

2.3 Concluding remarks

This chapter highlighted the main concepts needed to understand this study, as well as the complexity of designing DR programs and, in particular, how important and challenging 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 (INGEBORGRUD et al., 2020). Many papers point out 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 (SÜTTERLIN et al., 2011; TJØRRING, 2016; WYATT, 2013). 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 (PALM et al., 2014; SHOVE, 2003; SHOVE; WALKER, 2014; SHOVE; WATSON, et al., 2015; WATSON, 2012). Therefore, our proposed approach seeks to implement common aspects considered by literature the state of the art in HEMSs before investigating the impact of consumer preferences and flexibility on DR program.

3 Proposed Approach

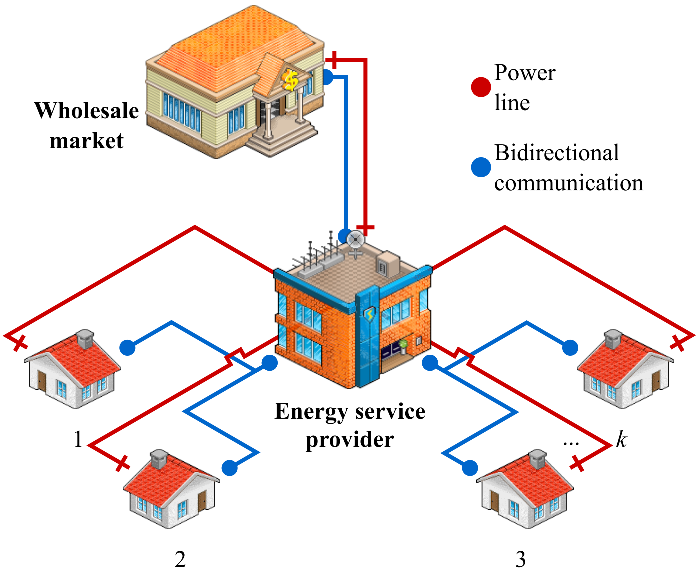
This chapter is structured in three main sections that explain each iteration of the model adopted by the proposed demand-side management approach. The first version of the model, published in Almeida, Silva, et al. (2020), is introduced in Section 3.1. Then, in Section 3.2, we present the developments of the second version published in Almeida, Rabêlo, et al. (2021), which made significant changes to the consumer preference and energy resource models. Finally, the third version, which formalizes the participation of the aggregator entity and modifies the inconvenience model, is detailed in Section 3.3. The changes to each version of the model are presented incrementally in their respective sections so that the reader can understand the current version without needing to read term redefinitions.

3.1 Baseline and demand profile combination model

The demand response problem at hand consists of two optimization tasks that are closely related: (a) optimizing the energy consumption of end consumers, and (b) optimizing the aggregate demand profile of a group or community of said consumers. The latter task can only be performed with the knowledge of a community-wide demand profile, which is a byproduct of the former. Because of this property, these tasks can be coupled together and interpreted as a bi-level optimization problem. In Section 3.1.1, we detail the inner optimization task or lower-level problem formulated as a load scheduling problem to minimize consumer expenses and inconvenience. Then, in Section 3.1.2, we explain the outer optimization task or upper-level problem formulated as a combinatorial optimization problem to minimize the peak-to-average ratio (PAR) of an aggregate demand profile.

The system architecture used in this section considers three main entities: the energy service provider (ESP), the end consumers, and a wholesale energy market. Figure 6 illustrates this scenario where the ESP resells electricity from the wholesale market to multiple price-taking end consumers partaking in a day-ahead price-based DR program. Each consumer household is equipped with a smart meter enabling a bidirectional communication with the ESP through an AMI. In order to manage their daily energy consumption, consumers must program how their home appliances are used throughout the day. For this reason, households are also equipped with a HEMS capable of scheduling household loads and interfacing with their smart meter. Since consumers receive energy price signals ahead of time, they can make informed decisions regarding their power consumption to achieve personal goals.

Figure 6 – System architecture with three entities



Source: (ALMEIDA; SILVA, et al., 2020)

3.1.1 Consumer load schedule optimization

Conceptually, we represent a load program or load schedule as a binary matrix, based on the model introduced by Veras et al. (2018). Given a planning horizon, e.g. the next 24 hours, we divide this time period into T discrete time steps of equal size $\Delta t = 24\text{h}/T$. Next, we define $\mathcal{T} = \{1, \dots, T\}$ as the ordered set of all time step indices and reserve the use of the lowercase term $t \in \mathcal{T}$ to represent an index element of this set. Similarly, a given number of A programmable electrical components or home appliances are indexed within a set $\mathcal{A} = \{1, \dots, A\}$, where $a \in \mathcal{A}$ denotes an index element of this set. Hence, it is possible to represent the operating state of all appliances throughout the planning horizon by defining a matrix $\boldsymbol{M}$ whose indices match the Cartesian product of $\mathcal{A}$ and $\mathcal{T}$ as illustrated below.

$$\boldsymbol{M} = (M_{a,t}) = \begin{pmatrix} M_{1,1} & M_{1,2} & \cdots & M_{1,T} \\ M_{2,1} & M_{2,2} & \cdots & M_{2,T} \\ \vdots & \vdots & \ddots & \vdots \\ M_{A,1} & M_{A,2} & \cdots & M_{A,T} \end{pmatrix} \tag{3.1a}$$

In Equation (3.1a), each element of $\boldsymbol{M}$ is a binary value defined as follows:

$$M_{a,t} = \begin{cases} 1, & \text{should appliance } a \text{ operate at time slot } t, \\ 0, & \text{otherwise.} \end{cases} \tag{3.1b}$$

This establishes $\boldsymbol{M}$ as a binary load schedule matrix indicating how each appliance should operate at any given discrete time step of the planning horizon. For example, let

$T = 4$, hence $\Delta t = 6\text{h}$, and $A = 2$, a TV and AC, then

$$\boldsymbol{M} = (M_{a,t}) = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 \end{pmatrix}$$

represents one possible load schedule matrix. In the following sections, we present the constraints related to consumer preferences and the optimization objectives that together configure a combinatorial optimization problem given a schedule matrix as the decision variable.

3.1.1.1 Scheduling patterns and preferences

Since loads refer to specific home appliances, the scheduling patterns that they can exhibit reflect consumer preferences and the type of appliance. By scheduling patterns, we mean any combination of binary values that describe the operation of a home appliance in a schedule matrix. In this model, these patterns are communicated through parameters and appliance groups that represent consumer preferences.

As defined by Veras et al. (2018), home appliances belong to one of three groups: the (i) shiftable loads $a \in \mathcal{A}^{I}$, that can freely exhibit any scheduling patterns, as long as their minimum demand is met; (ii) deferrable loads $a \in \mathcal{A}^{II}$, that can begin to operate at any moment of the planning horizon, but once started, they cannot be interrupted until they meet their minimum demand; and (iii) non-shiftable $a \in \mathcal{A}^{III}$ or inflexible loads that cannot be rescheduled and represent consumption patterns that will not be made flexible by the consumer. By defining to which group each appliance belongs, consumers express their scheduling pattern preferences. Additionally, they need to inform the minimum demand of each load in terms of a number of time intervals rt_a, and for non-shiftable loads, they need to indicate the first time interval they start operating st_a and their last time interval et_a in operation.

Finally, the consumer must also provide an auxiliary schedule matrix that represents their preferred scheduling, which is seen as the most convenient solution, or the solution closest to their scheduling history. This parameter is called the baseline matrix[1] $\boldsymbol{B} = (B_{a,t})$ and is an essential part of understanding the concept of inconvenience, which will be introduced in the next section.

3.1.1.2 Lower-level problem formulation

We assume that end consumers partaking in DR programs are primarily interested in spending less on their energy bill. Specifically, in day-ahead price-based programs, this can be achieved by shifting loads away from periods of peak consumption toward lower priced off-peak periods. However, reducing expenses in this way entails

[1] For more details, see Veras et al. (2018) and Silva et al. (2020)

changing appliance usage habits, which can be inconvenient for the consumer. For example, while a consumer may prefer to do their laundry in the afternoon, the optimal moment, 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. This situation illustrates the main challenge faced by end consumers under such DR programs. Therefore, we address this challenge by formulating a multi-objective optimization problem with two conflicting objectives: minimizing the load schedule cost and inconvenience.

The cost function of a load schedule matrix is defined below.

$$f_1(\boldsymbol{M}) = \sum_{t \in \mathcal{T}} \sum_{a \in \mathcal{A}} \Delta t P_a p_t M_{a,t} \tag{3.2}$$

In Equation (3.2), P_a denotes the nominal power rating in kW of the a-th appliance, while again Δt represents the sampling time granularity or the length in hours of a discrete time step. The energy cost at any given time step of the planning horizon is given by p_t ($\$/\text{kWh}$), and $M_{a,t}$, as shown in Equation (3.1b), denotes a binary value of the schedule matrix indicating the state of the a-th appliance at the t-th time step. This function is general enough to calculate the cost of any given schedule matrix with the expected shape.

The inconvenience function of a load schedule matrix is defined next.

$$f_2(\boldsymbol{M}) = f_1[(\boldsymbol{B} - \boldsymbol{M})^2] \tag{3.3}$$

In Equation (3.3), the concept of schedule inconvenience defined by Veras et al. (2018), i.e. the squared difference between a given schedule matrix and the baseline matrix, is used with f_1 to compose our inconvenience function. This adaptation allowed us to assess the cost associated with the changes between both schedule matrices. It is important to note that although the cost values associated with changes from the baseline matrix are not actual monetary values that the consumer will have to incur, they are useful for putting the inconvenience metric in the same perspective as the first objective function. In this way, the results of f_1 and f_2 use the same monetary unit of measurement, thereby facilitating future comparisons.

Based on the previous definitions, we formalize the lower-level multi-objective optimization problem as follows:

$$
\begin{aligned}
\min_{\boldsymbol{M}} \quad & f_i && i = 1, 2 && \text{(3.4a)} \\
\text{s.t.} \quad & d_t^{min} \leq \sum_{a \in \mathcal{A}} P_a M_{a,t} && t = 1, \cdots, T && \text{(3.4b)} \\
& d_t^{max} \geq \sum_{a \in \mathcal{A}} P_a M_{a,t} && t = 1, \cdots, T && \text{(3.4c)} \\
& r^U \geq \sum_{a \in \mathcal{A}} P_a (M_{a,t+1} - M_{a,t}) && t = 1, \cdots, T-1 && \text{(3.4d)} \\
& r^D \geq \sum_{a \in \mathcal{A}} P_a (M_{a,t} - M_{a,t+1}) && t = 1, \cdots, T-1 && \text{(3.4e)} \\
& mdc \leq \sum_{a \in \mathcal{A}} \sum_{t \in \mathcal{T}} \Delta t P_a M_{a,t} && && \text{(3.4f)} \\
& rt_a \leq \sum_{t \in \mathcal{T}} M_{a,t} && \forall a \in \mathcal{A}^I && \text{(3.4g)} \\
& 1 \leq \sum_{q=1}^{T-(rt_a-1)} \prod_{t=q}^{rt_a+(q-1)} M_{a,t} && \forall a \in \mathcal{A}^{II} && \text{(3.4h)} \\
& rt_a \leq \sum_{st_a}^{et_a} M_{a,t} && \forall a \in \mathcal{A}^{III} && \text{(3.4i)}
\end{aligned}
$$

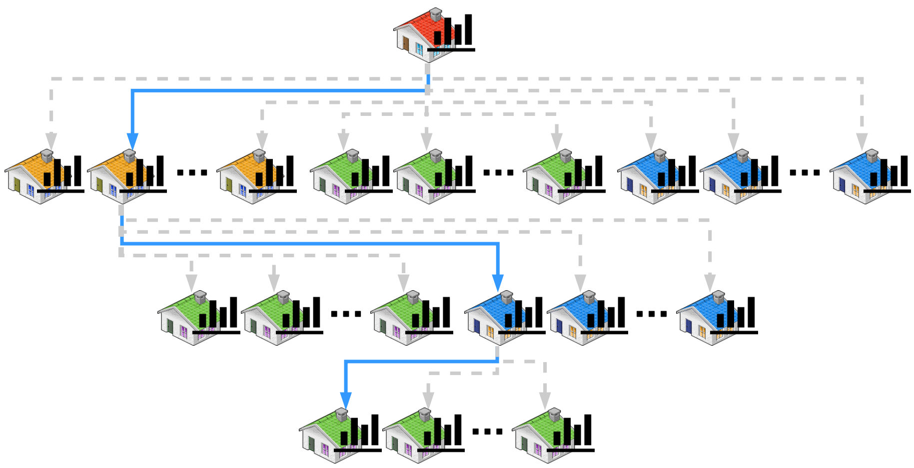
In Equation (3.4), we introduce some new parameters. The terms d_t^{min} and d_t^{max} represent the minimum and maximum demand limits (in kW) at each time step, respectively. Similarly, the terms r^U and r^D represent the maximum up and down demand ramp limits, respectively. The minimum energy consumption throughout the planning horizon is denoted by mdc. The last three constraints concern the scheduling patterns allowed for appliances of the respective three groups introduced in the previous section. For more details, we refer the reader to Veras et al. (2018).

3.1.2 Aggregate demand profile optimization

Since the lower-level problem is formulated as an optimization task with two conflicting objectives, the finite set of all feasible solutions denoting load schedules that a consumer could follow can be explored by a multi-objective optimization method. We direct our attention to the Pareto optimal set of this design space. In the words of Arora (2017), the Pareto set contains all solutions that are Pareto optimal, that is, a solution whose point in the feasible design space has no other point in the same space that improves at least one objective function without worsening another one. For the lower-level problem at hand, the Pareto optimal set of a consumer contains load schedules that are not objectively better or worse than the others among themselves without establishing preferences between the objective functions. In other words, the solutions in the Pareto set are equally satisfactory and the end consumer could perform any one of them. However, these solutions are not equal and each one has a different demand profile. This means that depending on the solution chosen by each consumer in a DR program, the aggregate demand profile of the community could be different.

Here we see an opportunity to influence the consumer's choice of load schedule in order to optimize the aggregate demand profile and benefit the community as a whole, which is the main innovation of our approach with respect to the work by Veras et al. (2018). 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 ESP's central controller. This centralization implies that the input data for the next optimization procedure will be transmitted via AMI. In the next sections, we present the constraints, parameters and objective that configure the second combinatorial optimization problem given the consumer's demand profile options as the decision variables. Figure 7 illustrates this problem as a possible choice is being made by the blue arrow's path and each house icon represents a consumer's load schedule.

Figure 7 – Example solution of the aggregate demand profile optimization



Source: (ALMEIDA; SILVA, et al., 2020)

3.1.2.1 Load schedules and demand profiles

After solving the lower-level optimization problem, end consumers may have one or more distinct load schedules as viable 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. Hence, we define I_k as the reported number of load schedule options available to consumer k, with $I_k \geq 1$. Hereafter, the term K denotes the amount of end consumers under consideration by the ESP, who are indexed within the set $\mathcal{K} = \{1, \ldots, K\}$, where $k \in \mathcal{K}$ refers to a specific consumer. We consider that consumers may deliberately exclude a subset of their load schedules from consideration for any reason so that the reported number of schedules they consider viable is smaller than the amount of optimal load schedules found by their HEMS. For all intents and purposes, the ESP considers the reported number of schedules to be the actual amount of schedules available to the consumer.

An important aspect to consider at this point is how much and what information needs to be exchanged between end consumers and the ESP. Due to the nature of the information provided by a consumer's load schedules, privacy concerns are raised and it is preferable that end consumers do not exchange data concerning their activities with the ESP to prevent sharing sensitive information that could reveal consumer habits. Therefore, our approach does not require the ESP to receive detailed information about consumer load schedules. Instead, for each schedule, the ESP receives its demand profile, defined as the aggregate consumption of all appliances per time step. Thus, we use $l^i_{k,t}$ to denote the total main grid demand from consumer k at time step t, calculated below from their i-th reported load schedule, with $i \in \{1, ..., I_k\}$:

$$l^i_{k,t} = \sum_{a \in \mathcal{A}_k} \Delta t P_a M^i_{k,a,t} \tag{3.5}$$

In Equation (3.5), the superscript i is added to some terms whose value 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, $M^1_{1,2,8}$ 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.

3.1.2.2 Upper-level problem formulation

Once the ESP receives the demand profiles for all reported consumer load schedules, the optimal aggregate demand profile of a community can be searched by using any profile evaluation metric as objective function. The load factor is a useful metric to assess the efficiency of energy use and is defined as the average load divided by the peak load of a given time period[2]:

$$f_{load} = \frac{\text{average load}}{\text{peak load}} \tag{3.6}$$

Specifically, we use the inverse of the load factor, also known as the peak-to-average ratio, to define a minimization problem. Smaller values of PAR indicate a smoother profile, while larger values signal a profile with peaks further away from the average. But in order for the ESP to calculate the PAR, it needs to decide which solution from

[2] See Watkins (1915)

each consumer should be taken into account. Thus, we define the PAR as a function of a vector $\boldsymbol{i}$ with K indices indicating which solution to use for each consumer:

$$f_{PAR}(\boldsymbol{i}) = \frac{T \cdot \max_{t \in \mathcal{T}} L_t(\boldsymbol{i})}{\sum_{t \in \mathcal{T}} L_t(\boldsymbol{i})} \tag{3.7}$$

In Equation (3.7), $L_t(\boldsymbol{i})$ stands for the aggregate demand of all consumers at time step t in function of the load schedule indices in $\boldsymbol{i}$:

$$L_t(\boldsymbol{i}) = \sum_{k \in \mathcal{K}} l_{k,t}^{i_k} \quad \text{where } i_k = [\boldsymbol{i}]_k \tag{3.8}$$

Based on the previous definitions, we formalize the upper-level single-objective optimization problem as follows:

$$\min_{\boldsymbol{i}} \quad f_{PAR} \tag{3.9a}$$

$$\text{s.t.} \quad i_k \geq 1 \quad \forall k \in \mathcal{K} \tag{3.9b}$$

$$i_k \leq I_k \quad \forall k \in \mathcal{K} \tag{3.9c}$$

In other words, the ESP's job is to select a demand profile for each consumer such that the aggregate demand profile of the community achieves the lowest peak-to-average ratio among all possible combinations. We hope that by minimizing the PAR of the community, the energy service provider can improve grid stability and avoid peak rebounds (SAFDARIAN et al., 2016).

3.1.3 Experimental design

We simulate a small consumer community with a total of $K = 11$ households, each with $A_k = 20$ home appliances, with the purpose of evaluating the impact of different search and optimization techniques on the aggregate demand profile introduced in the previous section. Each household was randomly assigned five shiftable, five deferrable, and ten non-shiftable loads from the ones shown in Table 3, thus covering all appliance categories described in Section 3.1.1.1. In addition, all consumer preferences and load parameters were set to be identical among consumers so that the effect of individual preferences could be ignored.

To solve the lower-level optimization problem presented in Section 3.1.1.2, one can use any method for solving Pareto optimization problems, and specifically in this case, integer nonlinear programmimg problems (ROSTAMI et al., 2020). In this experiment and subsequent ones, we use a modified implementation[3] of the classic NSGA-II (DEB et al., 2002). This choice was made mainly because this algorithm had already

[3] Multi-objective optimization in Python: pymoo.org

Table 3 – Load parameters per category

(a) Shiftable

$a \in \mathcal{A}^{I}$	P_a (kW)	rt_a (h)
Air conditioner	4.000	8
Coffee machine	1.100	1
Dish washer	1.500	1
Electric shower	8.500	2
Paper shredder	0.220	1
Phone charger	0.007	4
Pool pump	0.400	3
Water heater	6.600	2

(b) Deferrable

$a \in \mathcal{A}^{II}$	P_a (kW)	rt_a (h)
Toaster	1.000	2
Boiler	1.300	2
Washing machine	0.500	2
Clothes dryer	4.000	2
Laptop	0.100	2
Iron	1.000	2
EV charger	3.400	6
TV system	0.225	4

(c) Non-shiftable

$a \in \mathcal{A}^{III}$	P_a (kW)	st_a	et_a	rt_a (h)
Refrigerator	0.200	0	23	24
Electric stove	2.000	11	12	2
Light	0.100	18	21	4
Food blender	0.400	18	18	1
Light	0.060	16	19	4
Lamp	0.020	22	23	2
Freezer	0.400	0	23	24
Router	0.010	0	23	24

been used by experiments and papers within our research group, and it fit our particular problem case with two objectives. Since our focus is not to evaluate the performance of the optimization algorithm, we believe that this choice should not affect nor hinder the significance of our results, and we note that any other equivalent optimization method could be used instead. Algorithm parameters used to generate the optimized load schedules are shown in Table 4.

Table 4 – NSGA-II parameters

Parameter	Value
Iterations	500
Population size	100
Initial sampling	Random
Selection	Binary tournament
Crossover	Binary single point
Crossover probability	85%
Mutation	Bit flip
Mutation probability	1.5%

Further parameters such as the sampling time granularity Δt are set to one hour, with $T = 24$. The wholesale market price parameter p_t ($\$/$kWh) was obtained from Latifi et al. (2020) and is shown in Table 5. The minimum and maximum hourly demand, ramp limits, and minimum daily load demand parameters are set to 0, 24, 12, 12 and 0 kWh, respectively.

Table 5 – Day-ahead RTP energy tariff

(a) First 12 time steps

t	p_t
0	0.150
1	0.120
2	0.100
3	0.100
4	0.200
5	0.300
6	0.450
7	0.450
8	0.500
9	0.600
10	0.600
11	0.600

(b) Last 12 time steps

t	p_t
12	0.500
13	0.400
14	0.450
15	0.500
16	0.600
17	0.800
18	0.900
19	1.000
20	1.100
21	0.900
22	0.700
23	0.500

We consider two ant colony optimization algorithms to combine and calculate the best aggregated demand profile: ant system algorithm (AS) and ant colony system (ACS). This choice was made under the hypothesis that ant metaheuristics could operate well with the tree-like search problem structure as illustrated in Figure 7. To assess simpler search approaches and verify whether ant metaheuristics were necessary, these algorithms are compared with three other solutions: randomized search, greedy search, and greedy randomized adaptive search procedure (GRASP). The PAR is used as a metric to evaluate partial candidate components and guide the ants towards the best combined demand profile. Finally, to mitigate the effects of randomness, all iterative algorithms in direct comparison were given the same amount of iterations to execute and were repeated ten times with only the result closest to the average across all repetitions being used for comparison.

3.1.4 Model limitations

With the publication of a paper on this model[4] and the continued work of literature review, we were able to identify limitations concerning the consumer preference model. More specifically, the present model does not allow for the explicit specification

[4] Almeida, Silva, et al. (2020)

of flexible yet non-curtailable loads; technically, type $\mathcal{A}^{I}$ loads are curtailable, deferrable, and interruptible, while type $\mathcal{A}^{II}$ loads are curtailable and deferrable, and type $\mathcal{A}^{III}$ loads are fixed and not flexible. In addition, each load is limited to a single window of operation within the planning horizon, requiring new windows for the same appliance to be declared without any check for overlaps between schedules. Another limitation was the lack of a modeling approach that accommodates distributed energy resources. These limitations motivated us to develop a second version of the model, which is discussed in the next section.

3.2 Preferences and energy resources model

Although the model introduced in Section 3.1 is able to represent numerous consumption patterns, it is also important to allow end consumers to restrict the range of feasible load schedules to avoid undesired and uncomfortable scheduling patterns. This can be achieved by properly modeling consumer preferences that restrict and guide the optimization process towards comfortable solutions. Additionally, the management of distributed energy resources and multiple energy sources is a fundamental characteristic of modern energy management systems within microgrids. These aspects are further detailed and incorporated into the current model in the following sections.

In general, the proposed approach does not change and remains subdivided into two optimization steps referring to the bi-level optimization problem detailed earlier. The sequence of events of the optimization process as a whole is presented in Figure 8.

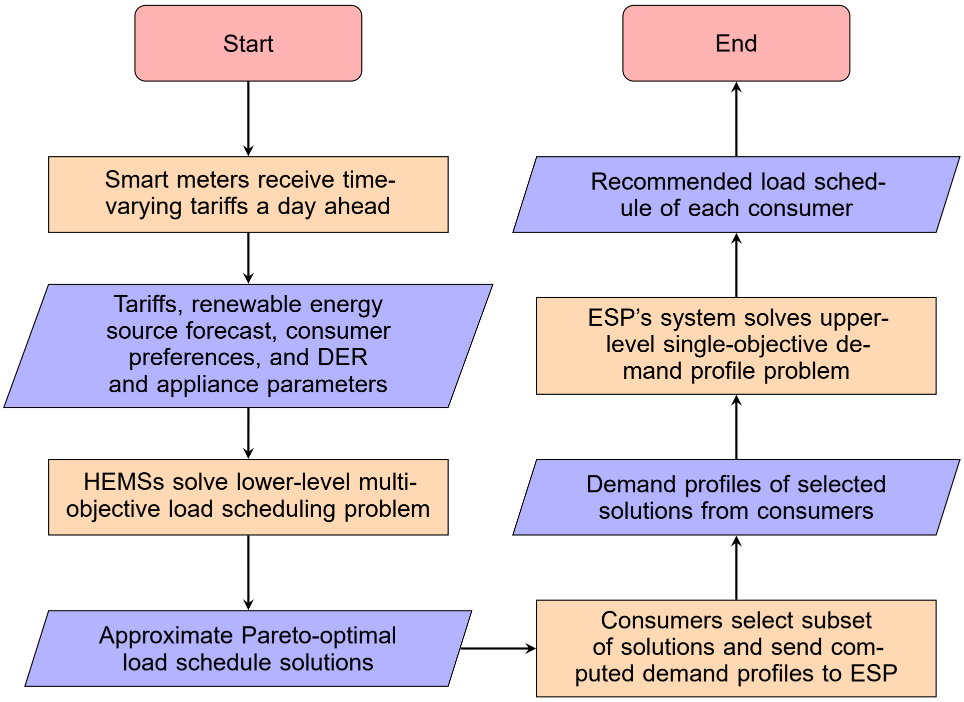
Similarly to the architecture presented in the previous section (see Figure 6), the model proposed in this section considers a set of K end consumers who are managed by an energy service provider via the underlying advanced metering infrastructure of the smart grid. As illustrated in Figure 9, this infrastructure assumes that each k-th consumer facility is equipped with a smart meter, DERs, and a HEMS capable of scheduling loads. Thus, consumers are now prosumers akin to microgrids who are able to freely shape their energy demand to achieve their individual goals within the DR program.

3.2.1 Multiple energy sources model

In the scenario illustrated by Figure 9, the main grid is no longer the sole energy source able to supply the prosumer's loads. In this section, we model multiple energy sources by using additional load schedule matrices, where each matrix represents the scheduling of appliances with respect to a unique energy source.

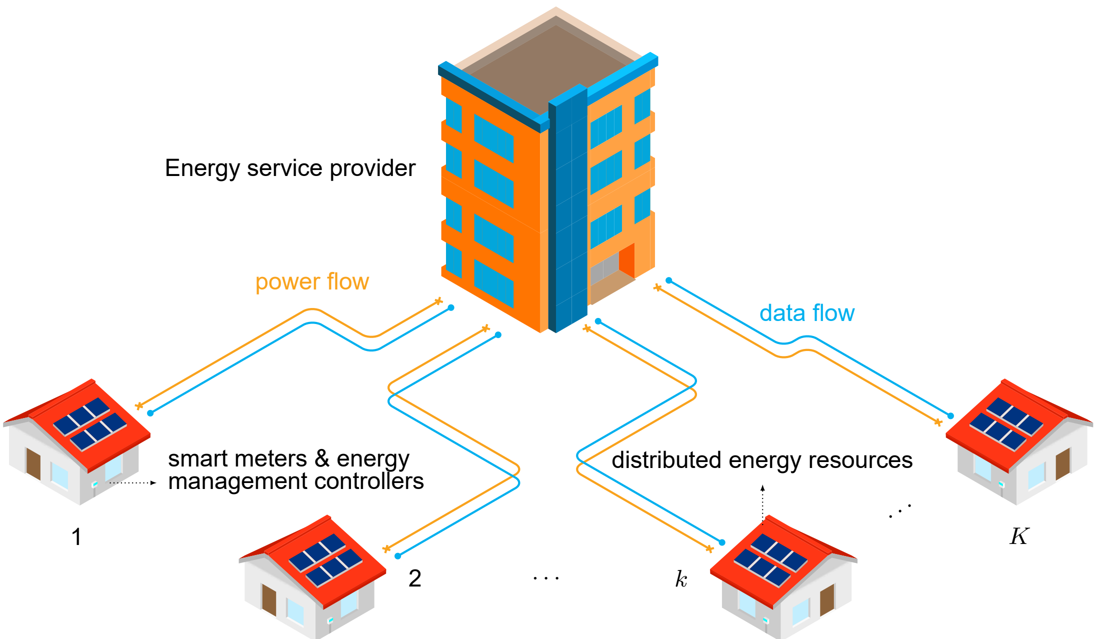
Given a set of J load schedules $\mathcal{J} = \{m_1, \ldots, m_J\}$ whose elements are defined to be schedule matrices $m_j := [\boldsymbol{M}]_j$ (see Equation (3.1a)) with equal dimensions (A by T), we consider that each matrix represents a distinct energy source of a consumer

Figure 8 – Flowchart of the proposed demand-side management process



Source: (ALMEIDA; RABÊLO, et al., 2021)

Figure 9 – System architecture with prosumers



Source: (ALMEIDA; RABÊLO, et al., 2021)

and define the auxiliary matrix $\boldsymbol{X}$ as the sum of all such matrices:

$$\boldsymbol{X} = (X_{a,t}) = \sum_{j=1}^{J} m_j \tag{3.10}$$

Thus, each element of $\boldsymbol{X}$ denoted by $X_{a,t}$ is the sum of all load state values of a given electrical component a at a given time step t from the multiple load schedule matrices in $\mathcal{J}$. In order to prevent appliances from being scheduled to multiple energy sources at the same time step, the following constraint must be respected:

$$X_{a,t} \leq 1, \quad \forall a, t \in \mathcal{A} \times \mathcal{T} \tag{3.11}$$

Based on the above notation, any number of alternative energy sources can be represented by the model as a new schedule matrix of decision variables. For example, let $T = 4$, hence $\Delta t = 6\text{h}$, and $A = 2$, a TV and AC, then with three energy sources

$$\boldsymbol{M} = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix} \boldsymbol{R} = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix} \boldsymbol{S} = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{pmatrix},$$

the resulting $\boldsymbol{X}$ matrix will look like

$$\boldsymbol{X} = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 \end{pmatrix}.$$

In the next sections, we describe two types of such energy sources considered in this thesis, namely renewable energy sources and energy storage systems.

3.2.1.1 Renewable energy sources

To consider consumers with access to distributed energy resources, we define $\boldsymbol{R} = (R_{a,t})$ as a load schedule matrix representing the RES system, where $R_{a,t} = 1$ when appliance a demands energy from RES at time t, or $R_{a,t} = 0$ otherwise. A typical example of renewable energy source is a solar power generation system.

We define $P_t^{res} \geq 0$ as the power generation profile of the solar power generation system throughout the planning horizon, i.e. the predicted active power output in kW at each time step t. Given the nominal power rating of the a-th appliance P_a in kW, we are able to compute the amount of energy demanded from the RES system at each time step t as R_t:

$$R_t = \sum_{a \in \mathcal{A}} \Delta t P_a R_{a,t} \tag{3.12}$$

As the demand cannot exceed the available power of the RES system, the following constraint must be respected:

$$R_t \leq \Delta t P_t^{res} \tag{3.13}$$

As the output of renewable energy sources such as solar power and wind power is intermittent, energy storage systems can help stabilize the output and reach of renewable energy units in microgrids, thus, promoting renewable energy efficiency (LI, C. et al., 2020). The next section describes our model for ESSs.

3.2.1.2 Energy storage system

Similarly to the RES model, we define $\boldsymbol{S} = (S_{a,t})$ as a load schedule matrix representing the ESS. A typical example of energy storage system is a home battery storage. We abstract the battery charge and discharge cycles with the following policies: (i) home appliances prioritize RES surplus energy, then the ESS spare capacity, and lastly the main grid; (ii) the ESS may only recharge with power from the RESs when it is not supplying appliances. This implies that the ESS in this study is never recharged by the main grid.

In order to model the ESS power exchanges, let S_t denote the total amount of ESS energy demanded by all appliances at time step t:

$$S_t = \sum_{a \in \mathcal{A}} \Delta t P_a S_{a,t} \tag{3.14}$$

Then, let Γ_t be an auxiliary binary variable to represent whether the ESS is discharging at time step t:

$$\Gamma_t = \begin{cases} 1, & \text{ESS is discharging, } (S_t > 0) \\ 0, & \text{ESS is either idle or charging, } (S_t = 0) \end{cases} \tag{3.15}$$

Consequently, we define the ESS power output as a bounded continuous value represented by P_t^{ess}:

$$0 \leq P_t^{ess} \leq P_{\max}^{ess} \tag{3.16}$$

So that the total amount of demanded energy when discharging must not exceed the current ESS energy output:

$$S_t \leq \Gamma_t \Delta t P_t^{ess} \tag{3.17}$$

Additionally, when the ESS is charging, the total charge amount is limited by the available RES energy:

$$(1 - \Gamma_t) \Delta t P_t^{ess} \leq \Delta t P_t^{res} - R_t \tag{3.18}$$

Finally, to model how the ESS energy capacity is determined as a consequence of the decision variables in $\boldsymbol{S}$, the ESS state of charge at time step t is denoted by E_t^{ess} and constrained by lower and upper bounds:

$$0 < E_{min}^{ess} \leq E_t^{ess} \leq E_{max}^{ess} \tag{3.19}$$

And the initial state of charge of the day must be maintained at the end of it:

$$E_0^{ess} = E_T^{ess} \tag{3.20}$$

Based on the previous definitions, the state of charge can be calculated for each time step as follows:

$$E_t^{ess} = E_{t-1}^{ess} + \Delta t P_t^{ess}[(1 - \Gamma_t)\eta^{cha} - \Gamma_t/\eta^{dis}] \tag{3.21}$$

Where η^{cha} and η^{dis} represent the ESS's charge and discharge efficiency, respectively.

3.2.2 Multiple preference windows model

In an effort to model flexible consumer preferences, we begin by defining the concept of time windows in which consumers prefer to have their appliances operating, i.e., when are loads allowed to operate in the planning horizon. We consider that consumers are allowed to define zero or more time windows for any given electrical component throughout the planning horizon. In each time window, the appliance operation and scheduling patterns are described independently from other time windows of the same appliance. For example, given a dishwasher, a consumer should be able to express how many times and when it operates over the planning horizon, and for each time window of operation the consumer should be able to specify how they prefer the dishwasher to operate.

3.2.2.1 Time windows of operation

We begin by defining a time window of operation as a contiguous non-empty ordered subset of the planning horizon. More precisely, let τ represent a time window with n index elements of the planning horizon $\mathcal{T}$:

$$\tau = \{t_1, \ldots, t_n \mid t_i \in \mathcal{T}\} \tag{3.22}$$

In case τ has more than one element, its elements should preserve the order from the planning horizon such that $t_i < t_{i+1}$ for all $i \in \{1, \ldots, n-1\}$. By contiguous, we mean that for every pair of subsequent time window elements t_i and t_{i+1}, there does *not exist* any third element in the planning horizon $t_j \in \mathcal{T}$ between them $t_i < t_j < t_{i+1}$, with $t_j \neq t_i$ and $t_j \neq t_{i+1}$.

Next, we use the term $\mathcal{T}_a$ to denote a family of time window sets for a given appliance. Each element of $\mathcal{T}_a$ is a time window in which the appliance a is allowed to operate. We define W_a to represent the amount of time windows in $\mathcal{T}_a$ whose indices are in $\mathcal{W}_a = \{1, \ldots, W_a\}$, such that $\mathcal{T}_a = \{\tau_{a,1}, \ldots, \tau_{a,W_a}\}$; we use the term $\tau_{a,w}$ from now on to indicate when a particular time window is associated with a given appliance. A family of time windows is valid if and only if the following conditions hold:

1. The family $\mathcal{T}_a$ does not contain the empty set;
2. The intersection of any two distinct sets in $\mathcal{T}_a$ is empty, meaning the elements of its time windows are mutually exclusive.

Some useful observations are that the union of all subsets of $\mathcal{T}_a$ indicates all time steps in which appliance a can operate in the planning horizon, denoted as $\mathcal{T}_a^{on}$:

$$\mathcal{T}_a^{on} = \{t \in \tau \mid \exists \tau \in \mathcal{T}_a\} \tag{3.23}$$

Conversely, the complement of $\mathcal{T}_a^{on} \subset \mathcal{T}$ indicates all time steps in which a cannot operate, denoted as $\mathcal{T}_a^{off}$:

$$\mathcal{T}_a^{off} = \{t \in \mathcal{T} \mid t \notin \mathcal{T}_a^{on}\} \tag{3.24}$$

At last, we define the terms $\alpha_{a,w}$ and $\omega_{a,w}$ to represent the respective indices of the first and last time steps delimiting the w-th time window of $\mathcal{T}_a$, meaning $\alpha_{a,w} \leq \omega_{a,w}$. Therefore, the closed interval $[\alpha_{a,w}, \omega_{a,w}]$ covers all indices of its time window. The terms $\alpha_{a,w}^+$ and $\omega_{a,w}^+$ are, respectively, the indices of the first and last time steps in which an appliance is operating ($X_{a,t} = 1$) within that time window. Thus, we define the subset $\tau_{a,w}^{(1)} \subset \tau_{a,w}$ containing all time steps in which a is operating:

$$\tau_{a,w}^{(1)} = \{t \in \tau_{a,w} \mid X_{a,t} = 1\}, \tag{3.25}$$

and, consequently, we obtain $\alpha_{a,w}^+ = \min\left[\tau_{a,w}^{(1)}\right]$, and $\omega_{a,w}^+ = \max\left[\tau_{a,w}^{(1)}\right]$.

3.2.2.2 Consumer preferences

Based on the previous definitions, it is possible to express a variety of consumer preferences about the scheduling patterns that each appliance can exhibit. In general, we model consumer preferences as additional parameters associated with a specific time window to restrict the range of other dependent variables.

Let $d_{a,w}$ denote the amount of scheduled time steps in which the a-th appliance is operating within the w-th time window:

$$d_{a,w} = \sum_{t \in \tau_{a,w}} X_{a,t} \tag{3.26}$$

Thus, we define the minimum required demand and maximum *curtailable* demand preferences in terms of operational time steps as $d_{a,w}^{min}$ and $d_{a,w}^{cur}$ respectively, such that:

$$0 \leq d_{a,w}^{cur} \leq d_{a,w}^{min} \leq \omega_{a,w} - \alpha_{a,w} + 1 \tag{3.27}$$

In addition, scheduling patterns may be allowed within a given time window based on a couple of extra parameters. We define the terms $p_{a,w}^{def}, p_{a,w}^{int} \in \{0, 1\}$ as preference parameters to indicate whether the operation of appliance a within the w-th time window can be deferred ($p_{a,w}^{def} = 1$) and/or interrupted ($p_{a,w}^{int} = 1$). Deferrable loads are those allowed to delay their start-up time of operation after the beginning of their time window ($\alpha_{a,w}$). Given an appliance, we define $\mathcal{W}_a^{ndf}$ as the set of all time window indices in which this appliance cannot have its initial operation deferred:

$$\mathcal{W}_a^{ndf} = \{w \in \mathcal{W}_a \mid p_{a,w}^{def} = 0,\ d_{a,w} > 0\} \tag{3.28}$$

Meanwhile, interruptible loads are those allowed to operate intermittently within their time window. Similarly, we define $\mathcal{W}_a^{uni}$ as the set of all time window indices in which a given appliance cannot have its initial operation interrupted:

$$\mathcal{W}_a^{uni} = \{w \in \mathcal{W}_a \mid p_{a,w}^{int} = 0,\ d_{a,w} > 0\} \tag{3.29}$$

In other words, time window indices in $\mathcal{W}_a^{ndf}$ indicate non-deferrable loads, while those in $\mathcal{W}_a^{uni}$ indicate uninterruptible loads.

In the same way as in the previous model, schedule changes are calculated with respect to a baseline load schedule matrix $\boldsymbol{B} = (B_{a,t})$, generated from either historical consumption data, direct consumer input, or from the consumer preferences themselves (SILVA et al., 2020). The idea of a baseline or preferred schedule has been addressed by Veras et al. (2018) and the specific details of its conception are outside of the scope of this study.

To express how desirable are changes to a particular appliance's operation, each time window is assigned an *inflexibility* factor $\gamma_{a,w} \geq 0$ as preference parameter. An inflexibility value of $\gamma_{a,w} = 0$ indicates a fully flexible load whose changes in schedule do not cause the consumer any discomfort. On the other hand, $\gamma_{a,w} = 1$ indicates that the resulting discomfort is proportional to its consumption cost, and $\gamma_{a,w} > 1$ scales the discomfort accordingly.

3.2.3 Lower-level problem reformulation

Henceforth, we use the symbol $\boldsymbol{x}$ as a shortcut to represent all decision variables of the present problem formulation. More precisely, the variables are the three demand schedule matrices introduced in Section 3.2.1, namely $\boldsymbol{M}$, $\boldsymbol{R}$ and $\boldsymbol{S}$, representing the respective load schedules for the main grid, renewable energy source and energy storage system. In total, the three matrices have $3 \times A \times T$ binary decisions.

The main changes to the cost function of this model compared to the previous one are related to the addition of DER. In order to account for the amount of energy sold to the main grid, the term $P_t^{\overline{res}}$ is defined as follows:

$$P_t^{\overline{res}} = \Delta t P_t^{res} - R_t - (1 - \Gamma_t)\Delta t P_t^{ess} \tag{3.30}$$

The net cost in $\$/\text{kWh}$ of a given load schedule is calculated by the function f_1 below, where negative costs correspond to profits made by the end consumer.

$$f_1(\boldsymbol{x}) = \sum_{t \in \mathcal{T}} \sum_{a \in \mathcal{A}} (\Delta t P_a p_t M_{a,t}) - \sum_{t \in \mathcal{T}} \left(p_t' P_t^{\overline{res}}\right) \tag{3.31}$$

The terms p_t and p'_t denote the energy tariff rate in monetary units per kWh for purchasing from/selling to the main grid, respectively.

The load schedule optimization process from the perspective of Equation (3.31) consists in strategically exploiting appliance flexibility by shifting loads towards off-peak periods or curtailing them during peak periods. However, these operations can at times be inconvenient to individual consumers, who may avoid following uncomfortable schedules altogether. Therefore, the concept of load schedule discomfort, based on the inconvenience function of the previous model, has been derived to allow us to assess the negative impact of load schedule changes and guide the optimization process towards more comfortable solutions. The cost of discomfort or *disutility* associated with a given demand schedule is calculated as follows:

$$f_2(\boldsymbol{x}) = \sum_{a\in\mathcal{A}} \sum_{w\in\mathcal{W}_a} \sum_{t\in\tau_{a,w}} \left(\Delta t P_a p_t \gamma_{a,w} (X_{a,t} - B_{a,t})^2\right), \tag{3.32}$$

Where $X_{a,t} = M_{a,t} + R_{a,t} + S_{a,t}$ is the sum of the load states for each appliance at the consumer's disposal, as described in Equation (3.10).

Based on the previous definitions, we formalize the lower-level following multi-objective optimization problem as follows:

$$\begin{aligned}
\min_{\boldsymbol{x}} \quad & f_i && i = 1, 2 && \text{(3.33a)}\\
\text{s.t.} \quad & \sum_{t\in\mathcal{T}_a^{off}} X_{a,t} \leq 0 && \forall a \in \mathcal{A} && \text{(3.33b)}\\
& d_{a,w} - d_{a,w}^{min} + d_{a,w}^{cur} \geq 0 && \forall a, w \in \mathcal{A}\times\mathcal{W}_a && \text{(3.33c)}\\
& \alpha_{a,w}^{+} - \alpha_{a,w} \leq 0 && \forall a, w \in \mathcal{A}\times\mathcal{W}_a^{ndf} && \text{(3.33d)}\\
& \prod_{t=\alpha_{a,w}^{+}}^{\omega_{a,w}^{+}} X_{a,t} \geq 1 && \forall a, w \in \mathcal{A}\times\mathcal{W}_a^{uni} && \text{(3.33e)}\\
& \text{constraints (3.11), (3.13) and (3.16) to (3.20).}
\end{aligned}$$

Constraint (3.33b) prevents appliances from operating outside of their configured time windows. Then, constraint (3.33c) guarantees that all loads are supplied a minimum demand, whether they are curtailable or not. Finally, the constraints (3.33d) and (3.33e) enforce the scheduling pattern restrictions for the respective non-deferrable and uninterruptible loads.

3.2.4 Experimental design

This time we simulate larger consumer communities with more household appliances and different distributed energy resource configurations to assess their impact on the final aggregate demand profile. In Section 3.2.4.1 we detail the lower-level simulation procedure followed by a description of the upper-level simulation in Section 3.2.4.2.

3.2.4.1 Lower-level problem simulation

We describe an energy consumption profile of a household with 33 domestic appliances throughout one day of operation. All simulations use the energy utility tariffs from Table 5, while the rates for reselling energy are set to one quarter of their cost at a given time interval. The sampling time granularity is set to one hour ($\Delta t = 1\,\mathrm{h}$), resulting in 24 time intervals ($T = 24$). Within the scheduling horizon, a total of 72 time windows were configured to characterize flexible and inflexible loads. The relevant parameters of 27 time windows with inflexible loads are shown in Table 6.

Table 6 – Parameters of inflexible loads

(a) Loads 1–8

Name	P_a	$\alpha_{a,w}$	$d^{min}_{a,w}$
Kettle	1.50	09h	1
–	–	16h	1
–	–	20h	1
Stove	1.20	09h	2
–	–	18h	2
Blender	0.50	09h	1
–	–	16h	1
–	–	20h	1

(b) Loads 9–27

Name	P_a	$\alpha_{a,w}$	$d^{min}_{a,w}$
Lighting x4	0.01	00h	1
Lighting x5	0.01	18h	6
Lighting x5	0.02	18h	6
Modem	0.01	00h	24
Refrigerator	1.00	00h	24
Router	0.01	00h	24
Smart TV	0.15	15h	4
Sound Sys.	0.35	15h	4

The remainder of the loads were represented by flexible time windows showcasing some degree of flexibility, such as delaying their starting time ($p^{def}_{a,w} = 1$), interrupting and resuming their operation ($p^{int}_{a,w} = 1$), or consuming less than their base demand ($d^{cur}_{a,w} > 0$). Table 7 lists the parameters of the remaining 45 flexible loads.

In addition to the appliance parameters, we define five settings to describe different levels of access to DERs. These settings are summarized in Table 8, and describe consumers: (A) without access to RES and ESS; (B) with a low-scale generation system ($8\,\mathrm{kW}$) and no storage system; (C) with low-scale generation and ESS; (D) with a high-scale generation system ($16\,\mathrm{kW}$) and no storage system; and (E) with high-scale generation and ESS. We expect that simulating these scenarios will help us assess the impact of DERs on the problem solutions.

We obtain the generation profiles from simulated roof-mounted solar panels provided by the PVWatts[5] tool, considering the weather profile of the Federal University of Piauí in Teresina, Brazil (DOBOS, 2014). The power outputs for the low- and high-scale generation systems are given in Table 9. The remaining parameters of the storage system were $E^{ess}_{min} = 0\,\mathrm{kWh}$, $E^{ess}_{max} = 13.50\,\mathrm{kWh}$, $P^{ess}_{\max} = 6.75\,\mathrm{kW}$, $E^{ess}_{0} = 5.00\,\mathrm{kW}$, and $\eta^{cha} = \eta^{dis} = 0.9$.

[5] Available at: pvwatts.nrel.gov

Table 7 – Parameters of flexible loads

(a) Loads 28–50

Name	P_a	$\alpha_{a,w}$	$\omega_{a,w}$	$d^{min}_{a,w}$	$d^{cur}_{a,w}$	$p^{def}_{a,w}$	$p^{int}_{a,w}$
AC	3.25	09h	13h59	4	2	1	1
–	–	14h	18h59	4	2	1	1
–	–	19h	23h59	4	2	1	1
AC	3.25	09h	13h59	4	2	1	1
–	–	14h	18h59	4	2	1	1
–	–	19h	23h59	4	2	1	1
Fan	$.150$	00h	02h59	2	0	0	1
–	–	03h	05h59	2	0	0	1
–	–	06h	08h59	2	0	0	1
–	–	12h	14h59	3	2	1	0
–	–	17h	19h59	3	2	1	0
–	–	21h	23h59	3	2	1	0
Fan	$.150$	00h	00h59	1	1	0	0
–	–	08h	10h59	3	2	1	1
–	–	12h	14h59	3	2	1	1
–	–	17h	19h59	3	2	1	1
–	–	23h	23h59	1	1	0	0
Dryer	3.00	06h	13h59	3	0	1	1
Washer	1.50	12h	18h59	2	0	1	1
–	–	20h	23h59	2	0	1	1
Shaver	$.015$	09h	14h59	1	0	1	0
Stove	1.20	11h	13h59	2	2	1	0
–	–	20h	22h59	2	2	1	0

Table 7 – (cont.) Parameters of flexible loads

(b) Loads 51–72

Name	P_a	$\alpha_{a,w}$	$\omega_{a,w}$	$d^{min}_{a,w}$	$d^{cur}_{a,w}$	$p^{def}_{a,w}$	$p^{int}_{a,w}$
Iron	1.20	08h	14h59	1	0	1	0
Laptop	$.100$	09h	13h59	4	2	1	1
–	–	14h	18h59	4	2	1	1
–	–	19h	23h59	4	2	1	1
Microwave	1.00	15h	16h59	1	1	1	0
–	–	18h	19h59	1	1	1	0
–	–	20h	21h59	1	1	1	0
Phone	$.010$	00h	11h59	3	1	1	0
–	–	12h	23h59	3	1	1	0
Smart TV	$.150$	15h	18h59	4	2	1	0
–	–	20h	23h59	4	2	1	0
Smart TV	$.150$	08h	11h59	4	2	1	0
–	–	12h	14h59	3	3	1	1
–	–	20h	23h59	4	2	1	0
Sound Sys.	$.350$	08h	11h59	4	2	1	0
–	–	12h	14h59	3	3	1	1
–	–	20h	23h59	4	2	1	0
Video Game	$.150$	15h	18h59	4	2	1	0
–	–	20h	23h59	4	2	1	0
Washer	$.800$	00h	05h59	3	0	1	1
Heater	5.50	04h	09h59	3	0	0	1
–	–	18h	23h59	3	0	0	1

Table 8 – DER access level settings

Setting	Generation scale	Storage system
A	None	No
B	Low	No
C	Low	Yes
D	High	No
E	High	Yes

Table 9 – Photovoltaic generation profiles (kW)

(a) First 12 time steps

t	Low	High
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0
6	0.818	1.637
7	2.378	4.757
8	3.662	7.324
9	4.579	9.159
10	5.120	10.240
11	5.368	10.736

(b) Last 12 time steps

t	Low	High
12	5.329	10.659
13	5.071	10.143
14	4.481	8.963
15	3.569	7.139
16	2.330	4.660
17	0.831	1.663
18	0	0
19	0	0
20	0	0
21	0	0
22	0	0
23	0	0

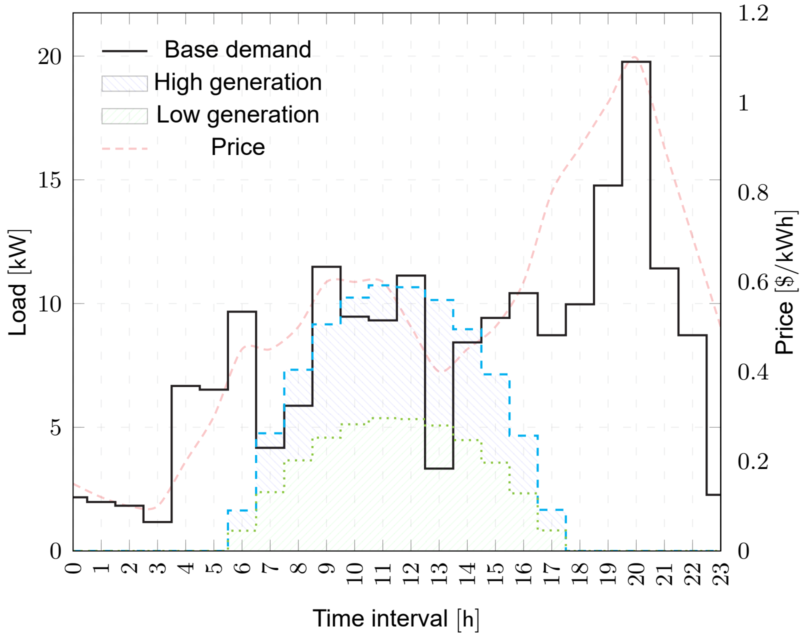
Figure 10 illustrates the base demand profile of the consumer model used, as well as the two generation profiles from Table 9. It is noticeable that the peak demand occurs around 8 p.m. ($19.70\,\mathrm{kW}$) and coincides with the peak price ($1.10\,\$/\mathrm{kWh}$). One can also see that power is only generated in the period from 6 a.m. to 5 p.m. from the generation profiles.

In summary, the modeled consumption profile illustrates the main mismatches between consumer demand and DERs. For example, high capacity generation periods do not coincide with peak demand periods, which in turn are reflected in high tariffs. This means that the ESS needs to be used to meet demands outside the periods of high generation capacity.

3.2.4.2 Upper-level problem simulation

In this experiment, we simulate the second step of the proposed approach whose optimization problem was presented in Section 3.1.2. Specifically, we generate four distinct consumer groups using the same consumer model presented in Section 3.2, and consider all their optimal solutions, in the form of load profiles, as inputs to the global

Figure 10 – Demand baseline, generation, and price profiles



Source: Desined by the author

problem. The dimensions of the consumer groups are summarized in Table 10. The number of solutions per consumer are also scaled along with the number of consumers in the group.

Table 10 – Test case dimensions of each consumer group

	Case A	Case B	Case C	Case D
Consumers (K)	10	10	25	100
Profiles (I_k)	8	50	50	100

It is important to note that only one consumer model was used to simulate the different consumers in each group. This means that all consumers have identical preferences and therefore prefer to consume energy in the same way as illustrated in the base demand plot in Figure 10. Thus, we evenly assigned consumers with each of the five DER configurations to each group in order to mitigate consumer similarities and also to evaluate how DERs impact the final solution. For example, in test case A, with 10 consumers, it means that we have: two type (i) consumers (without access to RES and ESS), two type (ii) consumers (with a low-scale generation system and no storage system), and so on.

Lastly, in this experiment we decided to compare the performance of different optimization algorithms with other search heuristics, due to the combinatory nature and simplicity of the problem. We evaluate this step with five distinct search approaches: genetic algorithms (WHITLEY, 1994), ant colony systems (DORIGO et al., 1997), particle swarm optimization (SHI et al., 1998), the greedy randomized adaptive search procedure (FEO et al., 1995), and a simple greedy search. Our intention with this comparison is not to determine which search strategy is best for each problem instance, but rather to assess the size of the search spaces of each instance in Table 10.

3.2.4.3 Active consumers decision making

The purpose of this experiment is to allow us to analyse the impact of active consumers on the final result of the DR system. Here, we define an active consumer as one whose actions diverge from the ideal behavior outlined in the proposed approach. Active consumers are unwilling to leave the choice of their load scheduling up to the ESP, thus choosing a solution by themselves. We believe it is important to investigate these scenarios because consumers tend to reject disruptive technologies in their residential environments (MCILVENNIE et al., 2020). By doing so, we hope to highlight the flexibility and robustness of the proposed approach in these situations.

We hypothesize that the interference of active consumers on the proposed approach will negatively impact the quality of the aggregate load profile of the community participating in the DR program. Considering the PAR as the quality metric, the null hypothesis and alternative hypothesis below are formulated.

$$\text{Null hypothesis } (H_0)\text{: } \mu \leq \mu_0 \tag{3.34a}$$

$$\text{Alternative hypothesis } (H_A)\text{: } \mu > \mu_0 \tag{3.34b}$$

In Equation (3.34), μ is the average PAR from a sample gathered from a given community. The symbol μ_0 represents the PAR of the same community in the ideal scenario in which all consumers are collaborating with the proposed approach.

We consider active consumers to be inflexible because they do not participate in the second step of the proposed approach, i.e., the step of optimizing the aggregate demand profile. However, the load scheduling choice of an active consumer still affects the aggregate demand profile, and this knowledge could affect the best choice of the remaining flexible consumers. In other words, provided that the demand profiles of inflexible consumers are known in advance, the remaining flexible consumers can still optimize the aggregate demand shape, although this time by considering the demand of the inflexible consumers as fixed.

To simulate the decision-making process of the inflexible consumers, we chose to use the technique for order of preference by similarity to ideal solution (TOPSIS). The motivation for this choice is that selecting a non-dominated solution from a Pareto set is a multiple-criteria decision-making (MCDM) problem. For an active consumer, the criteria characterizing a solution are its own objective function output values from the local optimization problem, that is, the energy consumption cost and load scheduling discomfort. TOPSIS is a hierarchical and compensatory method able to handle decision-making problems with two cost criteria, which fits our use case (YOON, 1987).

In order to use TOPSIS, we need to define how each criteria is weighed to reflect the preferences of a given consumer. To represent preferences, we generate random numbers between 0 and 1. More precisely, the weights of the two criteria, cost (c_1) and discomfort (c_2), are obtained from a single random value drawn from a given distribution $X \sim G$. For example, given a random value $X = 0.7$, the weight of the discomfort criterion is 0.7 ($w_2 = X$), and the weight of the cost criterion is 0.3 ($w_1 = 1 - w_2$).

To perform this experiment, we expect to use the same consumer community simulated in Case D in Table 10, with 100 consumers and each consumer with 100 feasible solutions. This way, we will know what the optimal outcome is in the ideal scenario where all consumers are flexible. Here we call this scenario edge case A. The second edge case happens when all consumers are inflexible. In this scenario, the global optimization process is not performed because there is only one possible aggregate load profile. This scenario is named edge case B. The scenarios of interest lie between these two edge cases, that is, when there are at least one and at most 99 inflexible consumers.

To observe the PAR progression with respect to the number of inflexible consumers, we divide the consumers into three quartiles. Since each consumer represents a unique individual with different solutions and preferences, determining which consumers play the role of inflexible in each quartile needs to be unbiased. We decided to assign the role of inflexible to consumers randomly and uniformly so that all of them have equal odds. This process is sampled 100 times for each quartile.

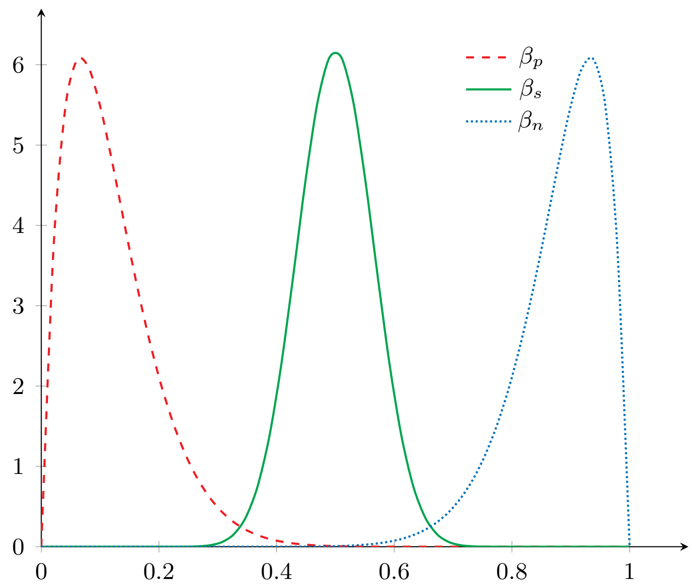
Finally, to observe how consumer preferences affect the final PAR, we use three Beta distributions from which the weights of each consumer's criteria will be obtained. Figure 11 illustrates three probability density functions corresponding to the beta distributions used. At each sampling, the choice of which solution is preferred by each inflexible consumer will be performed three times, once with each distribution.

In Figure 11, the leftmost function $\beta_p = Beta(2, 15)$ is positively skewed in order to model consumers who prefer more economical solutions. The centermost function $\beta_s = Beta(30, 30)$ is symmetric and models consumers with balanced preferences between cost and discomfort. At last, the rightmost function $\beta_n = Beta(15, 2)$ is negatively skewed to model consumers who tend to prefer more comfortable solutions.

3.2.5 Model limitations

The main limitation of this model, as published in Almeida, Rabêlo, et al. (2021), is a legacy of the first model, which is the baseline matrix. The baseline matrix is not

Figure 11 – Probability density functions to model consumer preferences



Source: Desined by the author

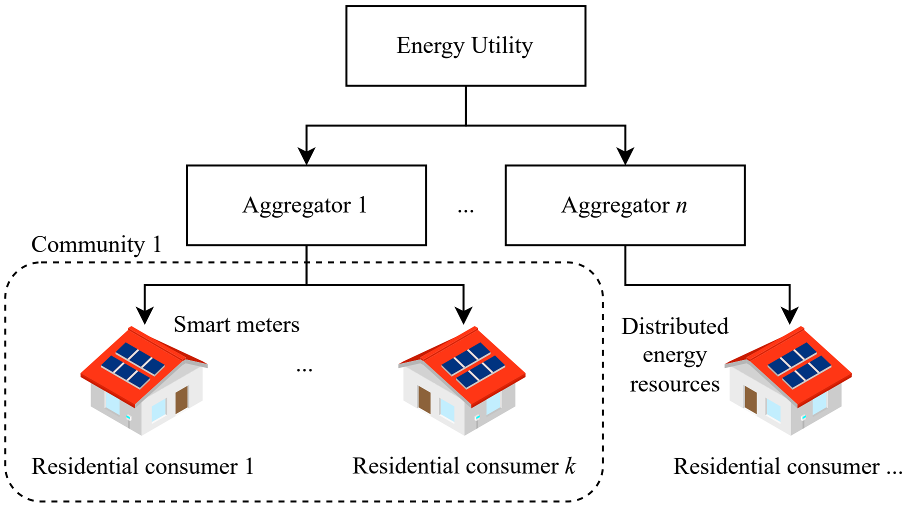
a simple parameter to obtain and it is not feasible to consider that it might be informed by the end consumer. Moreover, the calculation of the discomfort function based on this matrix gives too much importance to one-off changes in the optimal scheduling regardless of the distance in time between the moments when the schedule is changed. Another limitation was allowing the consumer to demand and sell power from the main grid at the same time. These limitations are addressed in the next section.

3.3 Aggregator and schedule discomfort model

In this section, we present the adaptations made to the demand-side management approach described in the previous section. A key entity for this new view of the system is the demand aggregator, which is responsible for encouraging and managing the demand flexibility of a consumer 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 supply their own demand through distributed energy resources and power exchanges between consumer facilities. However, they nonetheless may still rely on the main power grid to cover some of their energy demands and, thus, they partake in the demand response program. Figure 12 illustrates this scenario and the links between the entities involved.

The main change between the scenario presented in Figure 12 and the previous model scenarios is the introduction of the demand aggregator that takes over some responsibilities that were previously relegated to the ESP. The demand aggregator is seen as an entity closer to the end consumer and is in a privileged position to provide

Figure 12 – System architecture with demand aggregator



Source: Desined by the author

the load scheduling service and other services of DR programs (MENDES et al., 2020; RODRIGUES JUNIOR et al., 2019). Consequently, the upper-level optimization problem of the original model is now managed by the demand aggregator, but otherwise the approach remains the same as illustrated in Figure 8. In the next section, we describe only the changes to the formulation of the objective functions and preference parameters compared to the previous model.

3.3.1 Objective functions and preferences reformulation

Let us consider that a demand aggregator manages a community features that a total of K end consumers. From the perspective of a consumer k with access to distributed energy resources, the energy utility expenses of their facility (e.g. a residential household) can be expressed as the cost of its power consumption minus the revenue from its power generation system.

We denote the power consumption of consumer k at time t with respect to the main power grid as $c_{k,t}$:

$$c_{k,t} = \sum_{a \in \mathcal{A}_k} \Delta t P_{k,a} M_{k,a,t} \tag{3.35}$$

In Equation (3.35), $\mathcal{A}_k$ represents the set of all appliances under consumer k's domain. The parameter Δt still denotes the discrete time step size in hours, while $P_{k,a}$ refers to the nominal power rate in kW of the a-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. As in the previous models, the binary values encode decision variables that indicate whether an appliance is turned on or off at a given time step. When a value equals one, it indicates that a load should operate, or demand energy, at that time; otherwise, it equals zero.

Given the consumer's generation system's power output $P^{res}_{k,t}$ in kW, 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:

$$g_{k,t} = \Delta t P^{res}_{k,t} - \sum_{a \in \mathcal{A}_k} \Delta t P_{k,a} R_{k,a,t} - (1 - \Gamma_{k,t}) \Delta t P^{ess}_{k,t} \tag{3.36}$$

From left to right, the terms on the right-hand side of Equation (3.36) denote the available energy from consumer k's generation sources, minus the energy demanded by their appliances, minus the energy allocated to their storage system. The term $\Gamma_{k,t}$ represents an auxiliary binary variable that equals one when the storage system cannot recharge because it is supplying an appliance's demand, as seen in Equation (3.15). Here, we introduce the decision variable $R_{k,a,t}$, denoting the demand of the residential loads for the consumer's distributed generation resources. It is worth noting that these parameters are obtained through the consumer's smart meter infrastructure and HEMS.

Based on the previous definitions, we redefine the first objective function as the total expenses of an end consumer k:

$$f^k_{cost} = \sum_{t \in \mathcal{T}} (c_{k,t} p_t - \beta_{k,t} g_{k,t} p'_t) \tag{3.37}$$

In Equation (3.37), the terms p_t and p'_t still represent the tariffs for purchasing and selling energy at a time t, respectively, and $\mathcal{T}$ denotes the set of all time steps. 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, and it can be computed as follows:

$$\beta_{k,t} = \begin{cases} 1, & \text{there is no main grid demand, } (c_{k,t} = 0) \\ 0, & \text{there is main grid demand, } (c_{k,t} > 0) \end{cases} \tag{3.38}$$

As previously discussed, the discomfort of following a suggested load schedule directly influences consumers in residential load management. Previously, comfortable scheduling patterns for the consumer were represented using a complete schedule of all appliances, regardless of type, called the baseline matrix. Due to the difficulties of obtaining this extensive parameter, in this model the matrix is replaced by a time step that indicates when each appliance would preferentially start operating. The discomfort associated with a given load when scheduled at a different time step 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.

$$f^k_{disc} = \sum_{a \in \mathcal{A}^{flex}_k} (x_{k,a} - u_{k,a})[(1 - \delta_{k,a}) w^D_{k,a} - \delta_{k,a} w^A_{k,a}] \tag{3.39}$$

In Equation (3.39), $\mathcal{A}_k^{flex}$ represents the 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 $u_{k,a}$. These are the appliances for which the deferrable preference is enabled ($p_{a,w}^{def} = 1$) and the interruptible preference is disabled ($p_{a,w}^{int} = 0$). The difference between $x_{k,a}$ and $u_{k,a}$ is computed, which in turn is converted into a cost when multiplied by an appropriate cost factor. Here, the term $w_{k,a}^{A}$ represents the cost factor preference parameter 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 instead. 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.

3.3.2 Experimental design

In this section, we describe the design of experiments to assess the effect of flexible consumers on the final PAR of an energy community using the bi-level optimization method described in Section 3.3. This data set that serves as the base for all consumer profiles simulated in this experiment is briefly described in Section 3.3.2.1. The data transformation procedures required to adapt the data to our model and the experimental design are detailed in Sections 3.3.2.2 and 3.3.2.3, respectively.

For the optimization methods selected to solve the bi-level optimization problem introduced in Section 3.3, 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 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 non-dominated 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 NSGA-II optimization meta-heuristic (DEB et al., 2002). 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 multi-objective optimization problems (ROSTAMI et al., 2020).

3.3.2.1 Data set

The data set chosen for this experiment was collected by Pilloni et al. (2016). 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.

Pilloni et al. (2016) 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.

3.3.2.2 Data transformation

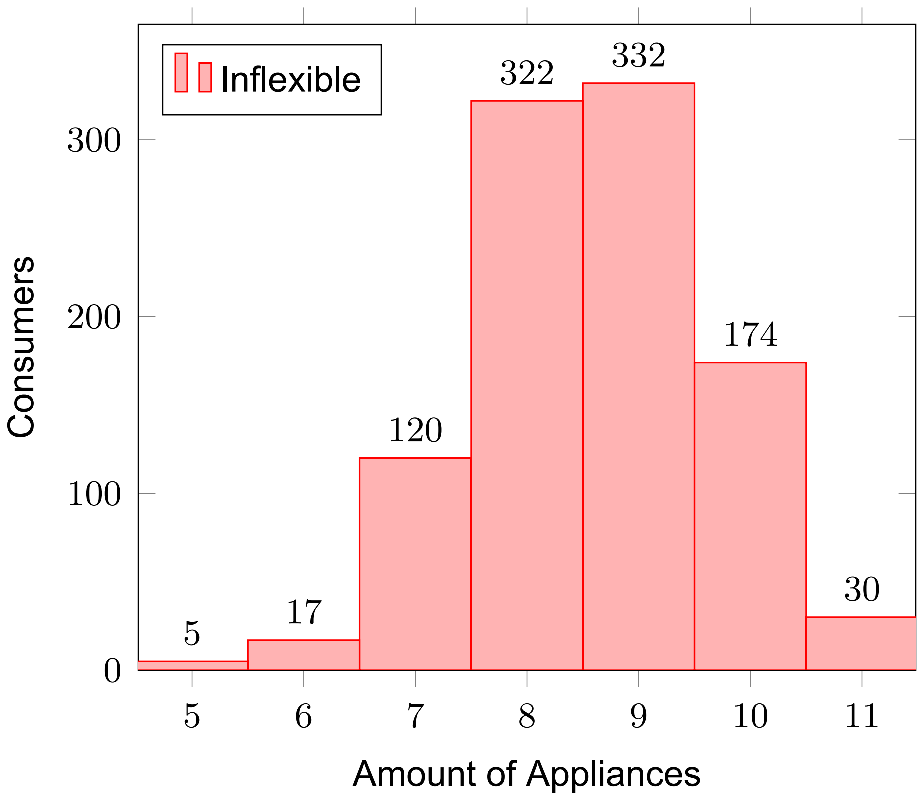
Although the data set introduced in the previous section realistically represents residential consumers, it was nonetheless necessary to adapt that data characterizing weekly usage preferences to the daily preferences model expected by the model proposed in Section 3.3. For example, the data available 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. 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. Nonetheless, the remaining loads are sufficient to represent the consumers and their range of flexibility as obtained from the original data set.

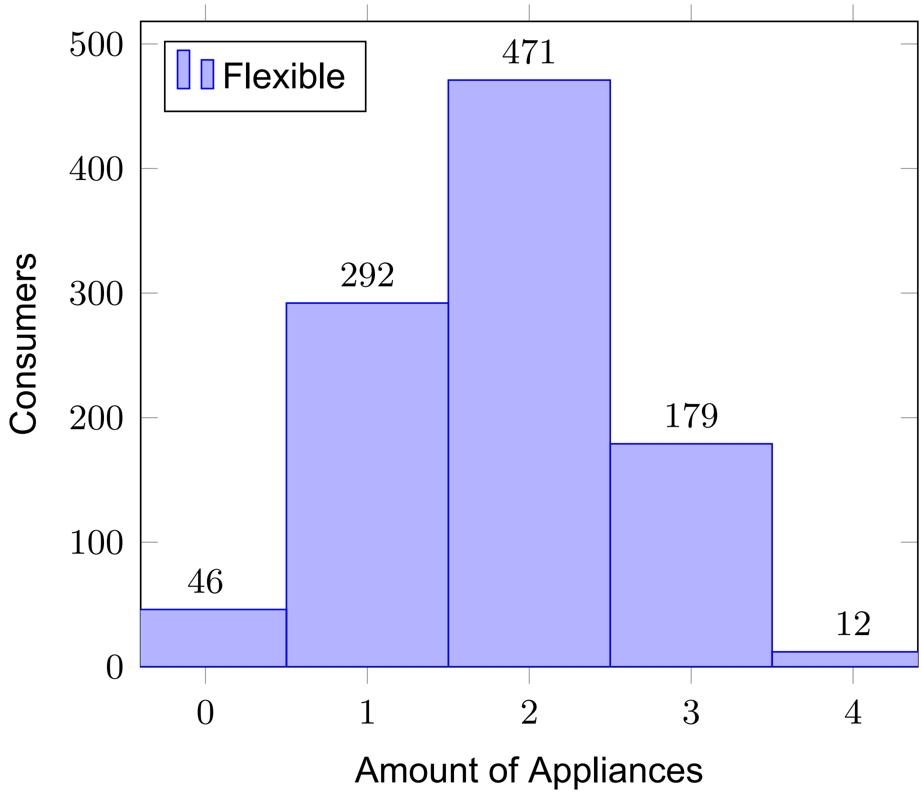
The above said, we henceforth call devices in G1 and G2 as *inflexible* and *flexible*, respectively, where flexibility means that some consumers are willing to accept delaying the operations of appliances. Figures 13 and 14 show the number of devices per category and the number of consumers who own these devices.

Figure 13 – Distribution of consumers per amount of owned inflexible appliances



Source: Desined by the author

Figure 14 – Distribution of consumers per amount of owned flexible appliances



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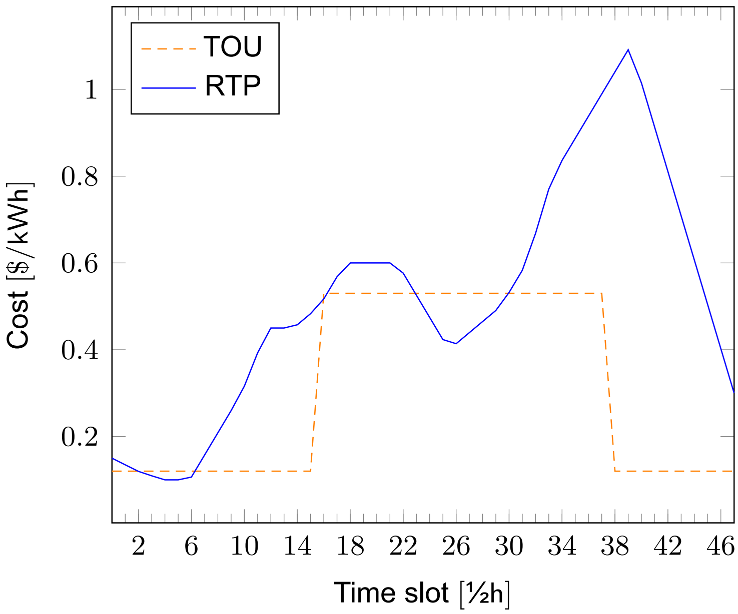
3.3.2.3 Procedure steps

In order to calculate reliable statistics in our data analysis, we used a bootstrapping technique to generate multiple re-samples from the initial sample of consumers (WASSERMAN, 2004). Specifically, the initial sample of 1,000 consumers was re-sampled 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.

In all experiments, the planning horizon was divided into $T = 48$ time steps, meaning the sampling time granularity Δt is set to $30\,\mathrm{min}$. 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 14. For the pricing strategy, we have adopted two pricing tariffs, the TOU tariff from Pilloni et al. (2016), and the RTP tariff from Table 5 interpolated to 48 time steps (ALMEIDA; RABÊLO, et al., 2021). We illustrate these tariffs in Figure 15 for a given day.

Figure 15 – TOU and RTP tariffs



Source: Desined by the author

3.3.3 Model limitations

Some of the limitations identified in the present model are that the uncertainty of renewable energy source such as solar power is not taken into account by the model, which only considers a generation profile ($P^{res}_{k,t}$) as a deterministic parameter. In addition, the simplified energy storage system management model does not consider battery deterioration over the course of its use. Despite considering the integration of distributed energy resource, grid stability is also abstracted from the model and the formulation does not contemplate power flow constraints or secondary control. Finally, it is important to recognize that the binary decision variable model abstracts away many complexities of appliance operation. Today, it is possible to find appliances with multiple modes of operation, each with different or even varying levels of energy consumption, and which would not be easily modeled by the current formulation.

3.4 Concluding remarks

This chapter presented the development timeline of the demand-side management model in three parts, indicating each milestone in the formulation that resulted in a scientific paper. The first version, presented in Section 3.1, introduces the general approach based on a bi-level optimization problem. The lower-level problem consists of scheduling residential loads to minimize the cost and inconvenience of scheduling, and is solved individually by each consumer's home energy management system. The upper-level problem consists of combining the demand profiles of the different consumer-optimized solutions and is solved by the energy service provider's system. The second version, presented in Section 3.2, enhances the lower-level model by including distributed energy resource management and a more flexible preference model, leading to the formulation of a discomfort function. The third version, presented in Section 3.3, updates the approach with the inclusion of the demand aggregator and reformulates the concept of discomfort associated with load schedules.

4 Results and Discussion

In this chapter we present and discuss the results of the experiments detailed in Chapter 3. The procedures[1] described hereafter were implemented using the Python language, version 3.8.5, with the JupyterLab environment (KLUYVER et al., 2016), and the Pymoo library (BLANK et al., 2020), using a laptop computer Intel(R) Core(TM) i5-8300H CPU, 2.30GHz, 16 GB.

4.1 Demand profile combination techniques

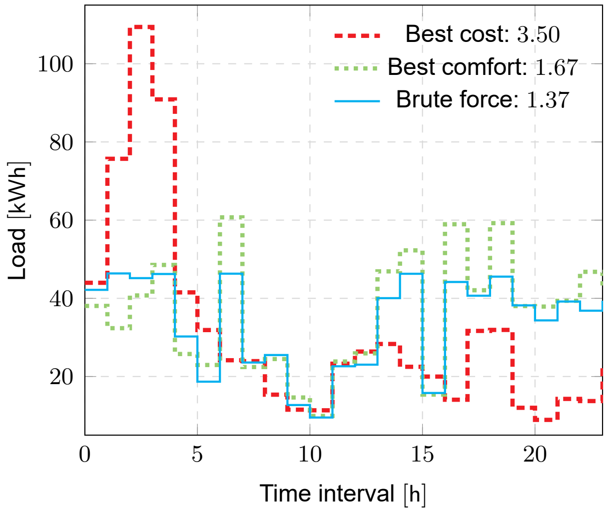
Given that the present experiment is executed for a specific instance of the DSM problem, it is important to understand the range of solution for this instance. Figure 16 illustrates the load profiles three edge-case combinations: in red, the schedule with the best cost objective was chosen for each household; in green, the schedule with the least inconvenience objective; and in blue, the best result from a brute force search. As expected, selecting only the solutions with the lowest individual cost leads to high PAR (3.50), peaking in the early morning when prices are the lowest. Meanwhile, the combination of solutions causing the least inconvenience, i.e. the most similar to each consumer's baseline schedule, show an improvement of over $50\,\%$ in relation to the best cost combination. It is worth noticing that the profile with the best comfort only showed a relatively flat curve due to the fact that the simulated consumers used the same preferences with a flat baseline matrix profile, which would not necessarily be true in a more realistic scenario. Through a brute force approach, the solution with the best result for this problem instance reaches a PAR of 1.370. This implies that the best combination of load profiles cannot be achieved my minimizing one single objective, and that the answer lies in between.

The randomized and greedy search algorithms provide initial references for further comparisons. The load profiles from randomized search and greedy search are shown in Figure 17. Greedy search always selects the load profile that best improves the PAR of its partial solution. The random search procedure, on the other hand, does not consider any heuristic information, simply aggregating a random combination of load profiles from all households. The greedy approach was able to find good results, achieving a PAR $8.40\,\%$ better than the least inconvenient solution and $10.80\,\%$ better than randomized, suggesting its heuristic improves the final result.

GRASP was able to outperform greedy search by $6.10\,\%$, as shown in Figure 18.

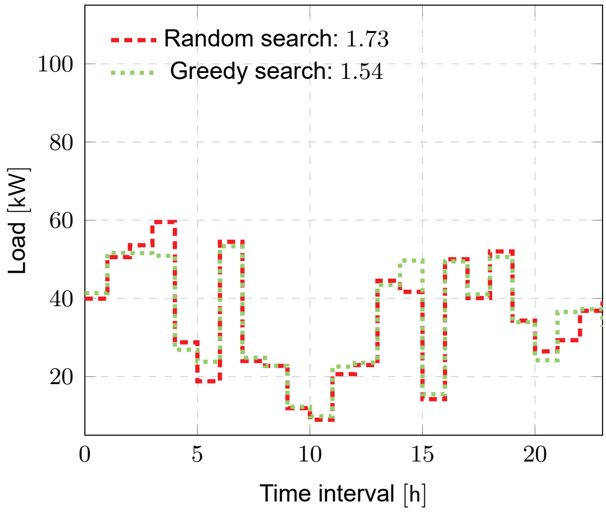
[1] Source code available at: github.com/vccortez/dsm

Figure 16 – System-wide demand profiles for edge-case solutions



Source: Desined by the author

Figure 17 – Randomized and greedy search load profiles

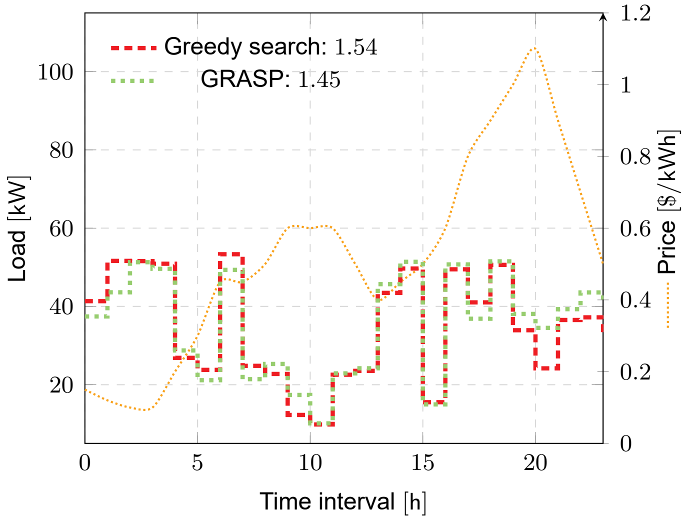


Source: Desined by the author

This confirms our previous statement that this combinatorial problem cannot be optimally solved by a greedy approach. It is possible to notice that GRASP improved its PAR by raising the demand around hours 18–23, which are higher priced time slots as illustrated by the orange line. The total cost differences are further discussed later in this section.

Finally, AS and ACS are compared to GRASP in Figure 19. Although AS showed an improvement of $4.50\,\%$ over GRASP, the best performing algorithm was ACS, with a PAR of 1.372 with an overall improvement of $12.40\,\%$ over the greedy search solution, nearly matching the optimal PAR of 1.369 obtained with a brute force method with less than one percent difference. In relation to GRASP, the ACS algorithm was able to not only improve the PAR, but also to reduce the total cost by shifting loads away from

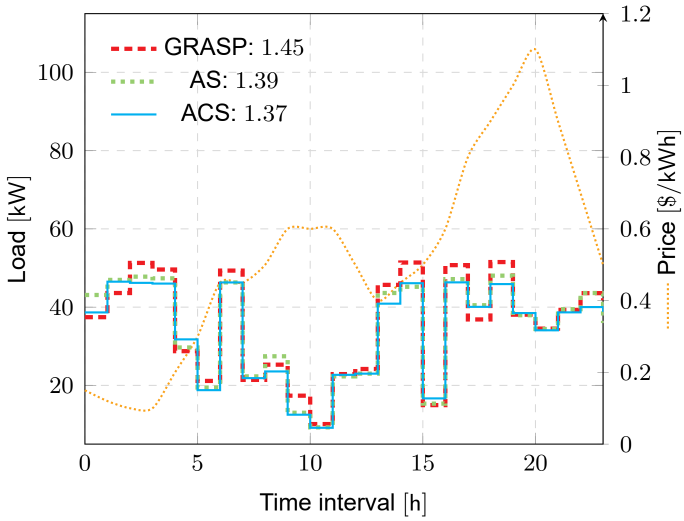
Figure 18 – Greedy search and GRASP load profiles



Source: Desined by the author

higher price time slots, although this behavior was not directly caused by the PAR minimization objective. In relation to AS, the difference between profiles is very small, but small load shifts allowed ACS to reduce its peak demand and consequently improve its PAR.

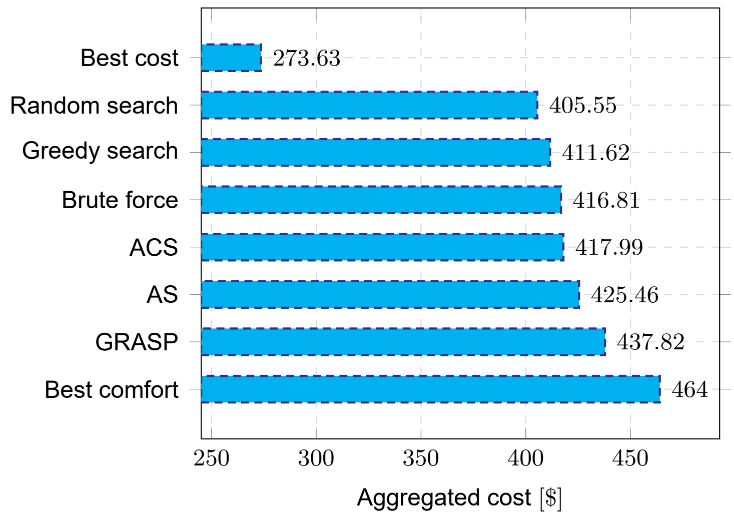
Figure 19 – AS, ACS and GRASP load profiles



Source: Desined by the author

Since the tree search algorithms are unable to change the demand, the PAR reduction is achieved solely by shifting demand from lower priced to higher priced time slots and vice versa. This means that the total cost of the system-wide demand profile varies accordingly. Figure 20 summarizes the cost values for each approach. As expected, the “Best cost” edge-case solution achieves the lowest total cost, and every algorithm outperforms the “Best comfort” edge-case solution in terms of cost. This suggests that even the solutions that achieved high peak-to-average ratios would inconvenience to consumers. As with the PAR, the ACS algorithm obtained nearly the same cost of the optimal solution found through brute force, sustaining that the algorithm was able to approximate the optimal PAR.

Figure 20 – Global demand profile cost for each solution



Source: Desined by the author

4.2 Distributed energy resources assessment

This section presents the results of the experiments described in Section 3.2.4. The results are divided according to the optimization tasks performed. In Section 3.2.4.1 we present and discuss the results of the lower-level optimization problem, followed by the results and discussion of the upper-level optimization problem in Section 4.2.2.

4.2.1 Lower-level problem simulation

The simulation results of the local optimization problem (whose parameters were explained in Section 3.2.4.1) are summarized in Tables 11 to 15. Five distinct consumers with different levels of access to DERs are simulated, corresponding to the settings presented in Table 8. To mitigate the impact of outliers, we simulated each scenario 15 times and chose the one whose result was closest to the average of all simulations, using the Euclidean distance metric.

In each table, a consumer is represented by two solutions. The solutions named “Economical” are those that achieved the lowest cost among all solutions for that consumer, and the solutions named “Comfortable” are those that achieved the lowest discomfort. Table 11 displays the results for the scenario in which the consumer does not have access to DERs. This means that a consumer in these circumstances could have only resorted to shifting loads in order to cut costs, leading to more discomfort. We consider this scenario as a reference for future comparisons between the other scenarios.

Table 11 – Best solutions for DER setting A

Solution	Cost ($\$/\mathrm{kWh}$)	Discomfort ($\$/\mathrm{kWh}$)
Economical	81.95	49.79
Comfortable	118.87	7.38

Next, Table 12 summarizes the results of a consumer with access to a low-scale generation system and no storage system. The Economical solution achieves a decrease of $20.00\,\%$ in cost and $1.20\,\%$ in discomfort over the reference scenario, while the Comfortable solution achieves a decrease of $14.40\,\%$ in cost and $67.10\,\%$ in discomfort. These results show the potential of DERs to reduce costs and discomfort.

Table 12 – Best solutions for DER setting B

Solution	Cost ($\$/\mathrm{kWh}$)	Discomfort ($\$/\mathrm{kWh}$)
Economical	65.53	49.18
Comfortable	101.64	2.43

In Table 13, we show the results of a consumer with access to a low-scale generation system and ESS. The Economical solution achieves a decrease of $23.90\,\%$ in cost and $6.70\,\%$ in discomfort over the reference scenario, while the Comfortable solution achieves a decrease of $16.80\,\%$ in cost and $64.30\,\%$ in discomfort. It can be noted that the effect of adding a storage system is not as significant in terms of cost savings and discomfort.

Table 13 – Best solutions for DER setting C

Solution	Cost ($\$/\mathrm{kWh}$)	Discomfort ($\$/\mathrm{kWh}$)
Economical	62.36	46.41
Comfortable	98.81	2.63

Next, we display the results for consumers with access to high-scale generation systems. Table 14 summarizes the results of a consumer with access to a high-scale generation system and no storage system. The Economical solution achieves a decrease of $38.50\,\%$ in cost and $18.30\,\%$ in discomfort over the reference scenario, while the Comfortable solution achieves a decrease of $33.00\,\%$ in cost and $46.10\,\%$ in discomfort.

Finally, Table 15 summarizes the results of a consumer with access to high-scale generation and ESS. The Economical solution achieves a decrease of $44.00\,\%$

Table 14 – Best solutions for DER setting D

Solution	Cost ($\$/\text{kWh}$)	Discomfort ($\$/\text{kWh}$)
Economical	50.39	41.08
Comfortable	80.77	3.98

in cost and $17.40\,\%$ in discomfort over the reference scenario, while the Comfortable solution achieves a decrease of $32.00\,\%$ in cost and $86.40\,\%$ in discomfort. Again, the improvement in cost and discomfort indexes were both small with the addition of the storage system.

Table 15 – Best solutions for DER setting E

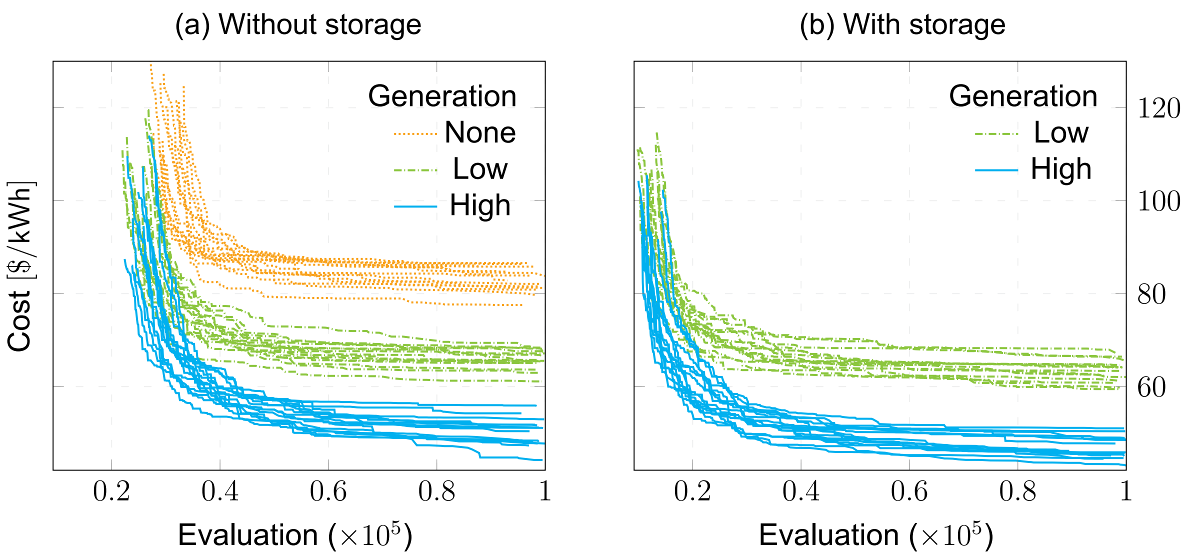
Solution	Cost ($\$/\text{kWh}$)	Discomfort ($\$/\text{kWh}$)
Economical	45.85	40.67
Comfortable	79.58	1.00

In all cases, solutions with access to at least one type of DER achieved better results in both cost and discomfort. The Economical solutions achieved the lowest costs, while the Comfortable solutions ensured the highest degree of similarity between the optimal load schedule and consumers' preferences. It can be seen that the solutions with access to ESS performed slightly better than their counterparts without it and that the profiles with high-scale generation obtained the most cost-effective results. In other words, these results suggest that, during the local optimization problem, it is most advantageous for consumers to have access to generation resources, as they help to decrease costs and discomfort. More studies need to be conducted to verify the cost-effectiveness of storage systems against the investment required to acquire them. In addition, the recharging policy of the storage systems adopted in this experiment, as detailed in Section 3.2.1.2, may have negatively impacted their performance.

4.2.1.1 Convergence of the optimization algorithm

To examine the pace of the optimization process, Figure 21 illustrates how the best consumption cost decreased over the course of the optimization process. In this plot, the x-axis represents all fitness-function evaluations for the 100 individuals over 1000 generations. For this problem instance, most of the cost improvement was achieved in the first 500 iterations. Profiles without access to ESS needed more iterations to find their first feasible solution, but they were nonetheless still able to find effective final results. However, it is clear that the RES scale has a direct influence on the final cost attained by each profile.

Figure 21 – Cost improvement throughout the optimization process



Source: Desined by the author

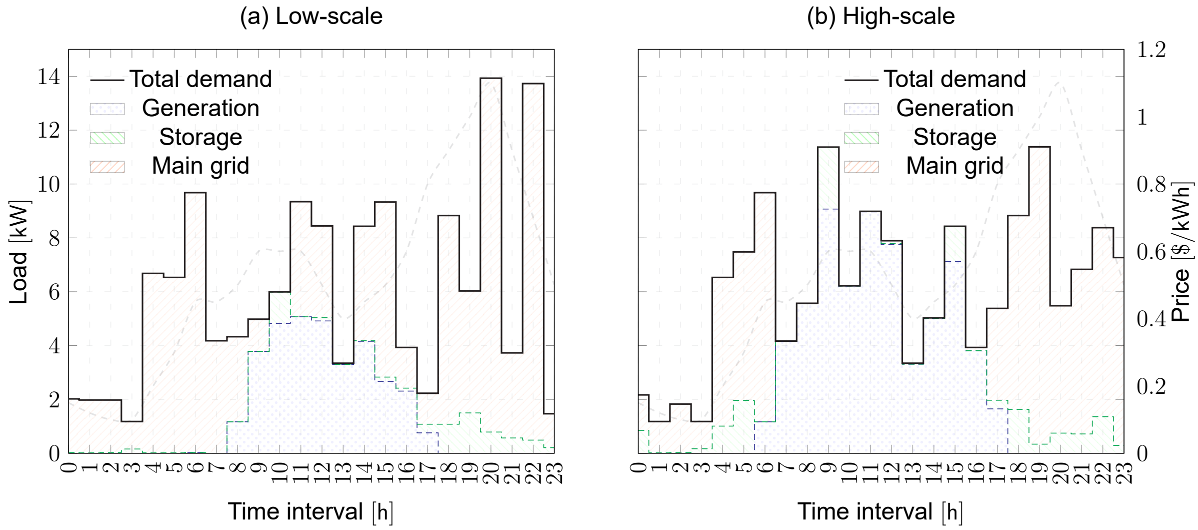
The parameters of the algorithm and its genetic operators were all chosen empirically by re-running the algorithm and observing the characteristics of the final populations. Thus, we conclude that a population with 100 individuals being recombined for 1,000 generations (100,000 evaluations) is enough to grant each individual sufficient time to exchange genetic material and result in a Pareto set with diverse solutions to this problem. We generated the initial populations using uniform distributions, applied an *integer bitflip* mutation operator with a fixed mutation probability of $0.28\,\%$, and employed a uniform crossover operator.

4.2.1.2 Contribution of the energy sources

To understand how each energy source contributed to supply the demand of the optimized schedules, Figure 22 illustrates the total demand at each time index and the proportion supplied by each source. The light gray and dashed line represents the energy prices as in Figure 10 Subfigure (a) shows the most economical result for the low-scale generation profile, while Subfigure (b) shows the most economical result for the high-scale generation profile, both with access to the storage system. The impact of the generation system scale is evident given that in Subfigure (b) the RES supplies almost the entirety of the mid-day demand, and the system is able to utilize the ESS more frequently at the beginning and end of the day. Accordingly, the higher the availability of photovoltaic generation, the larger the demand valley from the main grid during the middle of the day.

In contrast, Figure 23 highlights the difference between the demand profiles of the most economical and the most comfortable solutions for the consumer profiles with-

Figure 22 – Demand distribution for profiles with low- and high-scale generation



Source: Desined by the author

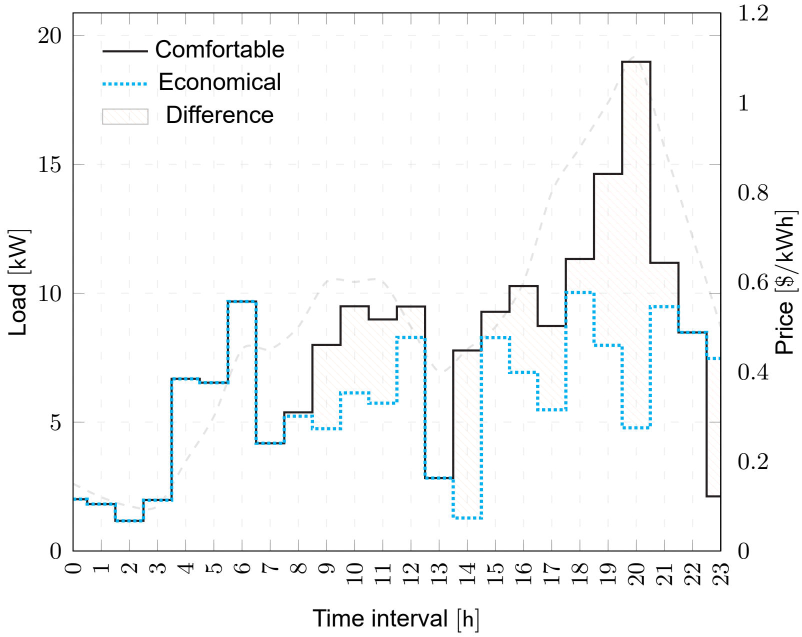
out access to DER. Note that the shape of the most comfortable profile matches the baseline demand shown in Figure 10. Most of the differences between both profiles are concentrated around the peak-price hours towards the end of the day. This example showcases how a demand response scheme achieves cost reductions by exploiting the flexibility of household appliances. Moreover, Figures 22 and 23 highlight yet again how decentralized energy generation and storage systems can significantly reshape energy demand from the main grid. For example, one can clearly see demand valleys when consumers' solar panels are at their peak in terms of generating energy, but peaks tend to appear in the evening when DER and ESS can no longer supply energy. As we discuss next, the existence of such valleys and peaks can bring substantial challenges to a utility company trying to smooth energy demand from the main grid.

4.2.2 Upper-level problem simulation

The first consumer group was considered to assess the performance of a set of techniques for solving optimization problems in relation to the optimal solution. A brute force search was performed to evaluate all 8^{10} possible solutions of this instance so as to find the optimal solution, which was then compared against standard implementations of a genetic algorithm (GA), particle swarm optimization (PSO), ant colony systems (ACS), and greedy randomized adaptive search procedure (GRASP).

The majority of the compared algorithms were able to find a near-optimal solution whose PAR value was approximately 2.271. All PAR results per algorithm are summarized in Table 16 along with the results of the single-objective strategies Economical and Comfortable. The percentages in parentheses represent the change in PAR for the best

Figure 23 – Different solutions for the consumer profiles without DER



Source: Desined by the author

result in relation to the Economical strategy's PAR These strategies represent simpler models that select the best solution per household for their respective single-objective function. The percentage change in PAR for the best result in relation to the Economical strategy's PAR is highlighted for each test case in the table. GA and ACS were the most successful algorithms achieving the best results in all cases. Nonetheless, even simple techniques like GRASP were able to find advantageous solutions when compared to the single-objective strategies.

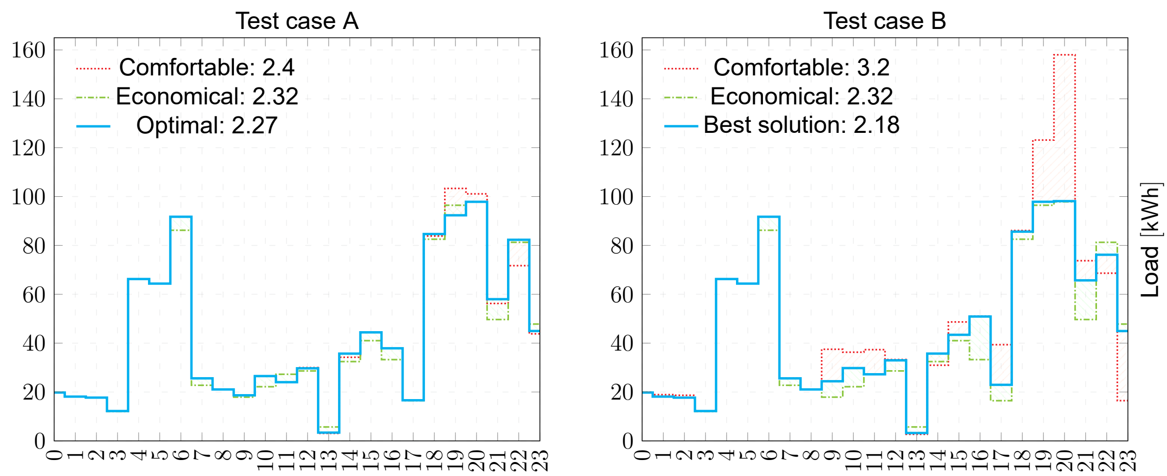
Table 16 – PAR results for each test case per optimization technique

Technique	Case A	Case B	Case C	Case D
ACS	*2.271* ($-2.40\,\%$)	*2.188* ($-5.90\,\%$)	2.138	2.185
GA	*2.271*	2.196	*2.134* ($-11\,\%$)	*2.078* ($-10\,\%$)
GRASP	*2.271*	2.203	2.177	2.194
Greedy	2.275	2.410	2.265	2.205
PSO	2.275	2.280	2.210	2.393
Economical	2.327	2.327	2.398	2.314
Comfortable	2.402	3.208	2.990	3.177

There are two main takeaways from the above results. First, Table 16 shows that virtually any modern optimization technique can be used to find optimal solutions during the second step of our proposed solution. In other words, our model is feasible to be used in practice. Second, simpler models that consider only one objective during the first step (either cost reduction or comfort) tend to result in less desirable solutions during the second step, i.e., solutions with higher PAR values.

The demand profiles resulting from the best optimization technique in test cases A and B are compared against their respective single-objective strategies in Figure 24. The small difference between the PARs resulting from the solutions for test case A is reflected in the minor differences between the demand profiles. Moving to the demand profiles of test case B, it is possible to observe that the Comfortable strategy presents a high-demand peak at around 8 p.m., which is expected since all consumers have the same preferences (see Figure 10) and some energy-intensive appliances, such as stoves and washers, might be turned on during that time (see Table 7).

Figure 24 – Load profile comparison for the best solutions from cases A and B



Source: Desined by the author

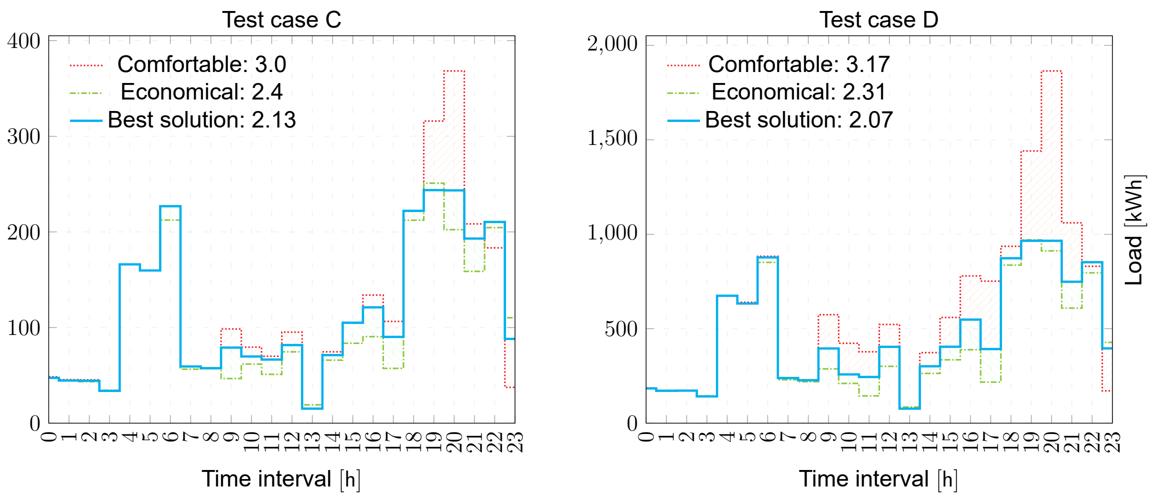
Similarly, Figure 25 compares the best demand profile of test cases C and D against their respective single-objective solutions. The Economical solutions achieved good results while guaranteeing the lowest costs for the end-consumer in exchange for higher discomfort. However, these solutions cannot guarantee the best possible PAR to benefit the ESP as their optimized schedules tend to shift loads toward off-peak periods.

Figures 24 and 25 show that the solutions having optimal PAR represent a compromise between the Economical and Comfortable strategies. In particular, the profiles with optimal PAR have consumers exchanging a bit of comfort for some financial benefits.

4.2.3 Impact of the consumer profiles

To verify the effect of consumer profiles on the results of the second step, 5 homogeneous communities were simulated corresponding to each consumer type presented in Section 3.2.4.1. Each community was composed of 15 households that share among

Figure 25 – Load profile comparison of best solutions for cases C and D



Source: Desined by the author

themselves the same preferences and DER parameters of the consumer profile they represent. Table 17 shows the final PAR results obtained using the genetic algorithm as the optimization technique. The percentages in parentheses represent changes with respect to the baseline solution in the first row.

Table 17 – Best PAR results for each profile

Generation Scale	Storage	Best PAR
None	No	*1.5384*
Low	No	2.0705 (+34.60 %)
Low	Yes	1.9581 (+27.30 %)
High	No	2.6584 (+72.80 %)
High	Yes	2.5976 (+68.90 %)

The best PAR was achieved by the group of consumers without access to DER while, in contrast, the group composed only of consumers with access to ESS and high-scale generation had the worst PAR. As we suggested before, these results can be explained by the fact that the demands from consumers in the latter group exhibited a valley by midday due to the higher generation capacity. Moreover, the aggregation of solutions having similar profiles elevates demand peaks at times of low photovoltaic generation. We posit that the more diverse the consumer demand profiles are, the greater the chances of producing a balanced aggregate profile that leads to lower peak-to-average ratios. Regardless of the above results, the use of RES and ESS is still beneficial from the environmental and economic standpoints. Furthermore, as discussed in Section 4.2.1, distributed energy resources allow consumers to achieve higher energy savings and comfort.

4.2.4 Discussion

The results presented in this chapter suggest that distributed energy resource have a positive impact on the cost and discomfort of consumers. The local optimization problem results suggest that even solutions that are close in terms of cost and discomfort can have distinct demand profiles. Consequently, the proposed demand response system is likely to assist utilities in finding balanced community-wide aggregate demand profiles, especially when most consumers are flexible and offer a diverse set of demand profile options. Additionally, the global optimization problem is able to find near-optimal solutions even when using simple optimization techniques (e.g., GRASP). Consumers with access to high-scale renewable generation systems can limit the ESP in terms of finding balanced aggregate demand profiles. This situation arises because these consumers can reduce energy expenses by reallocating their demands to other energy sources instead of shifting loads to off-peak periods. Hence, demand valleys followed by new peaks make it challenging to smooth energy demands from the main grid.

4.3 Active consumer decision making

The summary of the PARs resulting from the sampling at each quartile are presented in Tables 18, 19 and 20, respectively. The tables include the statistics for the mean, standard deviation, minimum and maximum value of the sample. In addition, the Beta distributions (see Figure 11) used by the inflexible consumers are separated with the PAR results shown.

Table 18 – Summary of PAR in the first quartile sampling

	β_p	β_s	β_n
Mean	2.21	2.33	2.33
Std	0.01	0.02	0.02
Min	2.17	2.29	2.29
Max	2.24	2.39	2.39

On one hand we can see a similarity between the values of the statistics for the β_s and β_n distributions in Table 18. On the other hand, the lowest average PAR among all quartiles was achieved in the first quartile with the β_p distribution. This is the first indication that fewer inflexible consumers benefit the PAR of the community, and that the economical solutions from this problem instance are more diverse than the comfortable solutions.

Table 19 – Summary of PAR in the second quartile sampling

	β_p	β_s	β_n
Mean	2.33	2.62	2.62
Std	0.03	0.02	0.02
Min	2.28	2.54	2.55
Max	2.39	2.68	2.67

Table 20 – Summary of PAR in the third quartile sampling

	β_p	β_s	β_n
Mean	2.48	2.91	2.92
Std	0.03	0.02	0.02
Min	2.42	2.83	2.83
Max	2.58	2.96	2.96

In Tables 19 and 20 we see the PAR growing on average with the increase in inflexible consumers. Again the β_s and β_n distributions show worse results than β_p, with the worst result among all quartiles being achieved in the third quartile with the β_n distribution.

Additionally, we show in Table 21 the summary results in the edge case B, in which all consumers are inflexible. As previously discussed in Section 3.2.4.3, this case does not require a second optimization step since there is only one possible aggregate profile. As expected, this table shows the largest PARs thus far.

Table 21 – Summary of PAR with only inflexible consumers

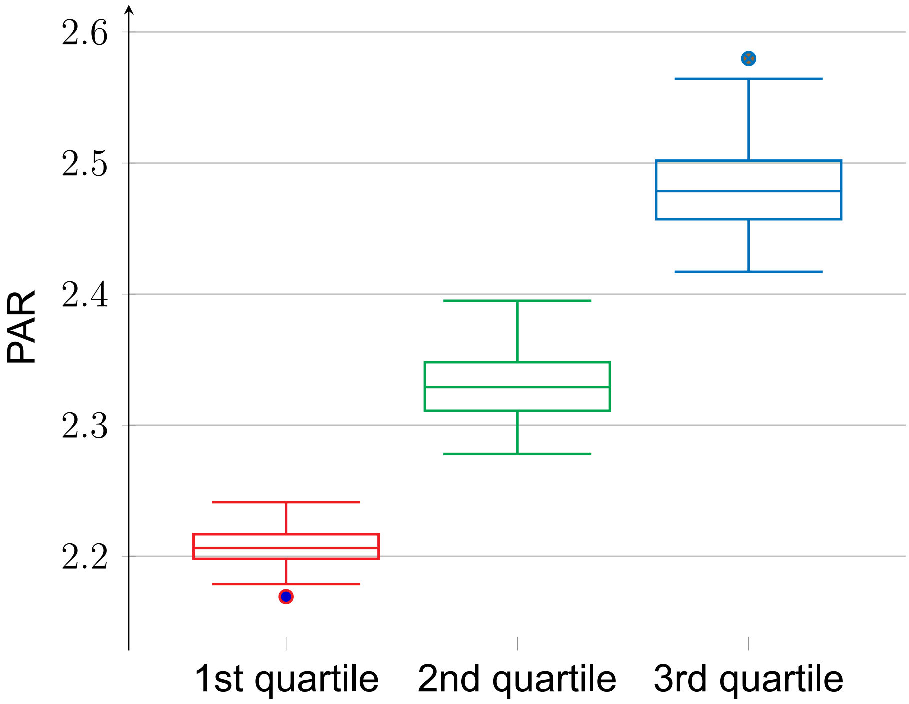
	β_p	β_s	β_n
Mean	2.68	3.18	3.18
Std	0.04	0.00	0.00
Min	2.60	3.17	3.18
Max	2.78	3.19	3.18

The box plots in Figures 26 to 28 further illustrate the differences between the samples. Each figure summarizes the samples for a single Beta distribution at each quartile.

In Figure 26, we can see that data dispersion seems to increase at each quartile. Naturally, it is possible to see a relationship between the increase in the number of inflexible consumers and the increase in PAR.

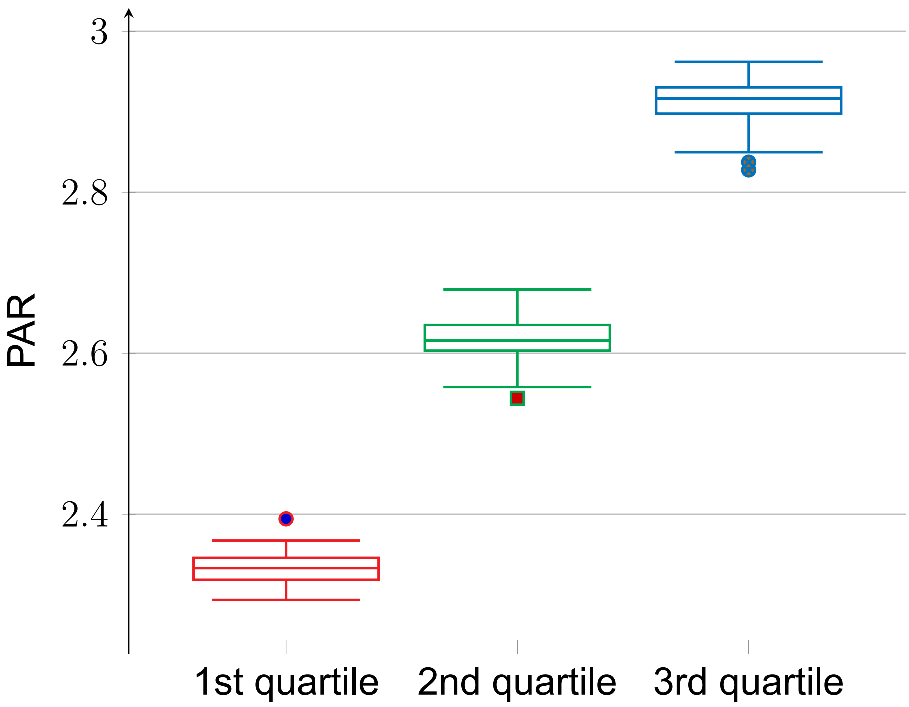
From the graphs in Figures 27 and 28, the distributions appear quite similar and show little to no asymmetry. This reflects the similarity between the statistics of the β_s and β_n distributions shown earlier. Finally, all samples from quartile to quartile

Figure 26 – Box plot of the samples with the β_p distribution



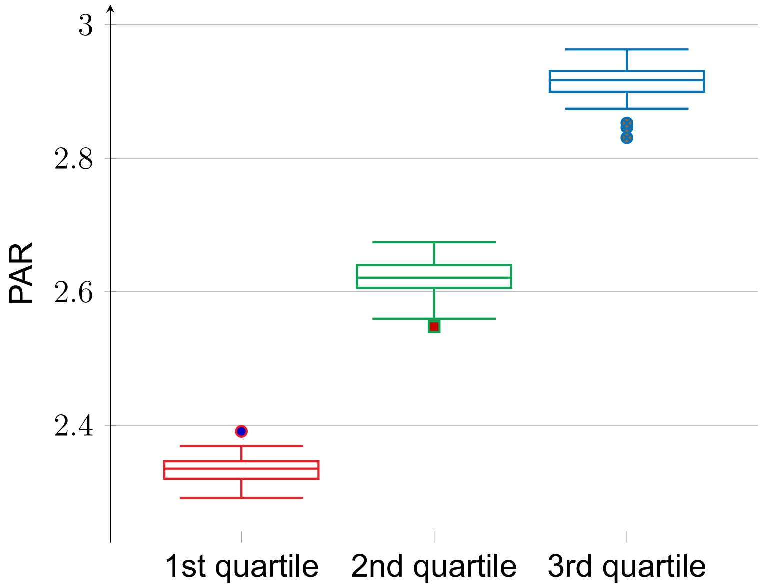
Source: Desined by the author

Figure 27 – Box plot of the samples with the β_s distribution



Source: Desined by the author

Figure 28 – Box plot of the samples with the β_n distribution



Source: Desined by the author

appear to be quite distinct, since none of the graphs showed an overlap between the box whiskers.

4.3.1 Hypothesis testing

Given the results of the box plots presented earlier, one can infer that there is a strong relationship between the amount of inflexible consumers and the optimal PAR of the aggregate load profile. Additionally, the dispersity between the samples are a strong indicator that the null hypothesis presented in Section 3.2.4.3 will be rejected.

Next we perform a one-tailed t-test to evaluate the null hypothesis for all samples using a given Beta distribution. Tables 22 to 24 summarize the results at each respective quartile. The critical value for this experiment was chosen beforehand to be equal $\alpha = 0.001$. The average PAR chosen to perform the test was set to $\mu_0 = 2.09$, equivalent to the median value in the ideal case where all consumers are flexible.

Table 22 – Results of the t-test in the first quartile

Distribution	T score	p-value
β_p	77.84	6.48×10^{-91}
β_s	125.19	3.93×10^{-111}
β_n	128.71	2.55×10^{-112}

As expected, the null hypothesis was rejected for all samples at each quartile. The statistical power of the t-tests were large, indicating that the groups are indeed

Table 23 – Results of the t-test in the second quartile

Distribution	T score	p-value
β_p	92.17	4.43×10^{-98}
β_s	213.05	6.60×10^{-134}
β_n	212.89	7.12×10^{-134}

Table 24 – Results of the t-test in the third quartile

Distribution	T score	p-value
β_p	111.23	4.38×10^{-106}
β_s	340.81	4.45×10^{-154}
β_n	351.63	2.03×10^{-155}

different. The p-values were well below the stipulated critical value, suggesting that there is strong evidence against the null hypothesis.

4.3.2 Discussion

Based on the results of the impact of active consumers, it was possible to observe the direct relationship between the number of inflexible consumers and the increase in peak-to-average ratio. Considering that the PAR reflects the smoothness of the aggregate demand profile, we can consider that the number of inflexible consumers in a community affects the operating cost of the utility, i.e., inflexibility incurs a cost. Still, we can see that even in scenarios with a considerable number of inflexible consumers, a demand profile with better PAR than the base cases is still possible, as long as the demand profiles are different enough from each other. Therefore, the diversity of the demand profiles is the most important factor to consider in the second step of the proposed approach. Further studies can investigate the relationship of PAR with consumer heterogeneity.

4.4 Appliance flexibility and pricing assessment

We first discuss our findings for the lower-level optimization problem (consumer-level optimization) in Section 4.4.1. In this step, the parameters applied to NSGA-II were: (i) population of 100 individuals; (ii) iteration of 500 generations; (iii) polynomial mutation with probability of 0.006 and crowding degree of 3.00; and (iv) simulated binary crossover with crowding degree of 3.00. Next, Section 4.4.2 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 (ROSTAMI et al., 2020). Finally, Section 4.4.3 presents the results of statistical tests performed on the PAR values of the bootstrap samples.

4.4.1 Individual consumer optimization

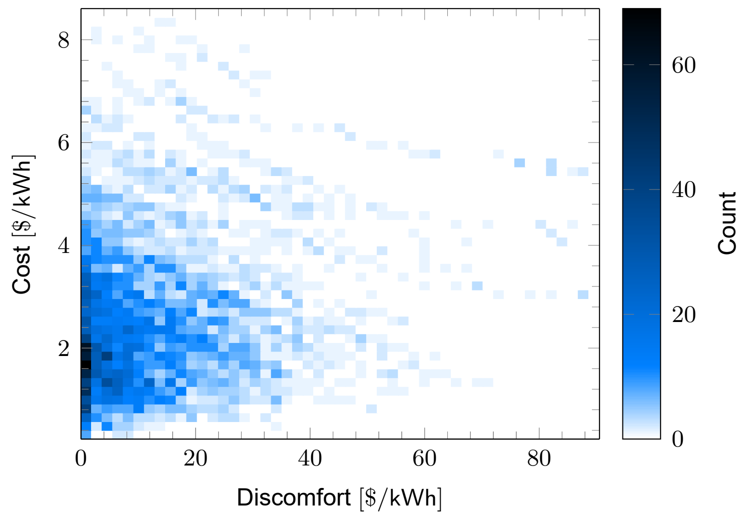
Since we cannot yet measure the impact of different degrees of consumer flexibility on the PAR values during the first consumer-level optimization phase, this subsection, thus, focuses on explaining the differences between the intermediary results found under the RTP and TOU tariffs. The individual optimization results are summarized in Table 25. 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 more flattened TOU price curve (see Figure 15) 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 non-dominated solutions by multi-objective optimization methods.

Table 25 – Summary of resulting load schedules from lower-level 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

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 29 and 30 with the TOU and RTP tariffs, respectively. To generate these histograms, we binned the range of solution space values within a 50×50 grid.

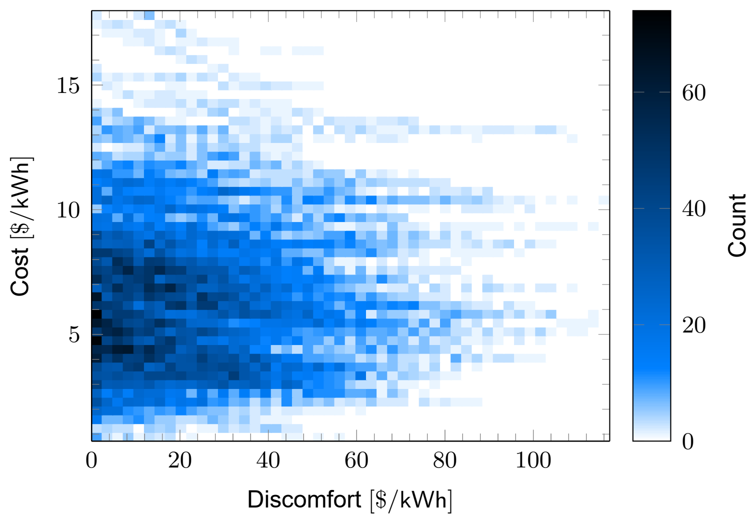
Figure 29 – 2D histogram of all base case solutions under the TOU tariff



Source: Desined by the author

One can see that the range of values occupied by the solutions under the TOU tariff in Figure 29 is less comprehensive than the range under the RTP tariff in Figure 30. 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.

Figure 30 – 2D histogram of all base case solutions under the RTP tariff

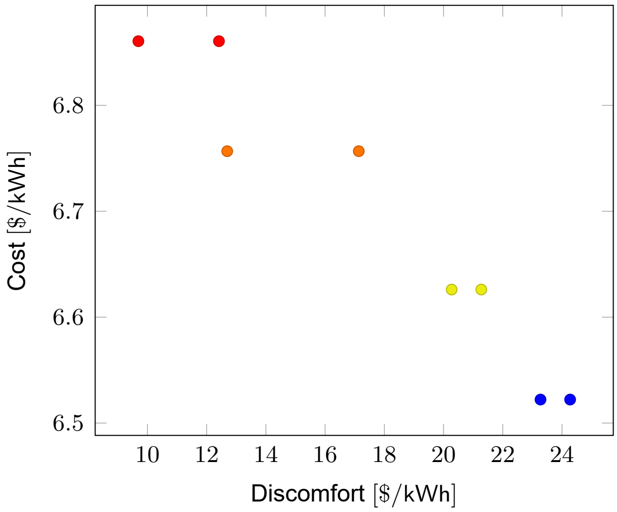


Source: Desined by the author

Considering that the number of non-dominated 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.

Next, we illustrate a consumer's Pareto front under each pricing method in Figures 31 and 32. More specifically, the figures show the Pareto fronts of consumer #655 under TOU and RTP, respectively. We chose this consumer in particular because they presented a greater than average number of flexible appliances (4) and an average number of inflexible appliances (10).

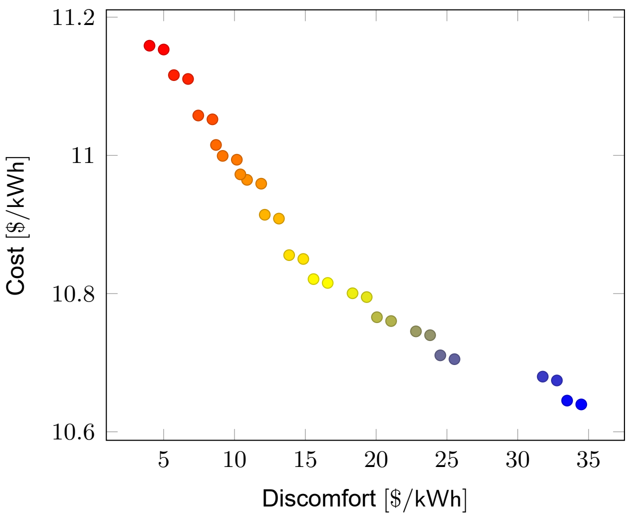
Figure 31 – Consumer's base case Pareto front under the TOU tariff



Source: Desined by the author

Figure 31 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 32 – Consumer's base case Pareto front under the RTP tariff

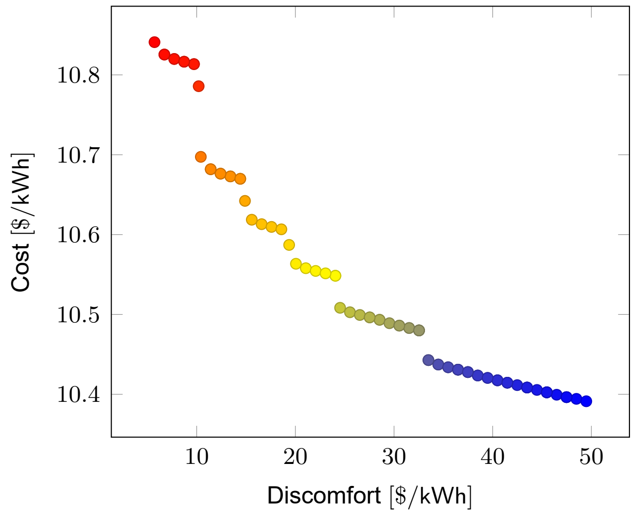


Source: Desined by the author

Figure 32 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.

Besides differences produced by distinct tariffs, we can also see in Table 25 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 33 shows 87 solutions in the Pareto front for the consumer #655, the same consumer we highlighted in Figures 31 and 32, but now under the flexible treatment. Alternatively, the results for the inflexible treatment group showed a very low number of solutions compared to the other groups.

Figure 33 – Consumer's flexible case Pareto front under the RTP tariff



Source: Desined by the author

We can see in Table 25 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.

4.4.2 Consumer 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 26 summarizes the PAR values resulting from each group. Recall that we obtained these values by following the bootstrapping procedure previously described in Section 3.3.2.3, i.e., these results refer to the 100 trials based on randomly selected groups of 100 (out of 1,000) consumers. Initially, we can notice that the average PAR value is lower for the flexible group, and the results under the RTP tariff seem either similar or slightly better (lower) than the results under the TOU tariff. Figure 34 highlights that difference in average PAR values.

Table 26 – Summary of the PAR results for different groups

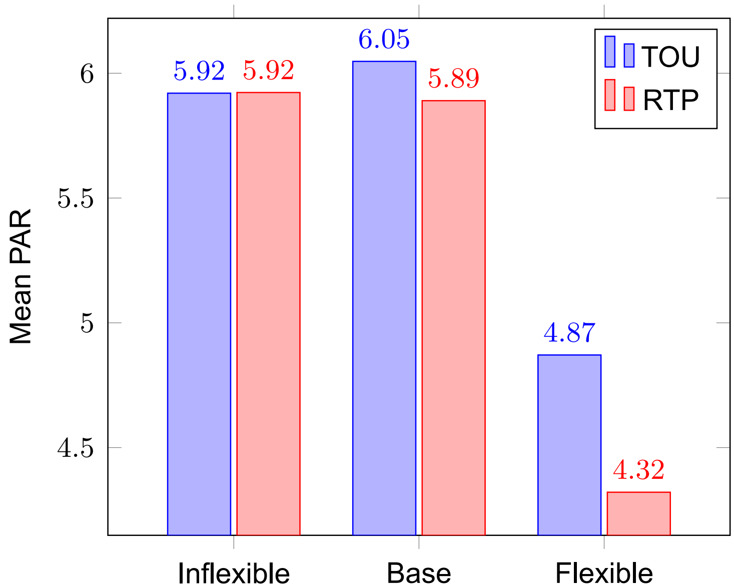
	Base	Inflexible	Flexible
	PAR	PAR	PAR
$p =$ TOU			
mean	6.048	5.920	4.871
SD	0.001	≈ 0	0.009
min	6.047	5.920	4.868
max	6.051	5.920	4.906
$p =$ RTP			
mean	5.890	5.923	4.321
SD	0.004	≈ 0	0.004
min	5.883	5.923	4.314
max	5.902	5.923	4.332

Based on Figure 34, communities under RTP pricing achieved, on average, a lower PAR value than 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 corroborate the point stated previously, we illustrate some aggregate demand profiles under different tariffs. As stated in Section 3.3.2.3, the planning horizon was divided into $T = 48$ time steps, meaning that the time horizon is divided in steps of $30\,\mathrm{min}$. Starting with the base case, Figures 35 and 36 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.

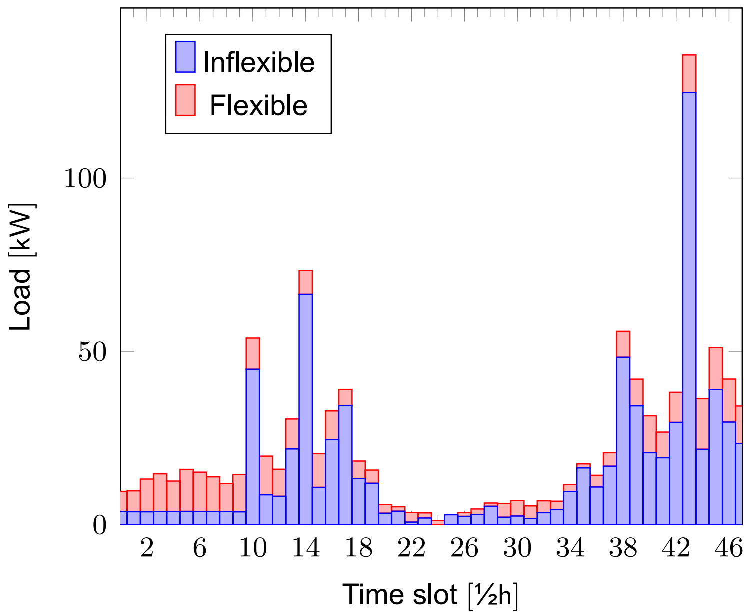
In Figure 35 one can see that part of the flexible loads have been shifted to the beginning of the day. This observation is compatible with the logic of the lower-level

Figure 34 – Bar chart comparing the mean PAR values for all groups



Source: Desined by the author

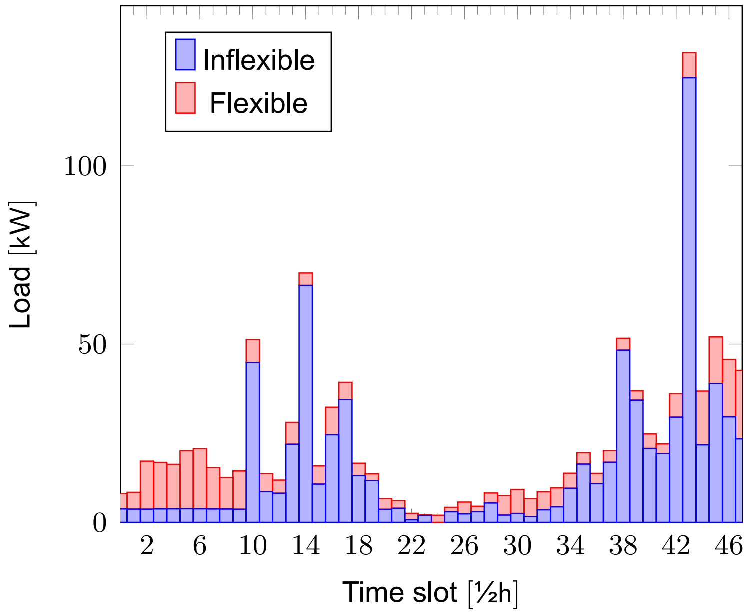
Figure 35 – Sample aggregate load profile of base group under the TOU tariff



Source: Desined by the author

optimization problem, which seeks to shift loads to off-peak times represented by lower prices.

Figure 36 – Sample aggregate load profile of base group under the RTP tariff



Source: Desined by the author

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

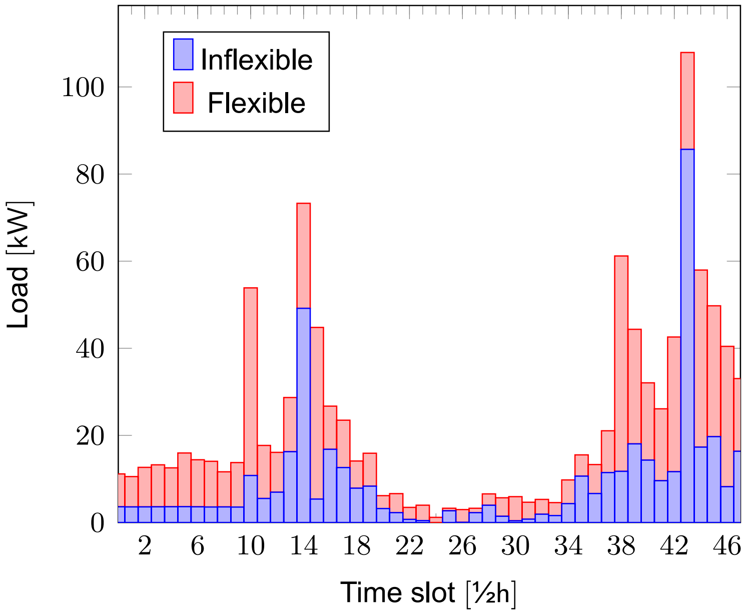
For the flexible treatment group in Figures 37 and 38, the effects of the greater diversity of load profiles are more noticeable. The aggregate profile under the TOU tariff achieves a PAR of 4.87, while the profile under the RTP tariff achieves 4.32.

An interesting observation is that even with the number of flexible devices being less or equal to the number of inflexible devices, flexible loads represent a large part of the demand profile. This suggests that flexible load management should not be thought of on an individual basis, but rather at the scale of a community represented by an aggregator.

Finally, the sample profiles for the inflexible treatment group are nearly identical under both tariffs, as Figures 39 and 40 show. This result is expected since no flexible devices are used by consumers in these scenarios, which means that only inflexible loads are present and no discomfort is created.

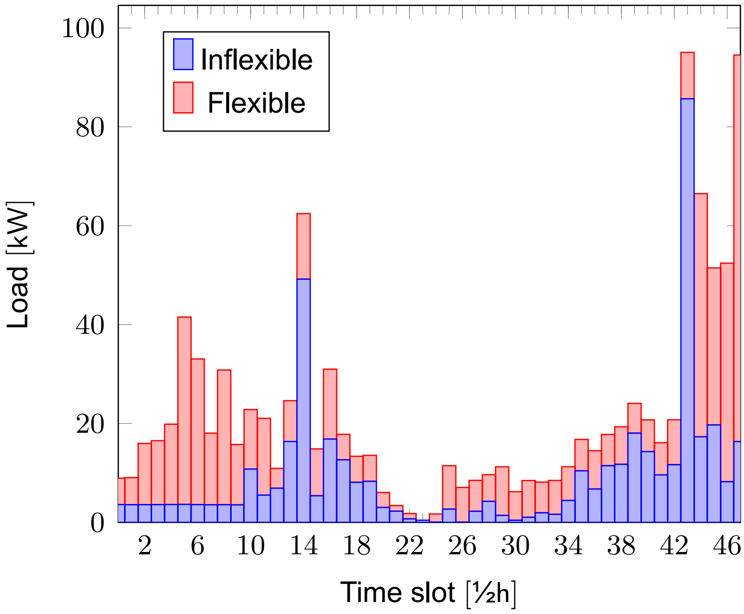
Despite the noticeable differences between the treatment groups, it is important that we assess whether these differences are statistically significant and not just the result of chance. In the next section, we present the results of our statistical analysis.

Figure 37 – Sample aggregate load profile of flexible group under the TOU tariff



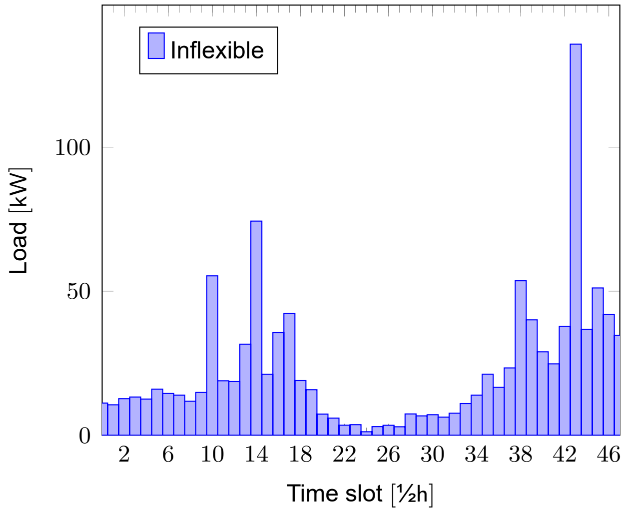
Source: Desined by the author

Figure 38 – Sample aggregate load profile of flexible group under the RTP tariff



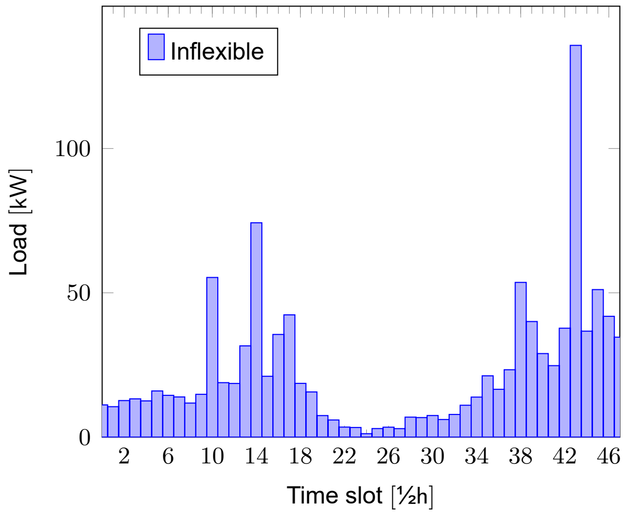
Source: Desined by the author

Figure 39 – Sample aggregate load profile of inflexible group under the TOU tariff



Source: Desined by the author

Figure 40 – Sample aggregate load profile of inflexible group under the RTP tariff



Source: Desined by the author

4.4.3 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 26 are statistically significant. In particular, we performed two-sample, two-sided t-tests, whose results are presented in Table 27.

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 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 4.4.1, 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 26 and 27 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.

Table 27 – 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	$1,316.66$	$< 10^{-16}$	$3,095.80$	$< 10^{-16}$

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. This observation naturally calls for more research on human behavior under different DR programs, a point that we further elaborate upon in the following section.

4.5 Concluding remarks

This chapter presented the results and discussions referring to the experiments presented in the previous chapter. Following the same order of presentation of the experiments, the first results of Section 4.1 refer to the optimization algorithms used in the upper-level optimization problem. These results were complemented by the comparisons in Section 4.2, which led us to the conclusion that the complexity of the outer optimization task is lower than the inner optimization task, and that a simple genetic algorithm is sufficient to achieve satisfactory results. Section 4.2 also investigated the effects of distributed energy resources on the peak-to-average ratio of simulated consumer communities, reaching the conclusion that these resources benefit the grid as a whole when used during peak demand periods, but for this, a better management of energy storage systems is necessary, considering that solar generation is limited to meeting demands in the middle of the day. Section 4.3 observed the impact of inflexible consumers and their decision making on the results of the outer optimization task, concluding that the flexibility and active participation of end consumers in shifting loads is essential for the demand response program to present positive results. Finally, Section 4.4 adapted a data set with 1,000 consumer profiles to the proposed model and verified the effect of individual flexibility of consumer appliances on the aggregate demand profile of the community. It was possible to observe that, even when considering communities with low overall flexibility, flexible loads have a considerable effect when aggregated, and that the study of consumer behavior and strategies towards motivating end consumers to make even a small portion of their household loads become more flexible can largely benefit the community as a whole.

5 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. This goal naturally relies on consumer acceptance and behavioral changes. In this research, we review models and approaches from the literature and identify characteristics and aspects focused on consumer needs. We then design a home energy management system based on a bi-level optimization model considering these characteristics and investigate the impact of optimization methods, distributed energy resources, consumer preferences and consumer behavioral changes on the benefits of a demand response program. A set of experiments were conducted throughout the development of the approach, the latter of which used a data set with 1,000 residential household profiles based on data from questionnaires offered to real-life consumers. The results show that flexibility does increase grid stability under a real-time pricing strategy, but surprisingly, that is not necessarily true under a time-of-use tariff. This finding is explained by the peculiar interplay between tariffs and flexibility and their joint influence on consumer behavior. Thus, in view of the activities performed in this study, we consider that the stated research aims have been achieved.

In general, our experiments and results shed light on the importance of understanding energy consumers (and prosumers) when designing demand response 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 socio-technical knowledge to be incorporated into technology design and education since energy consumer behavior and the expectations of demand response designers might not be well-aligned (SKJØLSVOLD et al., 2017). It is by recognizing that consumer behavior is just as important as new technologies to a sustainable energy system that we open up research opportunities for understanding how to influence end consumers and their energy consumption habits by considering their goals and preferences, and how these aspects are affected by other factors. 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 an answer to the above questions is crucial for the successful implementation of future demand-side management policies and practices.

5.1 Limitations and future works

The main limitation of the proposed method is the lack of a systematic literature review to minimize the risk that the aspects considered by the reviewed optimization models are not representative of the state of the art. This also reflects the main lesson learned: while the methods of reading and evaluating related works became simpler as we gained more knowledge about the research area, the methods of searching and selecting new papers while maintaining knowledge about previous research organized became more challenging over time. It was only later in the doctorate that the author adopted an article review system that made the whole process much easier, and which would have been very useful if used from the very beginning of the research. As for other method limitations, the simulations performed, even though they used data from real consumers, do not reflect the full complexity of real case studies. Also, it is known that the statistical tests performed to evaluate the effect of the modeled features are not infallible and do not explain causes (WAZLAWICK, 2014).

In the course of this research work, several limitations of the proposed approach were also identified, as well as ideas for research opportunities that were not investigated due the study's time and scope constraints. Regarding model limitations, we mention in Section 2.2.2 and Chapter 3 that the current model does not cover some aspects considered relevant by other state-of-the-art studies, such as handling the uncertainty of intermittent generation from renewable energy sources, and considering sustainability and environmental aspects in load management (see Table 2). Other aspects that were not considered concern the primary and secondary control of the grid in response to the integration of distributed energy resources that may affect grid stability. An unexplored opportunity was to consider power exchanges between microgrids or communities and even between consumers and prosumers, configuring a multi-microgrid scenario. Since the proposed approach is performed at two levels, the demand aggregator could manage the energy exchange between consumers aiming to reduce costs, increase community income or even reduce energy losses. These goals could be seen as new objectives of the upper-level optimization problem.

Last but not least, the residential energy management system envisioned in this study has abstracted several aspects relevant to its practical application in the residential setting. For example, what happens when the consumer does not follow the load scheduling suggested by the system? In this case, we do not foresee any form of direct control that forces the consumer to follow the schedule, and it can be deduced that the consumer is free to choose to follow it or not. If the scheduling is not performed, there will be a discrepancy between the demand predicted by the system, which is used in the upper optimization problem, and the actual demand. These and other issues, such as the cost-benefit of investing in storage systems, the specific characteristics of the communication architecture required for data transmission, and the magnitude of the volume of consumer data traffic during system operation, are important issues that need to be developed in order to achieve a prototype deployable application. In this line of thought, future work could also consider the feasibility of modularizing the load scheduling process to suggest the most advantageous schedules for the least possible number of loads, considering only those that the consumer is historically willing to shift.

5.2 Scientific production

As this study progressed, the milestone developments of our approach were presented through scientific papers. Table 28 lists the publications in which the author of this thesis appears as first author.

Table 28 – Scientific production stemming from the present study

Title	Year	Type	Status	Scores
A multiobjective-based approach for demand-side management in smart distribution grids	2020	Conference	Published[1]	H5: 16 (A4)
Aligning the interests of prosumers and utilities through a two-step demand-response approach	2021	Journal	Published[2]	Scopus: 98th percentile (A1)
Towards Consumer-Oriented Demand Response Systems	2022	Conference	Published[3]	H5: 22 (A3)
On the Impact of Flexibility on Demand-Side Management: Understanding the Need for Consumer-Oriented Demand Response Programs	2023	Journal	Submitted	—

[1] Almeida, Silva, et al. (2020)
[2] Almeida, Rabêlo, et al. (2021)
[3] Cortez et al. (2022)

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